Detecting Collusion in High-Dimensional Oligopoly Models: The Case of the U.S. Corn Seed Industry

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Abstract

The nature of firm conduct significantly affects market outcomes. Existing research estimating conduct parameters of a large number of firms suffers from the curse of dimensionality. This paper develops a novel structural model of demand and supply that allows for the flexible estimation of the degree of collusion. The proposed framework is empirically tractable even for a large number of multiproduct firms. The model is applied to the U.S. corn seed industry using farm-level transaction data. Despite concerns about the ramifications of the growing market power of large biotech firms in the seed industry, little is known about how firms compete or collude in their pricing. The estimation results indicate a distinct difference in the conduct of the two largest firms: one operates under imperfect collusive conduct, while the other engages in Bertrand price competition. The remaining three firms also exhibit the conduct of imperfect collusion. The estimated markups are approximately 36%-53%, reflecting both product differentiation and the degree of collusion. Counterfactual simulations imply that the observed average corn seed price was 37% lower than it would be in a perfect collusive equilibrium but 6% higher than in a Bertrand price competition scenario.

1 Introduction

How firms compete (or collude) with each other has significant implications for market outcomes. A lack of competition allows firms to set higher prices that extract excess surplus from consumers. The recent literature documents a growing prevalence of high concentration and rising markups across a wide range of industries (De Loecker et al., 2020). For example, in the U.S. seed market, farmers and other stakeholders raise concerns about the impacts of growing market power on competition and innovation (USDA, 2023). However, the observed rising prices are not necessarily caused by anti-competitive conduct such as implicit collusion because they can be attributed to several other factors, such as changes in production cost or demand elasticity (Chavas et al., 2020; Döpper et al., 2023). Therefore, empirically identifying firm conduct has been the central issue for policy makers and researchers in the field of industrial organization for obtaining policy-relevant implications in industries with dominant players.

Seminal work by Bresnahan (1982) shows that exogenous rotation of the demand curve can be used to distinguish different oligopoly models with a homogeneous good. Motivated by his finding, many papers have estimated firm conduct parameters to measure the degree of competition in numerous markets.[1] Nevo (1998) shows how to extend such models to accommodate product differentiation. He argues that it is possible to identify conduct parameters of multiproduct firms in principle, but it is infeasible due to the requirement of a large number of excluded instruments for a large number of

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[1] See Ciliberto and Williams (2014) for the airline industry, Miller and Weinberg (2017) for the beer industry, and Michel et al. (2023) for the cereal industry. See, also a survey by Bresnahan (1989).

parameters. This curse of dimensionality problem forces researchers to rely on arbitrary assumptions about how firms compete with each other, which may lead to misleading evaluations of market power and policy recommendations.

In this paper, we develop a novel structural model of demand and supply that allows for estimating the degree of collusion of multiproduct firms in a differentiated products market. A main advantage of the proposed model is that it avoids the curse of dimensionalty problem and is empirically tractable even in an oligopoly model with multiple firms strategically interacting with each other. Importantly, the model also retains the flexibility that allows each firm to operate at any level of competition from perfect collusion to monopolistic competition.

On the supply side, we extend an oligopolistic model developed by d'Aspremont et al. (2007) to construct an empirical framework to estimate conduct parameters. In the oligopolistic model, each firm maximizes its own profit given prices and quantities of other firms under two demand constraints: market share constraint which determines firm-level demand, and market size constraint which governs market-level demand. The conduct of each firm is measured by a parameter that captures its relative attitude toward these two constraints, with different conduct reflecting different degrees of collusion. Intuitively, when firms compete aggressively with each other, they put more weight on the firm-level demand (market share constraint) and may try to obtain higher market shares by lowering prices. By contrast, when firms collude with each other, they put more weight on the market-level demand (market size constraint) and tend to maintain higher prices by decreasing the total supply in the market compared to the competitive outcome.

