R&D Concentration under Endogenous Fixed Costs: Evidence from Genetically Modified Corn Seed

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November 2015

Abstract

We derive the theoretical lower bound to concentration in R&D activity and empirically testable hypotheses for an industry characterized by endogenous fixed costs. Using data on field trial applications of genetically modified corn seed, we estimate the lower bound to R&D concentration. The theoretical results reveal a lower bound that is increasing in market size, but is less than the lower bound for market concentration. The empirical results imply that the markets for genetically modified corn seeds are characterized by endogenous fixed costs with predicted lower bounds to the one-firm R&D concentration ratio for an infinitely-sized market of 45.3% to 57.2%. We find evidence that adjusting for mergers and acquisitions raises the theoretical lower bound for infinitely-sized markets, but has no effect upon the predicted lower bound for current market sizes.

Keywords: *market structure, R&D, endogenous fixed costs, genetically modified corn seed*

JEL Codes: L22, Q16

Acknowledgements:
This project was supported by the Agricultural Food Research Initiative of the National Institute of Food and Agriculture, USDA, Grant #2008-35400-18704. Previous versions of this article have been circulated with the titles "Endogenous R&D Investment and Market Structure: A Case Study of the Agricultural Biotechnology Sector" and "R&D Concentration under Endogenous Fixed Costs: Evidence from the Agricultural Biotechnology Industry". The authors wish to thank participants at the 9th Annual International Industrial Organization Conference, April 8-10, 2011, Boston, MA, the 82nd Annual Meetings of the Southern Economic Association, November 16-18, 2012, New Orleans, LA, and the Social Sciences Brown Bag Series at Colgate University, October 8, 2015.

In 2009, the US Department of Justice and US Department of Agriculture announced a series of joint public workshops exploring issues of competition in agriculture. (DOJ Press Release, 2009) The public comments submitted in support of these workshops raised concerns of anticompetitive practices and "excessively" high levels of concentration across a variety of agriculture-related industries with many focusing specifically on the seed industry and agricultural biotechnology firms. A group of fourteen state attorney generals were one group raising concerns of concentration in the seed industry citing that "increased vertical integration and acquisitions may have raised the bar for entry so high that entry into the *trait market* is difficult, or nearly impossible" [emphasis ours]. (Munson, London, and Lindeback, 2010) One of the primary concerns regarding concentration in the seed industry is not solely the levels of market concentration as measured by sales, but rather the concentration in seed traits and germplasm. (Hubbard, 2009)

In order to examine concerns about concentration in research and development (R&D) in agricultural biotechnology, we derive the theoretical lower bounds to R&D concentration based upon Sutton's (1998; 2007) theory of market structure under endogenous fixed cost (EFC) and empirically test the model's predictions using field trial data on releases of genetically modified (GM) corn seed varieties. We exploit variation in market size along two dimensions: (i) geographically as adoption rates for GM corn seed varieties vary by state and agricultural region; and (ii) inter-temporally as adoption rates for GM corn seed have been steadily increasing over time. We test the robustness of our estimation results by considering alternate definitions of geographic sub-markets, R&D concentration measures, minimum setup costs, and product heterogeneity. Finally, we examine the concern that mergers and acquisitions have increased the concentration of innovative activity and intellectual property (IP) in the agricultural biotechnology sector, an issue discussed in Moss (2009), Dillon and Hubbard (2010), and Moschini (2010).

In the US in 2006, private-sector firms spent $1.2 billion in crop seed research and development which accounts for half of all R&D expenditure on crops and one-fifth of all R&D expenditure on food and agriculture. (Fuglie, et al., 2011) In addition to the large amounts of private R&D expenditures, the agricultural biotechnology seed sector has become increasingly concentrated as the four-firm market concentration ratio increased from 21.1% in 1994 to 53.9% in 2009. (Ibid) However, the relationship, if any, between the increased market concentration and R&D investments remains ambiguous. R&D intensity, measured as the share of industry-level R&D expenditure to sales, increased from 11.0% in 1994 to 15.0% in 2000 before falling back to 10.5% in 2009. (Ibid) These aggregate numbers obscure significant heterogeneity across firms as the eight largest seed companies have an average R&D intensity of 15.8% while accounting for 75.6% of the global R&D share. (Ibid) Figure 1 plots the three-year average one-firm concentration ratios and adoption rates for GM corn seed from 1996-2010 and illustrates two important trends: (i) increasing rates of adoption of GM seed varieties across time; and (ii) single firm R&D concentration ratios that initially increased, peaked at 80% in the early 2000s, and have remained consistently above 50%.

A critical assumption in our analysis is that R&D investments in GM corn seed made by firms in the US are recouped via commercialization in the US market. The disparate regulatory processes across countries provide an additional regulatory hurdle to firms seeking to innovate domestically and commercialize abroad. Recent surveys of global agricultural biotechnology firms indicate that many of the GM crop varieties adopted outside of the US have also been developed abroad. (James, 2010) The US constitutes 66.7% of global area harvested with GM corn varieties in 2010 which was down from much higher levels that persisted from the first GM adoptions in 1997 through the mid-2000s. (Barrows, Sexton, and Zilberman, 2014) Figure 2 illustrates the trends in global, US, Argentinean, and South African acreage of GM corn varieties starting with their introduction in 1997 through the present. Although the gap between worldwide and US acreage has been widening since 2007, for the vast majority of our sample the US was the primary market for GM corn seed varieties. According to the ISAAA GM Approval Database, there have been 95 approvals for cultivation of GM corn seed varieties globally with 37 of these varieties approved in the US. Of the varieties approved in the US, 7 have been approved in the US only with an additional 17 also being approved by either Canada or Japan who jointly account for less than 1.5% of global maize production.

A second critical assumption relies on the observable variation across geographic regions in the US for different corn seed varieties. As highlighted in Shi, Chavas, and Stiegert (2010), Stiegert, Shi, and Chavas (2011), and Ma and Shi (2013), there is variation in the varieties, both GM and non-GM, of corn seed that retail in different geographic regions. They find that the differential availability of varieties and the suitability of each variety to the agro-climatic conditions in a particular region lead to variation in both the prices charged and the product life cycles of corn seed varieties across regions. We extend their analyses, which focus upon geographic variation within the Corn Belt, to non-Corn Belt regions as well which are also characterized by differences in agro-climatic conditions.

The model of endogenous market structure and R&D investment developed by Sutton (1998; 2007) has been utilized to empirically examine a variety of industries including food and beverage manufacturers (Sutton, 1991), online book retailers (Latcovich and Smith, 2001), chemical manufacturing (Marin and Siotis, 2007), supermarkets (Ellickson, 2007), banking (Dick, 2007), newspapers and restaurants (Berry and Waldfogel, 2010), and across industries (Robinson and Chiang, 1997; Sutton, 1998). These analyses have focused on examining the relationship between market 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, 2010), or advertising (Robinson and Chiang, 1997; Latcovich and Smith, 2001). 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. We 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 EFC. Additionally, our analysis extends previous examinations into merger and acquisition activity in agricultural biotechnology in estimating whether 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.

If the GM corn seed market is characterized by EFC, the high levels of concentration, accompanied with high levels of innovative activity amongst the largest firms, are a natural outcome of technology competition. Therefore, as market size becomes large, these industries are characterized by firms that are able to gain an increased market share by investing in product quality and preclude entry by additional competitors, thus bounding concentration away from perfectly competitive levels. We draw upon the results of Sutton (1998; 2007) 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 as market size becomes large is less than the lower bound to market concentration, defined as firm sales relative to industry sales; and (ii) the lower bound to R&D concentration is increasing in market size such that larger markets are characterized by greater concentration in R&D activity. In estimating a lower bound to R&D concentration under EFC, we would expect the concentration ratios to be less than what we observe for concentration measured by firm sales and for this concentration to be positively related to market size.

We use data on R&D investments, in the form of field trial applications for GM corn seed, to test for lower bounds to R&D concentration among agricultural biotechnology firms. Our empirical analysis relies on the assumption that field trial applications are a relevant indicator of intermediate R&D for GM corn seed. Moser, Ohmstedt, and Rhode (2015) find that the field trial information reported in patent citations are a robust indicator of the size of the inventive step for hybrid corn varieties. The results from the empirical estimations support the hypothesis that the GM corn seed markets are characterized by endogenous fixed costs to R&D with the theoretical lower bounds to R&D concentration ranging from 45.3% to 57.2% and are robust to alternate definitions of market size and R&D concentration. We also find that accounting for merger and acquisitions in the agricultural biotechnology industry increases the lower bound to R&D concentration as market size becomes large, but has little effect upon the predicted levels of concentration for current market sizes. The results reveal the importance of sunk, fixed

R&D investments in jointly determining both the levels of concentration and innovation activity and will be of interest to both regulators and policymakers concerned with the observed high levels of concentration, and in particular the high levels of concentration in intellectual property, in GM corn seed markets.