This formulation significantly reduces the dimension of conduct parameters because the degree of collusion is measured by a single parameter for each firm. d'Aspremont et al. (2007) show theoretically that, for single-product firms, this dichotomous characterization of competition accommodates varying degrees of competition, which nest the benchmark models such as perfect collusion, monopolistic competition, Nash-Bertrand price, and Cournot quantity competition. We extend this model to accommodate multi-product firms, and construct an empirical tractable structural model owing to a reduced number of parameters and simpler functional form.

On the demand side of the model, we use a variant of a random coefficients logit model originally proposed by Berry et al. (1995). We rely on the discrete/continuous choice framework in which consumers choose one of the products and then choose a purchase amount under their budget constraint (Hanemann, 1984; Björnerstedt and Verboven, 2016). To generate flexible substitution patterns, we incorporate a nesting parameter and demographic interaction parameters reflecting consumer heterogeneity. We choose the discrete/continuous demand system because it allows for recovering utility and expenditure functions of a representative consumer from a heterogenous population (Anderson et al., 1987; Dubé et al., 2023). This integrability property ensures theoretical consistency between the demand and supply model and enables us to conduct welfare analysis based on the structural model.

Our model is empirically tractable and we apply it to analyzing firms' conduct in the U.S. corn seed market. The corn seed industry has undergone considerable structural change since genetically modified (GM) seeds were introduced in 1996. The combined shares of the top five seed companies (Monsanto, Dupont, Syngenta, Dow AgroSciences, and AgReliant) expanded from 70% in 2000 to 86% in 2014 in the market.[2] The composition of market leaders in the industry has also changed, due to a number of vertical and horizontal mergers between biotech companies and seed companies. Furthermore, biotech firms that hold patent rights over GM traits, such as Monsanto, permit other firms to use the technology through licensing agreements. This business practice contributes to the expansion of GM traits, but it is sometimes considered a non-merger cartel because the web of cross-licensing agreements between firms may facilitate anti-competitive practices (Moschini, 2010; Howard, 2015).

The patented GM technologies and the consolidation of the seed industry raise concerns from policy makers and researchers about the pricing of GM seeds and its impacts on welfare (Clancy and Moschini, 2017; Deconinck, 2020). Surprisingly little, however, is known about the extent of competition between firms in the seed industry (OECD, 2018). Our study aims to fill the information gap and provide empirical evidence on how firms compete with each other in this highly concentrated

[2]The market shares are calculated from the GfK Kynetec data.

market. Using farm-level seed purchase data in the US, we estimate conduct parameters for the five largest firms in the corn seed market from 2005 to 2014. We focus on the core region of the Corn Belt spanning six major corn-producing states in the midwestern US, which account for about a half of US corn production and share similar agro-economic conditions.

We first estimate a random coefficient logit model that incorporate farmer heterogeneity with demographic interaction parameters. We find that product-level demand is quite elastic (the mean of own price elasticity is -4.460) while the mean of firm-level and market-level demand elasticities are -2.92 and -1.61, respectively. The firm-level nesting parameter is 0.49, indicating more substitution occurs within products supplied by the same firm.

We then estimate conduct parameters for each of the five firms along with marginal cost parameters. We find that the conduct parameters are all precisely estimated. Four of the five firms exhibit conduct of imperfect collusion, with their conduct parameters falling between perfect collusion and quantity competition. One firm, however, engages in Bertrand price competition. This competitive conduct may reflect the firm's strategy to maintain market shares in response to its major rival's growing presence and introduction of new GM traits. The estimated markups vary from approximately 36% to 53%, with the leading firm exhibiting the highest markup. The results of the counterfactual simulations indicate that the degree of collusion would significantly impact firms' pricing strategies: prices would increase by 37% under perfect collusion and decrease by 6% under competitive conduct, compared to the estimated conduct.

This paper contributes to the literature both methodologically and empirically. Methodologically, it provides a viable alternative to estimate firm conduct in differentiated products markets. Nevo (1998) suggests the use of selection tests for a menu of benchmark models rather than the estimation of conduct parameters, due to the severe requirement of excluded instruments. Many previous studies adopt and refine a testing-based approach in their empirical applications (Rivers and Vuong, 2002; Villas-Boas, 2007; Backus et al., 2021; Duarte et al., 2024). An advantage of the testing approach is that it is generally less demanding in terms of the number of excluded instruments. A disadvantage is that it requires researchers to specify a fixed set of oligopoly models in advance to test against each other. Yet, the true conduct may be in between the benchmark conduct models. Our estimation-based approach for conduct parameters can be more appropriate in such situations. It may also apply to the analysis of a large number of firms.[3]

Empirically, this paper provides additional empirical evidence of the degree of competition in the U.S. seed industry. The previous research focuses on the demand side of this industry (Ciliberto et al., 2019; Luo et al., 2023). Yet, the empirical evidence about firm conduct is limited, even though researchers and stakeholders have raised concerns about the growing concentration in the seed industry. Shi et al. (2023) is the only paper that explicitly analyzes the degree of collusion in the U.S. corn seed industry. They find that firms are implicitly colluding in both product lines and pricing, with a focus on three major players. We estimate the conduct of the five largest corn seed firms in their pricing and analyzes the welfare implications. Our analysis provides new policy-relevant empirical evidence, especially on the overall competitiveness in the seed industry.

The rest of the paper is organized as follows. The next section presents the background of the U.S. corn seed industry. Section 3 presents a structural model of demand and supply. The data and identification strategy are discussed in Section 4. Section 5 presents the estimation results. Section 6 concludes.

[3]Another strand of related papers includes Ciliberto and Williams (2014) and Miller and Weinberg (2017). They estimate continuous conduct parameters using a structural model of demand and supply for the U.S. beer industry and airline industry, respectively. While their approach provides valuable insights about how to estimate pair-wise relationships of coordination, it has difficulty in accommodating a large number of conduct parameters. On the other hand, although our approach cannot identify pair-wise coordination, it allows for flexible estimation of the degree of coordination of each firm. The degree of coordination is instead interpreted as the average conduct of each firm toward the whole industry. This approach is applicable even when researchers have an interest in many oligopolistic firms in an industry.

2 Background: The U.S. Corn Seed Industry

Rapid advancement of modern biotechnology has contributed to the strong growth of agricultural productivity in the U.S., including the development and commercialization of genetically modified (GM) seeds in corn, soybean and cotton since the mid-1990s. Recombinant DNA techniques make it possible to insert useful foreign genes into the seed germplasm, conferring valuable traits. Primary GM traits for corn seeds include herbicide tolerance and insect resistance. The herbicide tolerance trait makes corn resistant to certain herbicides applied to crops such as glyphosate. The insect resistance trait makes corn toxic to certain insects such as corn borer and rootworm. Farmers highly value these GM traits because they offer an effective tool for weed and insect control, which results in reduced variance of yield and lower production costs (e.g., Fernandez-Cornejo, 2004; Moschini, 2008; Shi et al., 2013).

Figures 1 and 2 show the adoption rate and the average price of GM corn seeds from 1996 to 2014 in the U.S. market. Farmers adopted GM corn seeds rapidly, with over 90% of seeds having GM traits by 2014. The figures also show that, in the early stage of diffusion, most GM seeds possessed a single trait of either herbicide tolerance or insect resistance, but seeds with stacked traits became more prevalent over time. The adoption rate of seeds with stacked traits was higher than 80% by 2014, and the adoption rate of triple-stacked traits increased to 55% of the total acreage. In tandem, the average prices have increased over the years with a jump in rising speed since 2008. Besides, farmers have paid higher prices for more traits included in the seed (the multi-trait-stacked GM seeds). The price difference among different stacking system seems enlarging since 2007 as well.