The remainder of the analysis is organized as follows: the second section presents a brief overview of the agricultural biotechnology industry and GM corn seed markets and discusses the literature addressing innovation and concentration in GM crops; the third section develops the theoretical model of R&D concentration and derives the empirically testable hypotheses; the fourth section discusses field trial applications as well as the other data utilized in the estimation; the fifth section presents the results and discussions; and the final section concludes.

The Agricultural Biotechnology Industry

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. Plants typically had to reach maturity in order to discern whether they displayed the selected traits, implying considerable time investment and uncertainty 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. The expansion of cellular and molecular biology throughout the 1960s and 1970s, 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 (James, 2010). These technological 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; and 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 (Moschini, 2010).

These innovations were accompanied by changes within the agricultural input industry in the 1980s and 1990s which have motivated several empirical examinations of market structure and innovation in the GM crop seed industry. The industry attributes consistently identified in the literature include: (i) substantial expenditures on R&D that may create economies of scale and scope within firms; (ii) seed and agricultural chemical technologies that potentially act as complements within firms and substitutes across firms; (iii) property rights governing plant and seed varieties that have become more clearly defined since the 1970s; (iv) high levels of consolidation activity in the form of mergers and acquisitions of seed manufacturers; and (v) an increasing number of cross-license agreements between patent holders over the transfer of complementary genetic traits. Regarding the third stylized fact, two U.S. Supreme Court decisions, *Diamond v. Chakrabarty* (1980) and *J.E.M. Ag Supply v. Pioneer Hi-Bred* (2001), upheld the use of utility patents for genetically engineered organisms and genetically engineered plants, respectively, notwithstanding limited forms of IP protection afforded via the Plant Patent Act of 1930 and the Plant Variety Protection Act of 1970. The consolidation activity alluded to in the fourth stylized fact refers to the widespread acquisition of seed manufacturers, and their germoplasm IP, by chemical conglomerates such as Monsanto, DuPont, Syngenta, Dow, Bayer, and BASF, which has resulted in considerable concentration in the global seed industry (King, 2001; Howard, 2009). These stylized facts motivate our interest in exploring the endogenous relationship between R&D expenditures and the number and concentration of GM crop seed manufacturers.

In the literature that examines the relationship between market structure and innovation, Schimmelpfennig, Pray, and Brennan (2004) find a negative and endogenous relationship between measures of industry concentration and R&D intensity whereas Brennan, Pray, and Courtmanche (1999) find a heterogeneous impact upon innovation activity following mergers and acquisitions. The explanations behind the high levels of firm consolidation activity in the agricultural biotechnology industry 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). Additional stylized examinations have identified an endogenous, cyclical relationship between industry concentration and R&D intensity (Oehmke, Wolf, and Raper, 2005), decreasing product life cycles associated with increasing innovation in corn seed (Magnier, Kalaitzandonakes, and Miller, 2010), and an endogenous relationship between firm innovation strategies, including complementary intellectual assets, and industry consolidation characteristics (Kalaitzandonakes and Bjornson, 1997). Whereas previous examinations have focused upon identifying the endogenous relationship between R&D intensity and concentration in agricultural biotechnology, we determine whether sunk R&D investments drive this endogeneity.

Endogenous Market Structure and Innovation: The "Bounds" Approach

A Lower Bound to R&D Concentration

We adapt the theoretical EFC model of market structure and sunk R&D investments developed by Sutton (1998) to derive the empirically testable hypotheses for the lower bound to R&D concentration under EFC. Sutton (1998) finds that the lower bound to market concentration, defined as the ratio of firm sales to total industry sales, is bounded away from perfectly competitive levels when an industry is characterized by EFC. Moreover, the EFC theory implies that R&D intensity, defined as the ratio of firm R&D to firm sales, is also characterized by a lower bound which is increasing in market size and equivalent to the bound to market concentration as market size becomes large. However, the theory fails to address the implications of the EFC model on the level of concentration in R&D within these industries.

The specification of the theoretical model, and subsequent empirical analysis, relies upon a set of assumptions regarding the nature of product differentiation in the agricultural biotechnology sector. First, we 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 sub-markets. This assumption corresponds with the empirical findings of Shi, Chavas, and Stiegert (2010) and Stiegert, Shi, and Chavas (2011) of spatial price differentiation in GM corn and implies that the agricultural biotechnology industry is characterized by horizontal product differentiation. Secondly, we assume that farmers value higher quality products such that a firm competes within each sub-market primarily via vertically differentiating the quality of its seed traits. We estimate a model of vertical product differentiation in the agricultural biotechnology sector while accounting for horizontal differentiation via the definition of geographically distinct product sub-markets.

To simplify the analysis, it is useful to introduce notation for industry sales revenue and R&D expenditure. Firm-level sales revenue Π_{im} is defined for firm i in sub-market m and total industry sales revenue Π_m is obtained by summing across all firms in sub-market m such that $\Pi_m = \sum_{i \in m} \Pi_{im}$. Similarly, R&D expenditure is also defined at the firm F_{im} and sub-market $F_m = \sum_{i \in m} F_{im}$ levels respectively. We define the degree of market segmentation, or product heterogeneity, $h_m \in [0,1]$ as the share of industry sales revenue in sub-market m accounted for by the largest product category l such that:

$$h_m = \max_l \frac{\Pi_{lm}}{\Pi_m}, \tag{1}$$

where $h_m = 1$ corresponds to a sub-market in which only a single product is offered.

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 sub-market m can be stated as:

$$C_{1m} = \frac{\widehat{\Pi}_m}{\Pi_m} \geq \alpha(\sigma, \beta) \cdot h_m, \tag{2}$$

where α is some constant for a given set of parameter values (σ, β), σ is a parameter capturing consumer preferences and product market substitutability, and β is a parameter capturing the elasticity of R&D expenditures. The firm offering the highest level of quality is identified by a hat accent character (i.e., $\widehat{\Pi}_m$ is the sales revenue for the quality-leading firm in sub-market m). The value of alpha α depends upon industry technology, product market competition, and consumer preferences and signifies the extent that a firm can escalate product quality via R&D investment and capture market share from rivals. Equation (2) implies that the lower bound to market concentration is independent of the size of the market in EFC industries which contrasts with exogenous fixed cost industries in which the lower bound to market concentration is decreasing and approaches zero as the size of the market increases.

Moreover, Sutton's (1998) Theorem 3.2 implies an equivalent expression for the lower bound to R&D-intensity $\widehat{\mathrm{P}}_m$ for the quality-leading firm such that:

$$\widehat{\mathrm{P}}_m = \frac{\hat{F}_m}{\widehat{\Pi}_m} \geq \alpha(\sigma, \beta) \cdot h_m - \frac{F_0}{\Pi_m} \tag{3}$$

where F_0 are the fixed setup costs associated with entering a sub-market. Equation (3) implies that the R&D-to-sales ratio shares the same lower bound as the single firm concentration ratio as the size of the market becomes large (i.e., $\Pi_m \rightarrow \infty$). For finitely-sized markets, the lower bound to R&D intensity is increasing in the size of the market as the largest firms respond to these increases with an escalation of R&D expenditures.

The lower bound to R&D concentration can be derived directly by multiplying both sides of equation (3) by the sales revenue of the market leading firm in sub-market m:

$$\hat{F}_m \geq \alpha(\sigma, \beta) \cdot h_m \cdot \widehat{\Pi}_m - F_0 \cdot \frac{\widehat{\Pi}_m}{\Pi_m}. \tag{4}$$

Dividing both sides of equation (4) by total industry sales revenue in sub-market m yields:

$$\frac{\hat{F}_m}{\Pi_m} \geq \left[\alpha(\sigma, \beta) \cdot h_m - \frac{F_0}{\Pi_m}\right] \cdot \frac{\widehat{\Pi}_m}{\Pi_m}. \tag{5}$$

However, free entry in equilibrium implies that total industry sales revenue Π_m equals total industry R&D expenditure F_m such that equation (5) can be written as:

$$\frac{\hat{F}_m}{F_m} \geq \left[\alpha(\sigma, \beta) \cdot h_m - \frac{F_0}{\Pi_m}\right] \cdot \frac{\widehat{\Pi}_m}{\Pi_m}. \tag{6}$$

R&D concentration $\hat{R}_m$ is defined as the amount of R&D for the quality-leading firm relative to total R&D in sub-market m such that $\hat{R}_m = \frac{\hat{F}_m}{F_m}$. After substituting equation (2) into equation (6), the single-firm R&D concentration ratio R_{1m}, which must be at least as large as $\hat{R}_m$, can be specified as:

$$R_{1m} \geq \left[\alpha^2(\sigma,\beta)h_m^2 - \alpha(\sigma,\beta)h_m \frac{F_0}{\Pi_m}\right]. \tag{7}$$

Equation (7) provides the empirically testable hypothesis of endogenous R&D expenditures. If sunk R&D costs are endogenous, there is a nonlinear relationship between the degree of market segmentation (product homogeneity) h_m and the single-firm R&D concentration ratio R_{1m} for a given sub-market m. Equation (7) also 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 which is less than the lower bound to market concentration $\alpha(\sigma,\beta)h_m$ since both the product homogeneity parameter and the α escalation parameter lie between 0 and 1. Additionally, for finitely-sized markets the lower bound to R&D concentration retains the feature of the lower bound to R&D intensity of increasing with 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 single-firm R&D concentration ratio in sub-market m can be expressed as:

$$R_{1m} = \frac{\hat{F}_m}{F_m} = \frac{F_0}{\Pi_m}. \tag{8}$$

For some minimum fixed setup cost F_0, concentration in R&D investments is decreasing in market size and approaches zero as market size becomes large. Therefore, R&D concentration under exogenous fixed costs is greatest in smaller-sized markets.