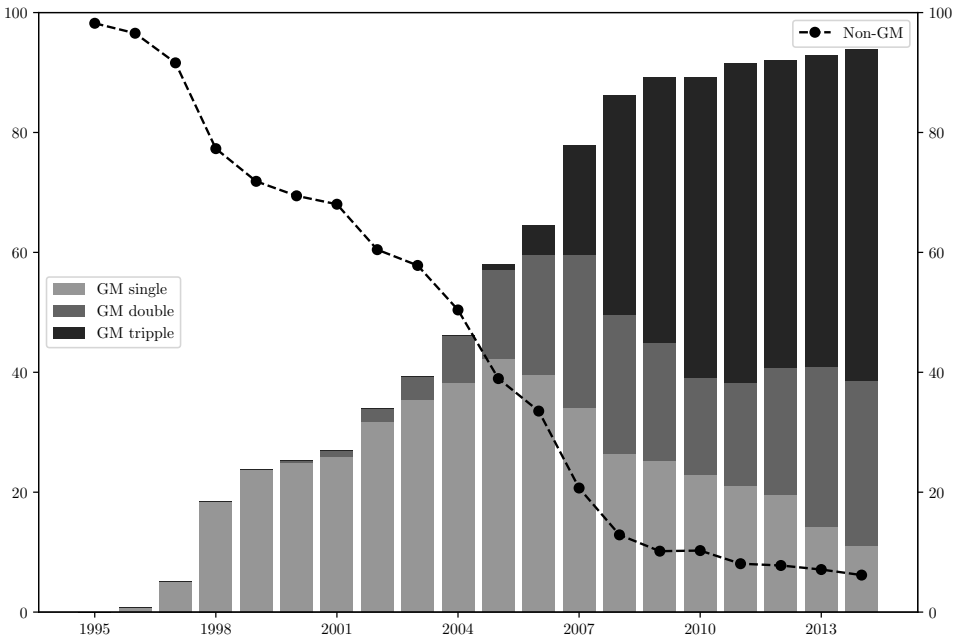


Figure 1: Adoption rate of GM corn seeds (in % of total corn acreage) in the U.S.
Source: Authors' calculation from the GfK Kynetec data.

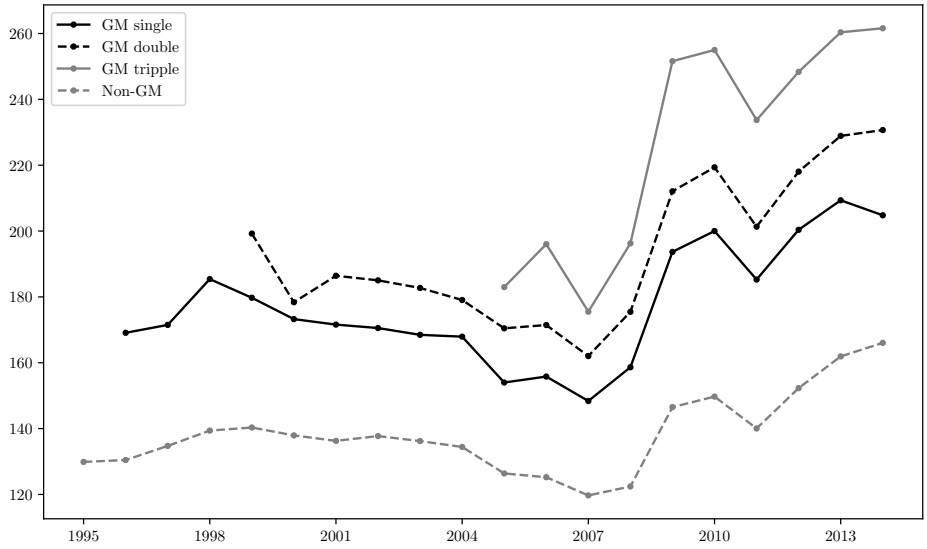


Figure 2: The average price of GM corn seeds (in $ per bag) in the U.S.
Note: The average prices are deflated by USDA's crop sector price index normalized to equal 1 in 2011.
Source: Authors' calculation from the GfK Kynetec data.

The U.S. seed industry has become more consolidated since the large-scale commercialization of GM seeds. One important aspect of GM technologies is that GM traits need to be inserted into elite germplasm during the breeding processes. GM traits are developed and owned by a few large biotech firms such as Monsanto and Syngenta, while the elite germplasm is owned by many local and regional seed companies. This complementary property between GM traits and elite germplasm has spurred a number of horizontal and vertical mergers (Graff et al., 2003; Fernandez-Cornejo, 2004). For example, when Monsanto originally developed one of its patented GM traits (Roundup Ready), it did not have its own seed subsidiary. A lack of direct access to the elite germplasm and distribution channels to farmers motivated Monsanto to pursue a series of acquisitions of seed companies, including the acquisition of Dekalb in 1998.

At the same time, other large biotech or agricultural input firms made similar strategic moves. In 1999, the agricultural chemical giant Dupont acquired Pioneer, which was the dominant seed company in the U.S. market at that time. Syngenta formed in 2000 as a result of the restructuring of the life science companies Novartis and AstraZeneca. Dow AgroSciences formed as Dow Chemical's subsidiary in 1997 and acquired Mycogen in 1998. AgReliant formed as a joint venture of European-based companies KWS and Limagrain in 2000. These five large firms (Monsanto, Syngenta, Dupont, Dow AgroSciences, and AgReliant) continued to acquire regional seed companies since then, resulting in a highly concentrated U.S. corn seed market.

Figure 3 shows the market shares of the major seed companies from 2004 to 2014: The total market share of the five firms increased from 65% to 87% during this time period. Monsanto and Dupont are the two dominant firms that control around 70% of the market. Dupont's market share was 42% in 2004, decreased to 30% by 2009, and subsequently recovered to 34% in 2014. In contrast, the share of Monsanto was 11% in 2004 and it significantly increased to 39% by 2009 and then decreased to 33% in 2014. The other three firms (Syngenta, Dow AgroSciences, and AgReliant) have relatively smaller shares but have maintained a significant presence. The Herfindahl-Hirshman Indexes (HHIs) exceed $2,500$ after 2011, which is the threshold level for a highly concentrated market based on the horizontal merger guidelines issued by the U.S. Department of Justice and Federal Trade Commission.

The business practice of cross-licensing agreements raises another concern of reduced competition. GM traits are developed and owned by six big biotech firms (Monsanto, Syngenta, Dupont, Dow, Bayer, and BASF). As Figure 4 shows, these firms sign cross-licensing agreements among themselves,

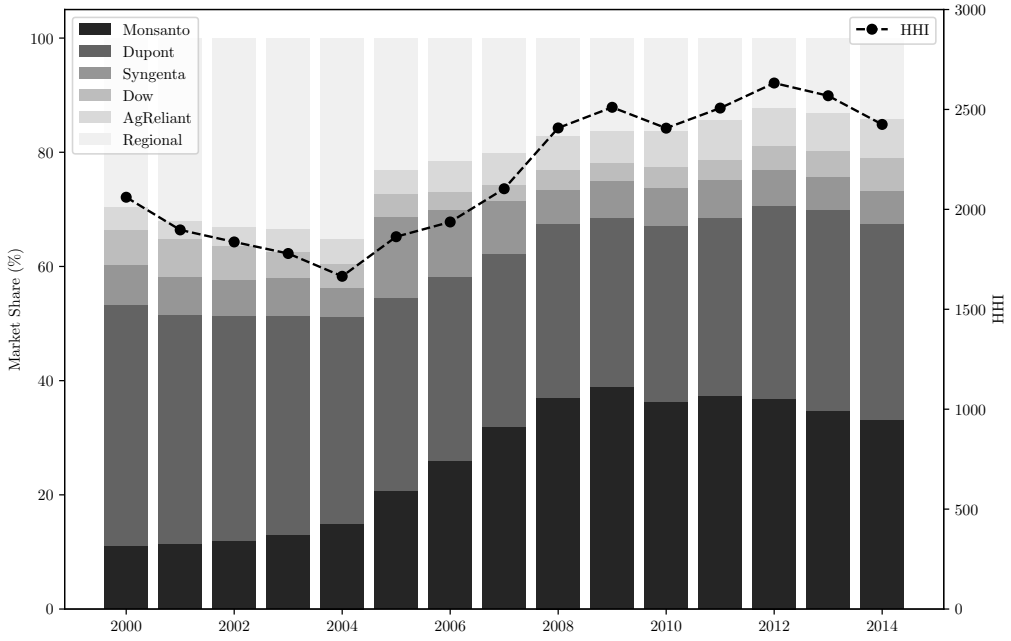


Figure 3: Market shares and HHI

Note: Market shares are measured by sales value for Monsanto, Dupont, Syngenta, Dow AgroSciences, and AgReliant. "Regional" refers to the total market shares of the other firms. The Herfindahl-Hirshman Indexes (HHIs) are scaled from 0 to 10,000 on right axis.