Figure 3 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 Π increases. If an industry is characterized by homogenous products (i.e., low $h = 0.75$), 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 $h = 0.25$) 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.

Empirical Specification

Equations (7) and (8) 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, equation (7), whereas R&D concentration in exogenous fixed cost industries is decreasing in market size, equation (8). The empirical specification that we adopt was developed in Sutton (1991) and has since been adapted and extended in Giorgetti (2003), Dick (2007), and Ellickson (2007). 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:[1]

$$\tilde{R}_n = \ln\left(\frac{R_n}{1 - R_n}\right). \tag{9}$$

We follow the functional form suggested by Sutton for the lower bound estimation such that for some sub-market m, the R_{nm} concentration ratio is characterized by:

$$\frac{\tilde{R}_{nm}}{h_m^2} = \theta_0 - \theta_1 \frac{1}{h_m \ln(\Pi_m / F_0)} + \varepsilon_m, \tag{10}$$

where h_m is the degree of product heterogeneity, F_0 is the fixed setup cost, Π_m is total industry sales, and (θ_0, θ_1) are the parameters of the empirical model. The intercept parameter θ_0 reflects the theoretical lower bound as the market size becomes large whereas the slope parameter θ_1 reflects how the lower bound changes with changes in market size. The residuals ε between the observed values of R&D concentration and the lower bound are distributed according the Weibull distribution such that:

$$F(\varepsilon) = 1 - \exp\left[-\left(\frac{\varepsilon - \mu}{\delta}\right)^{\gamma}\right], \quad \gamma > 0, \delta > 0 \tag{11}$$

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 whereas the scale parameter δ captures the dispersion of the distribution. To test for a lower bound to R&D concentration, it is equivalent to testing whether the residuals fit a two or three parameter Weibull distribution, that is testing whether $\mu = 0$. However, as Smith (1985) identifies, fitting equation (10) directly

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[1] As the transformed R&D concentration is undefined for values of $R_{nm} = 1$, we monotonically shift the R&D concentration data by -0.0001 prior to the transformation.

via maximum likelihood estimation is problematic for shape parameter values $\gamma \leq 2$.[2] 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), we 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:

$$\begin{aligned} &\min_{\{\theta_0,\theta_1\}} \sum_{m=1}^{N} \left[\frac{\tilde{R}_{nm}}{h_m^2} - \left(\theta_0 - \theta_1 \frac{1}{h_m \ln(\Pi_m/F_0)} \right) \right] \\ &s.t. \quad \frac{\tilde{R}_{nm}}{h_m^2} \geq \left(\theta_0 - \theta_1 \frac{1}{h_m \ln(\Pi_m/F_0)} \right), \forall m. \end{aligned} \tag{12}$$

From the first step, we 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, we maximize the log pseudo-likelihood function:

$$\max_{\{\gamma,\delta,\mu\}} \sum_{m=1}^{N-k} \ln \left[\left(\frac{\gamma}{\delta} \right) \left(\frac{\varepsilon_m - \mu}{\delta} \right)^{\gamma - 1} \exp \left[- \left(\frac{\varepsilon_m - \mu}{\delta} \right)^{\gamma} \right] \right] \tag{13}$$

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 distribution 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

[2] Specifically, for $1 < \gamma \leq 2$, a 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.

the data fits the restricted, two parameter model such that $\mu = 0$. For each estimation, we report the likelihood ratio statistic which is distributed with a chi-squared distribution with one degree of freedom. Finally, we 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 EFC model à la Sutton (1991, 1998), it is necessary to have both firm-level sales data and total market size for each associated sub-market. Although such data are of limited availability across all markets for GM corn seed, estimation of the endogenous lower bound to R&D concentration 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.

Measuring R&D Concentration

We exploit two dimensions of variation in R&D investment and market size by estimating the lower bound across geographic sub-markets as well as over time. In doing so, we are able to capitalize upon changes in farmer and 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 inter-temporal variation in market size permits the theory to be tested across a variety of market sizes.

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 are unavailable for the GM corn seed, there are publicly available data that capture 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 are 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 (FTA) data are appropriate for the analysis as they capture 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). (BRS, 2010) The database, covering 1985 through present day, includes the institution applying for the permit, the status of the application, the plant (or "article") type, the number of sites tested, 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 for all applications pertaining to the importation, interstate movement, or release of GE organisms. As of October 2010, the database includes 33,440 total applications for crop release across all crop types. After dropping non-profit institutions and research laboratories and limiting observations to permits or notifications for GM corn varieties, there are 6,696 remaining observations in the database. Previous analyses that have utilized FTA data have examined the relationship between R&D investment, firm output, and merger and acquisition activity (Brennan, Pray, and Courtmanche, 2000), the positive correlation between field trial applications and subsequent commercialization for corn and soybean varieties (Stein and Rodríguez-Cerezo, 2009), and the impact of labeling regime differences between the USA and EU upon firm incentives to engage in innovation (O'Connor, 2010).

Figure 4 plots the annual number of field trial applications by private enterprises for GM corn seed varieties between 1988 and 2010 as well as the yearly number of firms that submitted an application. The data reveal that the number of distinct firms applying for at least one field trial in a given year peaked in the mid-1990s with 25 firms submitting applications in 1995 before falling and roughly leveling off by the early 2000s. This is consistent with an industry characterized by a new technology in which significant initial entry occurred, followed by a "shakeout" of firms when the commercialization possibilities of the technology are realized. The FTA data indicate that GM corn applications increased throughout the 1990s, peaked in the early 2000s, before falling and leveling off by the mid-2000s. The number of yearly applications, together with the firm data, illustrates that average per firm R&D activity was increasing through the early 2000s for GM corn seed varieties before leveling off, a story that is consistent with the slow introduction of subsequent generations of GM crops.

A critical assumption of the EFC framework is the presence of geographically distinct sub-markets. As a robustness check, we estimate the lower bound to R&D concentration when field trials are conducted solely within a particular sub-market, both when permitting and excluding field trials that were also conducted in Hawaii and Puerto Rico where many agricultural biotechnology firms have research facilities. These robustness checks are valid under the weaker assumption that field trials that are conducted exclusively in a particular region are related to that region's product market and are independent of the product markets in other regions.

Finally, we also consider a measure of R&D concentration from field trial application data which has been adjusted for past mergers and acquisitions. If intellectual property assets are becoming increasingly concentrated among a smaller number of firms, then it is possible that the lower bound to R&D concentration is higher not due to endogenous fixed costs, but rather due to this consolidation activity. We utilize company histories and Lexis-Nexis news releases to identify merger and acquisition activity and the effective merger date in order to construct a measure of R&D concentration accounting for ownership changes. Although completed independently, our list of changes in corporate ownership, reported in Appendix A: Merger and Acquisition Activity in Agricultural Biotechnology, corresponds to the activity reported in Fuglie, et al. (2011).

The Market for GM Corn Seed

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 (2010), 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, both domestic and foreign.

Under the assumption that firms can only recoup investments in R&D in GM corn seed domestically, the identification of regional domestic sub-markets for different seed varieties remains problematic. As we only have data on firm R&D concentration available at the state level, the difficulty associated with defining relevant sub-markets is exacerbated as we are restricted to defining regional sub-markets as groups of entire states. In support of the idea that there exists regional variation in the market for GM corn seed, Shi, Chavas, and Stiegert (2010) and Stiegert, Shi, and Chavas (2011) find evidence of both spatial pricing differences across geographic regions in the US and product differentiation via the bundling of seed traits according to climate and other external factors related to production. Moreover, Ma and Shi (2013) find significant geographic variation in survival rates for both GM and non-GM hybrid corn seeds such that "the introduction of GM technology did not change the region-specific nature of seed development". (Ma and Shi, 2013, pp. 555) Although their data covers a substantial proportion of US corn production and is defined at a lower geographic level, it does not account for variation that occurs in regions outside of the Corn Belt.