Source: Authors' calculation from the GfK Kynetec data.

allowing them to produce GM seeds with patented traits from other firms. Although the licensing agreement can facilitate competition through widespread utilization of proprietary technologies, they can also function as non-merger cartels (Howard, 2009, 2015). Other local and regional seed firms have to sign licensing contracts with biotech firms to insert GM traits in their seed products. In particular, Monsanto aggressively licenses its patented GM traits, such as Roundup Ready and YieldGard, to other corn seed companies. As a result, the market share of corn seed products that incorporate Monsanto's patented traits was approximately 85% in 2014.[4] The terms of licensing agreements are confidential, but licensees are supposed to pay certain licensing fees to licensors (Moschini, 2010). This suggests that licensing agreements might affect firms' pricing strategies.

In recent years, this already highly concentrated industry has seen further waves of large M&A; the merger of Dow and DuPont in 2017, the acquisition of Syngenta by ChemChina in 2017, and the merger of Bayer and Monsanto in 2018. These mergers are seen to reinforce corporate power as they combine firms with a strong position in the agrochemical market (Bayer, Dow, ChemChina) with firms in a strong position in the seed and biotechnology industry (Monsanto, DuPont, and Syngenta) (OECD, 2018). Antitrust agencies extensively scrutinize the potential impacts of these mergers on market outcomes and approve them under certain conditions, such as divestiture of assets. For instance, Bayer was required to divest most of its seed business, including the GM traits named Liberty Link, and all of these assets were sold to BASF, which is a competitor to Bayer.

The growing concentration of the seed industry heightens concerns about its impacts on the pricing of GM seeds, its contribution to welfare, and incentives for innovation (Clancy and Moschini, 2017). However, little empirical information has been available (OECD, 2018).

[4] Authors' calculation from the GfK Kynetec data.

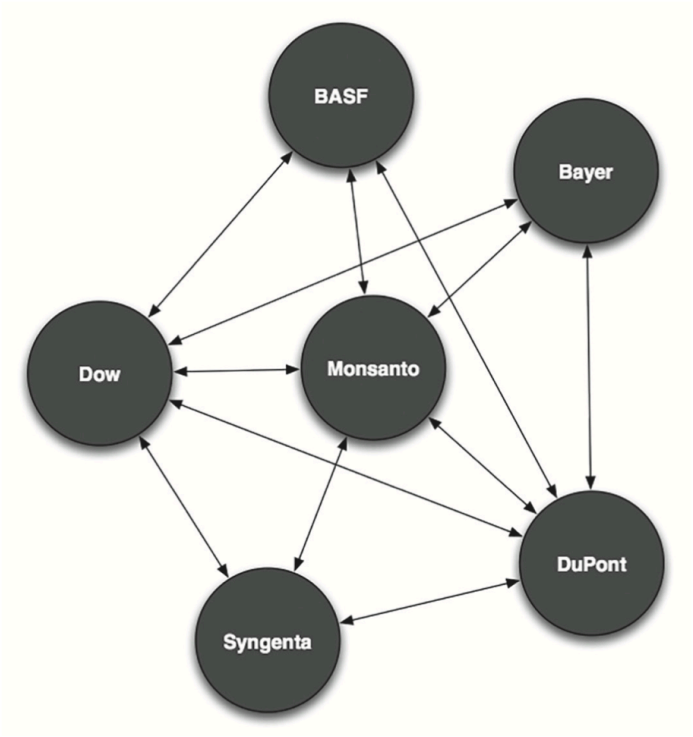


Figure 4: Cross-licensing agreements between big six biotech firms for GM traits
Source: Howard (2015)

3 Structural model of demand and supply

Several potential factors could explain the observed price patterns. Higher prices may be due to inelastic demand, higher marginal costs, or a high degree of collusion. A structural model makes it possible to separately identify these sources (Berry and Haile, 2014). We develop a novel structural model of demand and supply that allows for flexible estimation of the degree of collusion for a large number of multiproduct firms in an empirically tractable way.