In our first set of estimations, we consider three alternate classifications of regional sub-markets for corn seed varieties which account for both the categorization of corn-producing states into "core" and "fringe" regions according to Stiegert, Shi, and Chavas (2011) as well as state-level observable differences in climate, agricultural characteristics, and corn-specific production. First, we consider a direct implementation of the spatial corn seed markets implied by Stiegert, Shi, and Chavas (2011) by identifying three distinct and exclusive sub-markets for corn seed. We define the "core" Corn Belt region in all classifications to be comprised of Illinois and Iowa, the "fringe" Corn Belt region to contain Colorado, Indiana, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, N. Dakota, Ohio, S. Dakota, and Wisconsin, and the remaining states as a single non-Corn Belt region.

Although the separation of the US into "core" Corn Belt, "fringe" Corn Belt, and non-Corn Belt regions provides a useful first examination of the relationship between R&D concentration and sub-market size, this classification suffers from several limitations. First, the estimation of the lower bound to R&D concentration based on a limited number of observations is problematic from both a practical and inferential viewpoint. Second, it is not evident that the simple trivariate categorization sufficiently accounts for geographic differences in climate or agricultural production practices, especially pertaining to the use of fertilizers, herbicides, and insecticides which are particularly relevant to examinations of GM seed varieties. In order to overcome these limitations and introduce additional realism into the categorization of states, we use observable data on agricultural production from the period prior to the widespread adoption of GM varieties (1990-1995) to subdivide the "fringe" Corn Belt states according to observable differences.[3] The resulting classification considers four "fringe" sub-markets comprised each of three "fringe" Corn Belt states as identified in Stiegert, Shi, and Chavas (2011).

Finally, we relax the assumption of a unitary non-Corn Belt sub-market and allow for geographic variation in the sub-markets for corn seed within regions in which corn production is the not the primary agricultural commodity. We separate the non-Corn Belt states into five distinct geographic sub-markets, which when coupled with the "core" Corn

[3] For additional discussion of the analysis of the geographically distinct sub-markets, please refer to Appendix B: Sub-Market Analysis for GM Corn Seed.

Belt sub-market and the four "fringe" Corn Belt sub-markets, result in ten total sub-markets for GM corn seed which we observe across four separate time periods. We assume this final classification when performing our robustness checks and in our analysis of the impact of merger and acquisition activity. The three sub-market classifications are summarized in table 1 along with the 2010 market shares of corn production and total number of field trial applications for each region in our sample.

Measuring Market Size, Product Heterogeneity, and Minimum Setup Costs

In order to estimate the lower bound to R&D concentration, we require data on the size of the market, the amount of product heterogeneity, and the minimum R&D setup costs in addition to the measures of R&D concentration. Data on total annual corn acreage, both planted and harvested, at the state-level are available from the *Acreage* reports compiled from the June Agriculture Survey by the National Agricultural Statistics Service (NASS). The Economic Research Service (ERS) estimates yearly seed costs in dollars per acre based on crop-specific data collected in the Agricultural Resource Management Surveys (ARMS). After adjusting for inflation, we multiply seed costs by total corn acres planted in order to arrive at total market size which we treat as a proxy for industry sales in equation (10).

Since 2000, the June Agricultural Survey has also sampled farmers regarding the adoption of GM seed varieties across a sub-sample of states.[4] Using these survey data, ERS computes and reports estimates for the extent of GM adoption separated by crop type and GM characteristics for a sample of states. GM adoption rates, supplemented with the

[4] NASS estimates that the states reported in the GM adoption tables account for 81-86% of all corn acres planted. For states without an adoption estimate, overall US adoption estimates are used to compute the heterogeneity index.

adoption data from Fernandez-Cornejo and McBride (2002) for the years 1996-1999, are used to construct a product heterogeneity index for corn seed that varies across time. By definition, the product heterogeneity index is meant to capture the percent of industry sales of the largest product group. We treat corn seed varieties as homogenous within product groups, broadly 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. By constructing the heterogeneity index in this manner, we are potentially introducing measurement error as the broad categories contain a variety of sub-categories corresponding to more specific traits or combinations of traits. This potential measurement error, in which actual heterogeneity is greater than measured heterogeneity, would bias our results towards the alternative hypothesis that GM seed markets are characterized by exogenous fixed costs.

The final component required for the estimation of the lower bound to R&D concentration is the minimum setup cost associated with product market entry. We use data reported in Frey (1996) and Traxler, et al. (2005) 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), reported by the State Agricultural Experiment Stations (SAES) and the Agricultural Research Service (ARS), and dividing by the total number of projects reported for both agencies in order to obtain an average SY for a single crop.[5] Minimum setup costs are obtained by multiplying the average SY by the private industry cost per SY ($148,000) and adjusting for inflation.[6]

Empirical Results and Discussion

Prior to estimating the lower bound to R&D concentration, we examine graphically whether the GM corn seed market appears to be characterized by an endogenous lower bound to R&D concentration. In figure 5, the one- and four-firm R&D concentration ratios are plotted against the market size of each sub-market for every sample. Figure 5 illustrates that R&D concentration ratios are non-decreasing in market size, regardless of the definition of sub-markets, implying the possibility of a lower bound. However, these descriptive illustrations do not account for differing levels of product heterogeneity across time and it is not possible to reconcile these illustrations directly with the lower bound to R&D concentration implied by the theory.

After adjusting for R&D concentration in each submarket according to equation (9), we estimate the relationship between the single-firm R&D share and the ratio of total market size to private setup costs for each of the sub-market definitions. The subsequent section considers robustness checks including alternate measurements of R&D concentration according to field trials conducted only within each sub-market, considering an alternate measure of fixed setup costs, and exploring the assumption of product heterogeneity. In the final section, we adjust for merger and acquisition activity in the

[5] 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)."
[6] As a robustness check, we consider an alternate definition based upon public sector cost per SY ($296,750).

agricultural biotechnology sector and examine the impact of this consolidation activity upon concentration in R&D.

Estimating the Lower Bounds to R&D Concentration

The two-stage baseline estimation results of the lower bounds to R&D concentration in GM corn seed are reported in table 2 for each of the three sub-market definitions. The logit transformation of R&D concentration implies that a direct interpretation of the estimated coefficients is difficult, but the coefficient on the intercept term $\hat{\theta}_0$ can be interpreted as the theoretical lower bound as market size becomes large (i.e., $\frac{\Pi_m}{F_0} \rightarrow \infty$) and the coefficient on market size $\hat{\theta}_1$, adjusted for product heterogeneity and fixed setup costs, indicates whether the lower bound is increasing, decreasing, or unchanging to market size. The null hypothesis of exogenous fixed costs implies that the theoretical lower bound to R&D concentration converges to approximately 0 as market size becomes large and that the predicted lower bound is non-increasing in market size (i.e., $\hat{\theta}_1 \leq 0$). In our hypothesis testing of the theoretical lower bound, we test whether the share of R&D by the leading firm converges to less than 10% (i.e., $\hat{\theta}_0 \leq -2.197$) under product homogeneity (i.e., $h = 1$) and large market sizes.

The results from the first-stage estimation reveal that the predicted lower bound to R&D concentration is significantly increasing in market size (i.e., $\hat{\theta}_1 > 0$) for the six and ten region sub-market definitions and a theoretical bound to R&D concentration that is significantly different from zero for all three sub-market definitions. The fitted and theoretical lower bounds to R&D concentration under ten regional sub-markets, along with 95% confidence intervals, are illustrated graphically in figure 6 along with the current, observed levels of R&D concentration. These results are consistent with an endogenous lower bound to R&D concentration as illustrated in figure 3 in which concentration is very low in small-sized markets and increasing in market size. The clustering of observations between the theoretical and fitted lower bounds in GM corn seed (figure 6) illustrates a convergence to the theoretical lower bound as markets become large consistent with endogenous fixed costs.

In order to derive the predicted theoretical lower bound for infinitely-sized markets, we multiply the theoretical lower bound parameter $\hat{\theta}_0$ by the square of the product heterogeneity index for the largest sub-market (i.e., h = 0.479) and perform an inverse logit transformation. The theoretical lower bound, reported in table 2, implies that the largest firm in an infinitely-sized sub-market would account for 47.0-57.1% of R&D activity in GM corn seed varieties. Comparing the theoretical lower bounds to the fitted lower bounds for the largest-sized sub-market reveals that although the largest corn seed sub-market is already relatively concentrated in R&D, with the leading firm accounting for 31.6-41.2% of R&D activity, there is still significant room for additional concentration without violating the predicted lower bound. Importantly, we find that our results are robust to alternate specifications of the number of regional sub-markets.

In the second-stage estimations, we explore whether the first-stage residuals fit a two- or three-parameter extreme value, Weibull distribution. 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 and the scale parameter δ describes the dispersion of the data whereas a non-zero location parameter μ would reflect a shift in the distribution. In particular, we are concerned with testing the null hypothesis of $\mu = 0$ as a significant value of μ would imply that the non-zero residuals fit a three-parameter Weibull. This would be problematic as it could imply the shape of the lower bound does not accurately reflect the entire distribution of data.

The results on the shape parameter γ imply a high degree of clustering on the lower bound corn seed sub-markets. Moreover, γ is less than two in all estimations implying that the two-step procedure of Smith (1985, 1994), is appropriate. The estimations of the scale parameter δ indicate a relatively wide dispersion of R&D concentration in corn sub-markets. Finally, the likelihood ratio tests, with one degree of freedom, fail to reject the null hypothesis that the first-stage residuals fit a two-parameter, rather than a three-parameter, Weibull distribution implying a location parameter μ which is not significantly different from zero. Hence, we fail to reject the hypothesis that the sub-markets for GM corn are characterized by endogenous fixed costs.

Estimating the Lower Bounds to R&D Concentration: Robustness Checks

We consider three separate robustness checks, reported in table 3, of our estimations of the lower bound to R&D concentration for GM corn seed. We assume ten regional sub-markets which can be compared against the baseline results, reported in column 1. First, we consider an alternate definition of R&D concentration as measured from field trials occurring only within a particular sub-market, both including and excluding those trials which simultaneously occurred in Hawaii or Puerto Rico. By focusing on field trials that occur only within a single regional sub-market, this robustness check addresses the concern of properly attributing R&D that occurs across multiple sub-markets. This robustness check continues to rely on the assumption that field trials that are conducted within a single sub-market are intended for product development within that sub-market and that any subsequent spillovers to other markets would have to undergo additional field trials prior to commercialization.

Results from this first robustness check including and excluding field trials in Hawaii and Puerto Rico, reported in columns 2 and 3 in table 3 respectively, support our finding of endogenous fixed costs in GM corn seed. The theoretical lower bounds to R&D concentration decrease from the baseline estimation (from 0.571 to 0.471 and 0.453), but remain significantly different, at the 99% and 95% respectively, from what we would expect under exogenous fixed costs. Additionally, the fitted lower bound is increasing in market size when we consider field trials that are also conducted in Hawaii and Puerto Rico, but is not significantly different from zero when these field trials are excluded. The second-stage estimations fail to reject the non-zero residuals fitting a two-parameter Weibull which, taken jointly with the first-stage results, implies that we fail to reject the presence of endogenous fixed costs under the alternate specification of R&D concentration.

The second robustness check considers an alternate specification of minimum setup costs using public costs rather than private costs. If we are undervaluing the true minimum setup costs to R&D in our estimations, then our results could be biased towards finding endogenous fixed costs. We consider an alternate definition, public cost of science years rather than private cost of science years, which increases the minimum setup cost. Results from this alternate measurement of minimum setup costs, reported in column 4 in table 3, are remain comparable to our baseline estimation results. We continue to find evidence of endogenous fixed costs and our parameter estimates move in the predicted direction.

Specifically, the fitted lower bound increases more gradually with changes in sub-market size and the theoretical lower bounds are (insignificantly) smaller.

The final robustness check examines the importance of the heterogeneity index to our estimation results by assuming homogenous products (i.e., h = 1). The theory implies that this extreme assumption should yield lower bound estimations consistent with exogenous fixed costs and allows us to examine the importance of product differentiation for GM corn seed varieties. These results, presented in column 5 in table 3, illustrate that the estimated lower bounds to R&D concentration change significantly when we disregard the extent of product heterogeneity, but we fail to reject endogenous fixed costs even under the more extreme assumption. Although the decrease in the theoretical lower bound is significant, from 57.1% to 22.9%, it remains significantly greater than either the 0% predicted by the theory or the 10% threshold tested empirically. These results highlight the importance of product differentiation to EFC lower bound estimations while illustrating that our empirical results are not driven solely by our measure of heterogeneity.

Estimating the Lower Bounds to R&D Concentration under Firm Consolidation

In our final set of estimations, we consider the impact of mergers and acquisitions in the agricultural biotechnology sector upon R&D concentration in the GM corn seed market. Rather than consider R&D concentration based upon the firm applying for field trials as we have in the previous estimations, we now assign these field trials to firms according to the merger and acquisition activity that occurred between 1990 and 2010. For example, Asgrow conducted field trials prior to 1995 when it merged with Petoseed to form Seminis. In 1997, Monsanto acquired the corn and soybean division and continues to manufacture seeds under the Asgrow brand name. In our baseline estimations, the field trials conducted by Asgrow and Monsanto prior to 1995 are treated as two separate firms. In the M&A adjusted estimation results, we assign all of the field trials of Asgrow to Monsanto such that they are treated as a single firm.

This exercise allows us to explore whether merger and acquisition activity by agricultural biotechnology firms has served to increase concentration in R&D activity. The results in the "Unadjusted" column in table 4 correspond to our baseline estimations for ten regional sub-markets whereas the results in the "M&A Adjusted" column account for the merger and acquisition activity. After controlling for firm consolidation, we continue to fail to reject the null hypothesis of endogenous fixed costs and a lower bound to R&D concentration that is increasing in market size.

In figure 7, we plot the theoretical and fitted lower bounds, along with the 95% confidence intervals, for both the baseline and merger and acquisition adjusted estimations. This figure illustrates that adjusting R&D activity for mergers and acquisitions significantly raises the theoretical lower bound to R&D concentration from 57.1% to 66.0% for the market-leading firm. However, we fail to reject equivalence of the fitted lower bounds at currently-sized markets as the unadjusted fitted lower bound falls within the 95% confidence interval for the M&A-adjusted fitted lower bound. Jointly, these results imply that merger and acquisition activity has significantly increased the concentration of R&D activity in GM corn seed, but that this increase has had little economic significance at current market sizes and relative to the concentration in R&D due to the endogenous fixed cost nature of innovation in agricultural biotechnology.

Conclusions

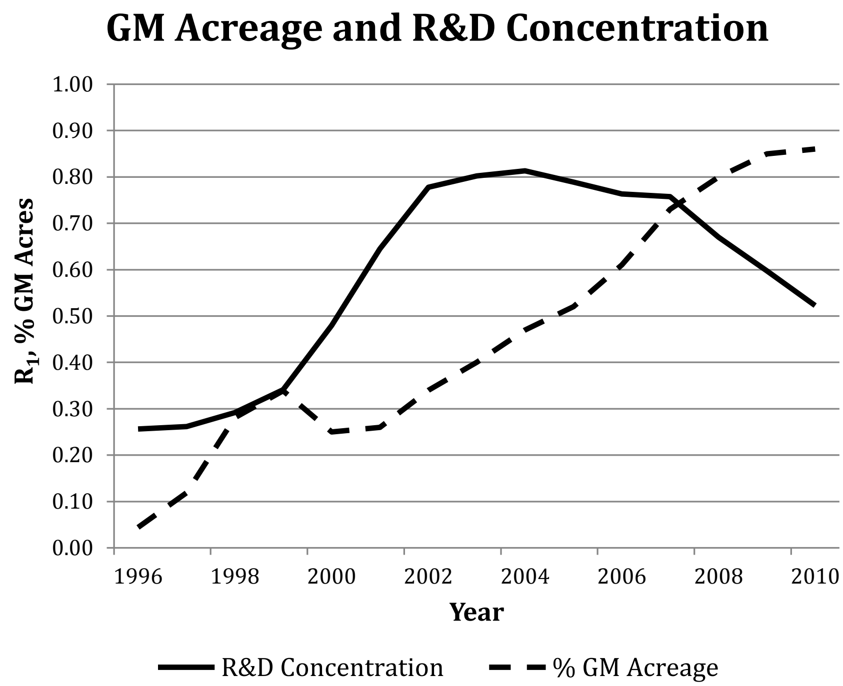
We examine whether the market for genetically modified (GM) corn seed is characterized by endogenous fixed costs (EFC) associated with R&D investment. In a mixed model of vertical and horizontal product differentiation, we derive the theoretical lower bound to R&D concentration from Sutton's (1998) EFC model of market concentration and innovation. The model implies that the lower bound to R&D concentration under EFC will be less than the lower bound to market concentration, but is increasing in the size of the market.

Using data on field trial applications, we estimate the lower bound to R&D concentration in GM corn seed varieties. We 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. We find evidence supporting the hypothesis that GM corn seed markets are characterized by endogenous fixed investments in R&D which is robust to alternate definitions and measurements of regional markets, R&D concentration, and minimum setup costs. As market sizes become large, the empirical results imply that the R&D share of the market leading firm converges to 45.3% to 57.2% and that under current market sizes the estimated share of R&D activity is 31.6% to 41.2%. Adjusting for firm consolidation via merger and acquisition activity significantly increases the lower bound to R&D concentration as markets become large (57.1% to 66.0%), but has no significant impact for current market sizes (31.6% to 34.1%). Although there is significant concentration in R&D activity, as measured by field trial applications, the empirical results are consistent with an industry characterized by endogenous fixed costs. Accounting for the additional concentration from mergers and acquisitions results in additional R&D

concentration, but the magnitude of these impacts is small relative to the concentration that arises due to the nature of investment and innovation in the corn seed market.

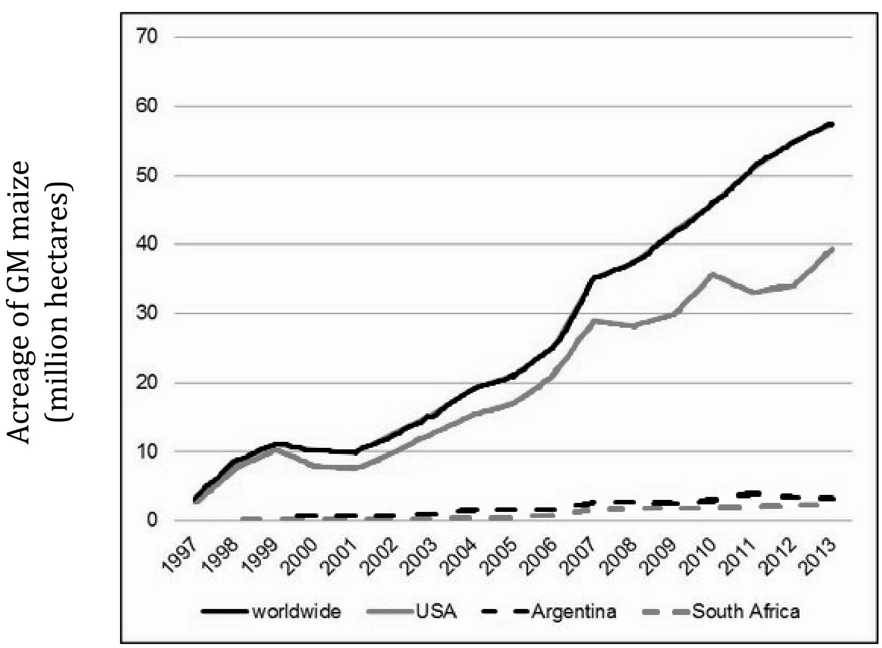
Given the increased concerns over concentration in agricultural inputs, and in particular in agricultural biotechnology, regulators and policymakers alike will find these results of particular interest even though we cannot examine the welfare implications of our results without explicit expressions of consumer utility and product market competition. 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 in thet corn seed market and the ratio 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.

Figure 1: Single-Firm R&D Concentration Ratios (R_1) and GM Adoption



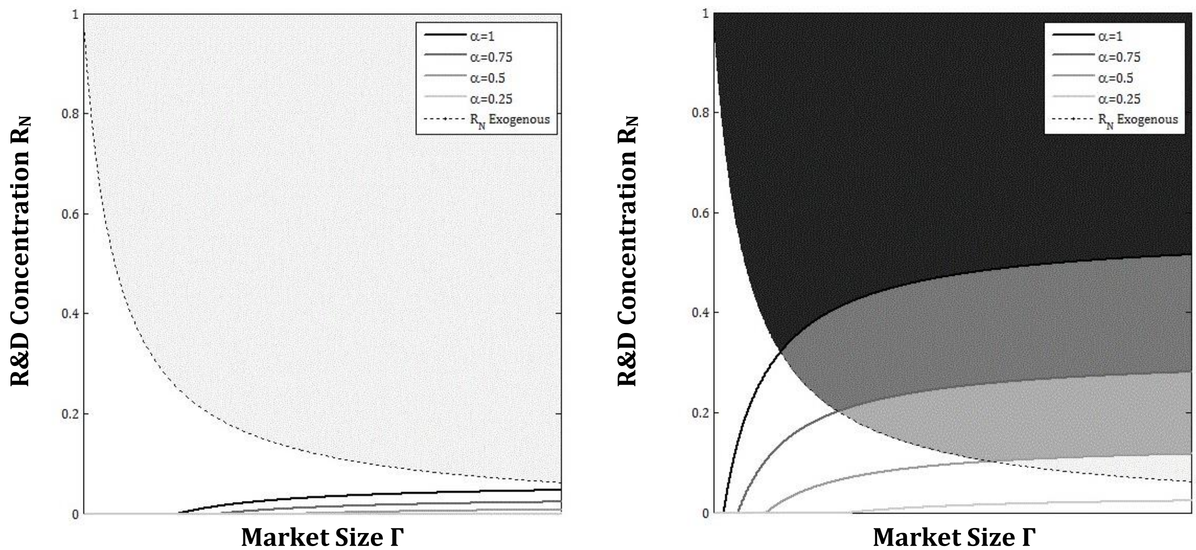
Source: Authors' calculations from APHIS data and Fernandez-Cornejo (2013).

Figure 2: Total Acreage Planted with GM Corn Varieties



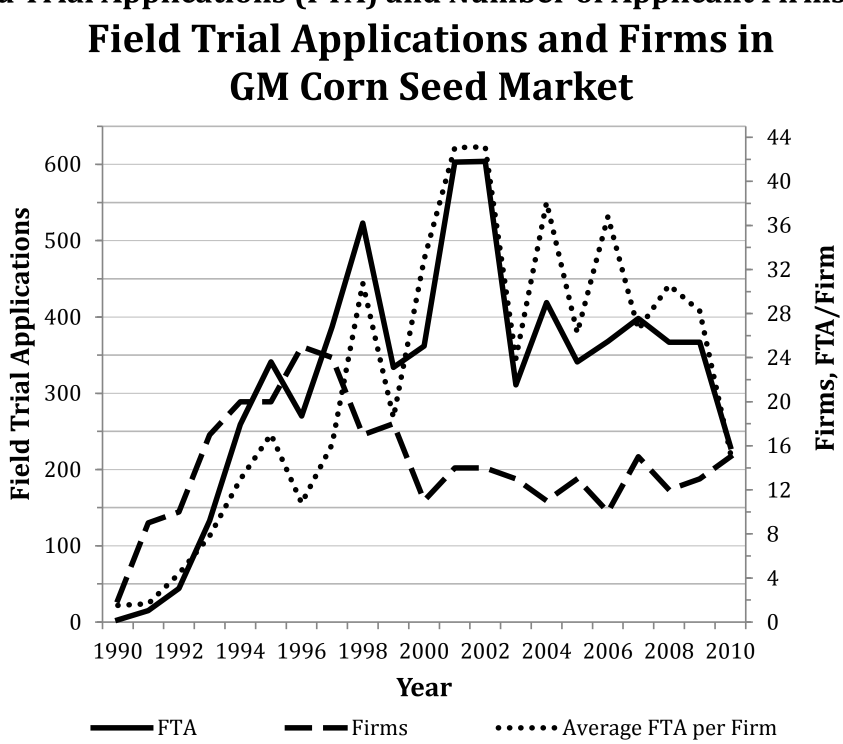
Source: GMO Compass (2014)

Figure 3: Equilibrium R&D Concentration Levels and Market Size



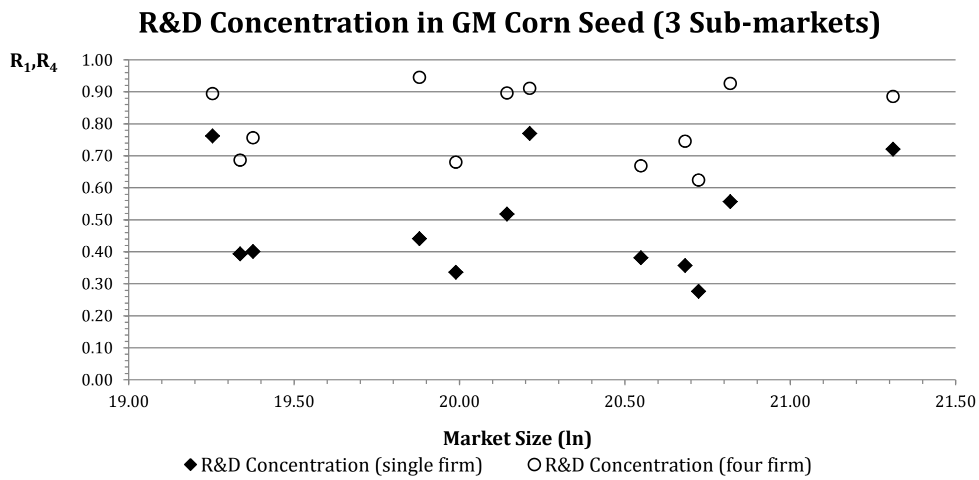
(a) Low *h* (*h* = 0.75) (b) High *h* (*h* = 0.25)

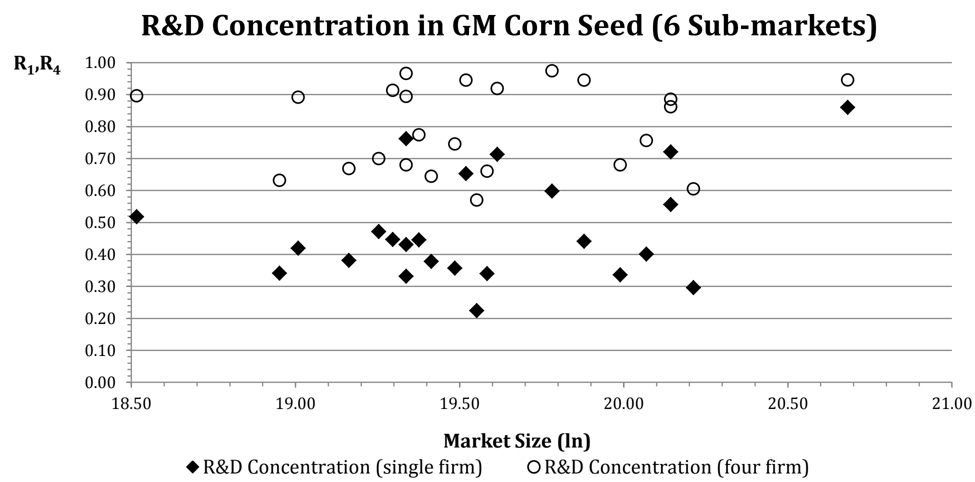
Figure 4: Field Trial Applications (FTA) and Number of Applicant Firms

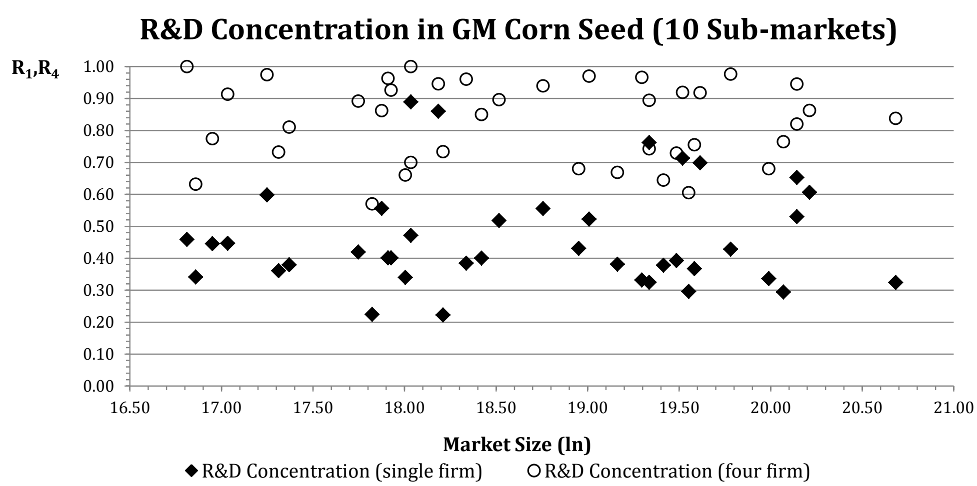


Source: Authors' calculations from APHIS data.

Figure 5: R&D Concentration and Market Size in GM Corn Seed

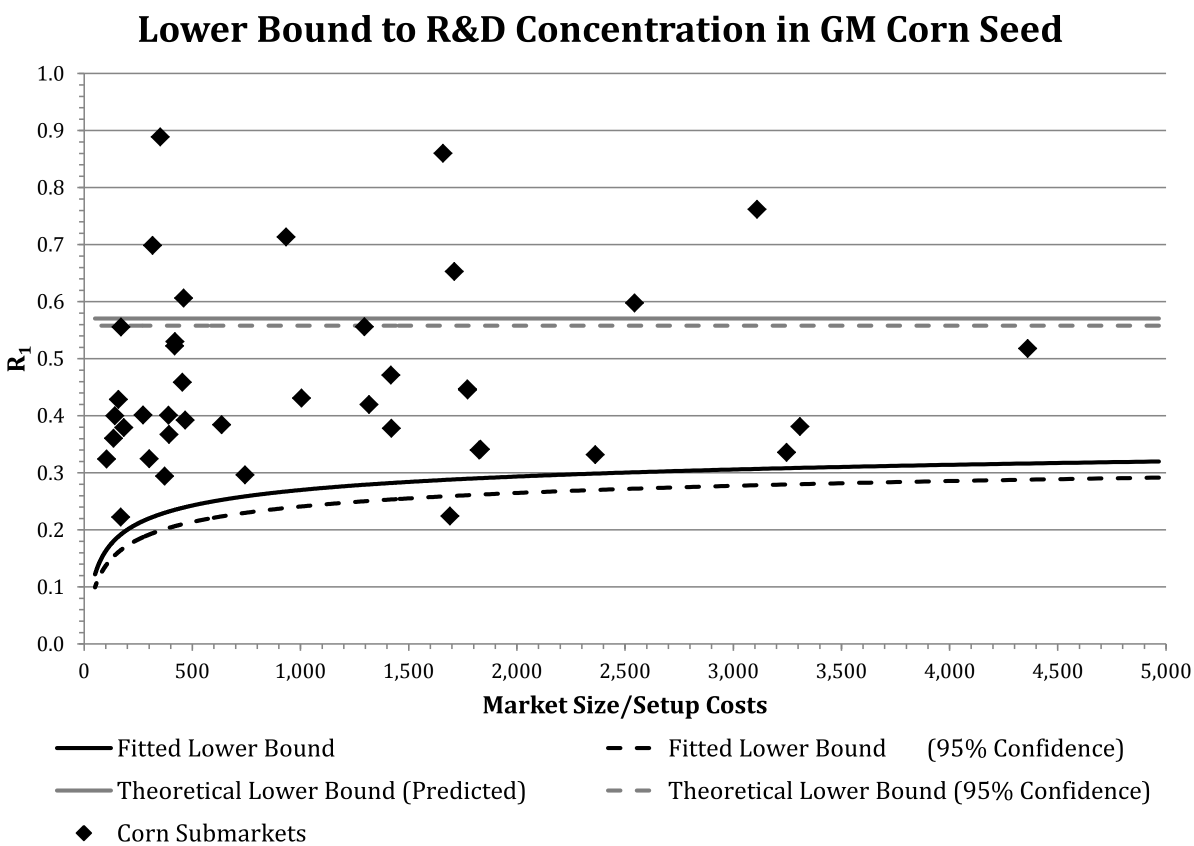






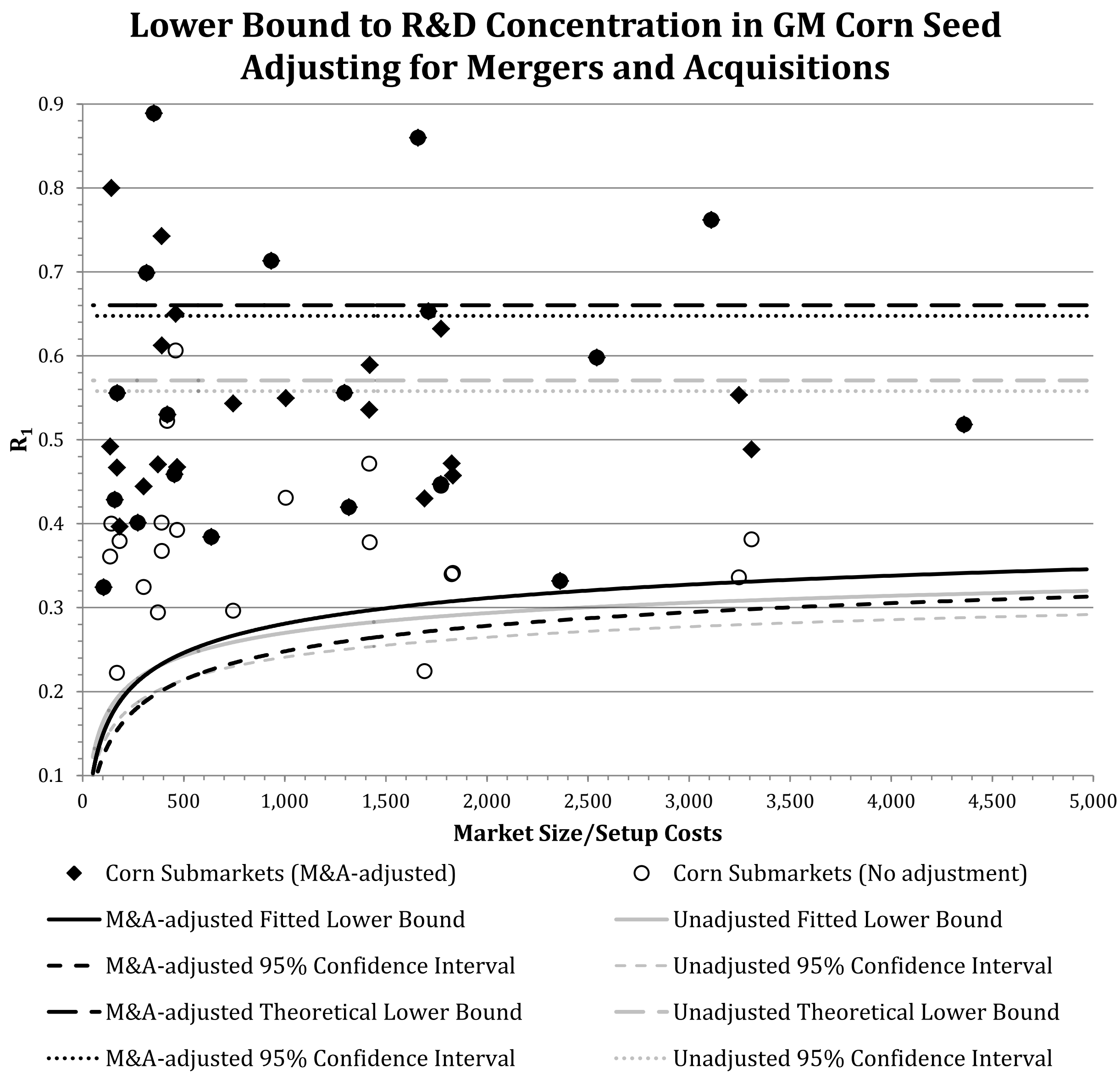
Source: Authors' calculations.

Figure 6: Lower Bound to R&D Concentration in GM Corn Seed



Source: Authors' calculations.

Figure 7: Lower Bound to R&D Concentration Adjusting for Mergers and Acquisitions



Source: Authors' calculations.

Table 1: GM Corn Seed Sub-Markets			
Sub-Market	**2010 Market Shares (%)**	**Field Trial Applications**	**States**
Classification #1			
"Core" States	29.47	2,650	IL, IA
"Fringe" States	56.47	2,315	CO, IN, KS, KY, MI, MN, MO, NE, ND, OH, SD, WI
"Non-Corn Belt" States	14.06	1,574	All others (33)
Classification #2			
"Core" States	29.47	2,650	IL, IA
Eastern "Fringe" States	12.43	949	IN, KY, OH
Northern "Fringe" States	15.76	824	MI, MN, WI
Southern "Fringe" States	10.64	736	CO, KS, MO
Western "Fringe" States	17.64	911	NE, ND, SD
"Non-Corn Belt" States	14.06	1,574	All others (33)
Classification #3			
"Core" States	29.47	2,650	IL, IA
Eastern "Fringe" States	12.43	949	IN, KY, OH
Northern "Fringe" States	15.76	824	MI, MN, WI
Southern "Fringe" States	10.64	736	CO, KS, MO
Western "Fringe" States	17.64	911	NE, ND, SD
Mid-Atlantic/Appalachia	3.15	592	DE, MD, NC, TN, VA, WV
Northeast	3.03	480	CT, ME, MA, NH, NJ, NY, PA, RI, VT
Southeastern	1.16	386	AL, FL, GA, SC
S. Plains/MS Delta	4.87	401	AR, LA, MS, OK, TX
Western	1.84	364	AZ, CA, ID, MT, NM, OR, UT, WA, WY

Source: Authors' estimates from NASS (2010) Acreage Report and Field Trial Applications

Table 2: Lower Bound Estimations for GM Corn Seed			
	Regional Sub-market Sample		
	1	**2**	**3**
Theoretical Lower Bound (R_1^{∞})	**0.470**	**0.571**	**0.571**
Lower Bound (95% confidence)	0.406	0.543	0.558
Fitted Lower Bound (Largest Submarket)	0.412	0.317	0.316
First-Stage			
Intercept (θ_0)^	-0.500 **	1.178 **	1.178 **
	(0.592)	(0.266)	(0.126)
Adjusted Market Size (θ_1)	4.014	17.986 **	17.986 **
	(3.745)	(1.709)	(0.844)
First-stage Observations	12	24	40
Second-Stage			
Shape Parameter (γ)	1.003 **	1.143 **	1.332 **
	(0.081)	(0.039)	(0.027)
Scale Parameter (δ)	1.960 **	3.306 **	3.747 **
	(0.207)	(0.139)	(0.078)
Likelihood Ratio (χ^2=1)^^	0.117	-0.086	-0.038
Second-stage Observations	10	22	38
Number of Regional Sub-markets	3	6	10
Include Hawaii & Puerto Rico Field Trials	Y	Y	Y
h value for bounds calculations	0.491	0.491	0.491

Source: Authors' estimates.

Standard errors in parentheses.

^: Null hypothesis (H_0): Under product homogeneity (h = 1) and as market size becomes large, does the lower bound to R&D concentration converge to less than 10% (θ_0 = -2.197)?

^^: Null hypothesis (H_0): Non-zero first-stage residuals fit a two-parameter Weibull distribution.

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

Table 3: Robustness Checks on Lower Bound Estimations for GM Corn Seed

	Baseline	Field Trials In Sub-Market Only		Public R&D Setup Costs	Product Homogeneity
	1	2	3	4	5
Theoretical Lower Bound (R_1^{∞})	**0.571**	**0.471**	**0.453**	**0.572**	**0.229**
Lower Bound (95% confidence)	0.558	0.409	0.392	0.559	0.188
Fitted Lower Bound (Largest Submarket)	0.316	0.390	0.409	0.318	0.225
First-Stage					
Intercept (θ_0)^	1.178 **	-0.484 **	-0.784 *	1.196 **	-1.215 **
	(0.126)	(0.616)	(0.614)	(0.125)	(0.148)
Adjusted Market Size (θ_1)	17.986 **	5.620 *	3.033	16.435 **	0.198
	(0.844)	(2.861)	(2.698)	(0.764)	(0.887)
First-stage Observations	40	40	40	40	40
Second-Stage					
Shape Parameter (γ)	1.332 **	0.865 **	0.832 **	1.348 **	1.826 **
	(0.027)	(0.018)	(0.018)	(0.027)	(0.035)
Scale Parameter (δ)	3.747 **	5.449 **	5.196 **	3.880 **	1.316 **
	(0.078)	(0.175)	(0.173)	(0.080)	(0.020)
Likelihood Ratio (χ^2=1)^^	-0.038	-0.015	0.004	-0.027	-0.318
Second-stage Observations	38	38	38	38	38
Number of Regional Sub-markets	10	10	10	10	10
Include Hawaii & Puerto Rico Field Trials	Y	Y	N	Y	Y
h value for bounds calculations	0.491	0.491	0.491	0.491	1.000

Source: Authors' estimates.
Standard errors in parentheses.
^: Null hypothesis (H_0): Under product homogeneity (h = 1) and as market size becomes large, does the lower bound to R&D concentration converge to less than 10% (θ_0 = -2.197)?
^^: Null hypothesis (H_0): Non-zero first-stage residuals fit a two-parameter Weibull distribution.
**,*: Significance at the 99% and 95% levels, respectively.

Table 4: Lower Bound Estimates Adjusting for Mergers and Acquisitions in GM Corn Seed		
	Unadjusted	**M&A Adjusted**
Theoretical Lower Bound (R_1^{∞})	**0.571**	**0.660**
Lower Bound (95% confidence)	0.558	0.648
Fitted Lower Bound (Largest Submarket)	0.316	0.341
First-Stage		
Intercept (θ_0)^	1.178 **	2.752 **
	(0.126)	(0.136)
Adjusted Market Size (θ_1)	17.986 **	22.554 **
	(0.844)	(0.951)
First-stage Observations	40	40
Second-Stage		
Shape Parameter (γ)	1.332 **	1.285 **
	(0.027)	(0.026)
Scale Parameter (δ)	3.747 **	3.777 **
	(0.078)	(0.082)
Likelihood Ratio (χ^2=1)^^	-0.038	0.003
Second-stage Observations	38	38
Number of Regional Sub-markets	10	10
Include Hawaii & Puerto Rico Field Trials	Y	Y
h value for bounds calculations	0.491	0.491

Standard errors in parentheses.

^: Null hypothesis (H_0): Under product homogeneity (h = 1) and as market size becomes large, does the lower bound to R&D concentration converge to less than 10% (θ_0 = -2.197)?

^^: Null hypothesis (H_0): Non-zero first-stage residuals fit a two-parameter Weibull distribution.

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

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