3.1 Demand model

On the demand side, we use a variant of a random coefficient logit model used in Björnerstedt and Verboven (2016). The theoretical model builds on the discrete/continuous demand model proposed by Hanemann (1984). In this model, a consumer first chooses a product and then decides on the quantity to purchase under his/her budget constraint to maximize his/her utility. The discrete/continuous demand specification allows for recovering utility and expenditure functions of a representative consumer corresponding to the population of heterogeneous consumers. This integrability property ensures the existence of price and quantity aggregators and makes it possible to conduct welfare analyses in a theoretically consistent way.

There are I_{rt} farmers in region r and year t. In each market, there are J_{rt} products. we consider farmers to be utility-maximizing individuals who choose the alternative in production process with the highest utility.[5] Farmer i chooses one of the corn seed products ($j = 1, ..., J_{rt}$) or the soybean seed as an outside option. In our empirical application, we focus on the Corn Belt region in the U.S., where corn and soybean are primary alternatives for farmers.[6]

The conditional indirect utility function of farmer i given that he/she chooses corn seed product j is:

[5]Previous studies take the same approach. For instance, using a discrete choice model, Qaim and De Janvry (2003) model farmers' choices of genetically modified cotton using the utility maximization framework. See also Hubbell et al. (2000) and Breustedt et al. (2008).

[6]Lee and Moschini (2022) estimates a nested logit demand for soybean seeds in Iowa and Illionois, where the outsode option is choosing corn seeds.

$$u_{ijrt} = \boldsymbol{x_j'}\boldsymbol{\beta}_i + \alpha_i(\ln y_{irt} - \ln p_{jrt}) + \phi_b + \phi_r + \phi_t + \xi_{jrt} + \epsilon_{ijrt} \tag{1}$$

where $\boldsymbol{x_j}$ is a vector of observed product characteristics for product j, y_{irt} is the corn seed expenditure of farmer i in region r at year t, and p_{jrt} is the price. The terms ϕ_b, ϕ_r, ϕ_t represent multiple fixed effects: ϕ_b allows for the mean valuation of the unobserved product characteristic to vary freely by brand (e.g., Dekalb, Pioneer, etc.); ϕ_r and ϕ_t allow the mean valuation of the utility from choosing the inside products to vary freely by region and year, respectively. We control for ϕ_b, ϕ_r, and ϕ_t using brand, region, and year dummy variables, respectively. The term ξ_{jrt} represents an unobserved quality variation specific to region r and year t, and ϵ_{ijrt} is a random utility term or an individual-specific taste parameter. We normalize the mean utility of the outside option ($j = 0$) to zero.

The observable product characteristics include indicator variables for GM traits, which provide useful attributes such as glyphosate tolerance (GT), corn borer resistance (CB), and rootworm resistance (RW). Firms often stack multiple GM traits in a single seed to enhance product quality. With this specification, the values of the parameters for each GM trait are measured relative to the valuation of non-GM corn seeds. We will discuss the types of GM traits in our application in Section 4.

We include farmer demographic variables to allow for flexible substitution patterns.[7] We specify the farmer-specific coefficients as $[\alpha_i, \boldsymbol{\beta}_i'] = [\alpha, \boldsymbol{\beta}'] + \Pi D_{irt}$, where D_{irt} is a vector of farmer i's demographic variables and Π is the corresponding parameter matrix. We allow the price-sensitive coefficient α to vary by the logarithm of farm size, measured by planted corn acreage. We also allow the valuation of GM traits $\boldsymbol{\beta}$ to vary by farm size.

Assuming that farmer i chooses a product that maximizes the utility u_{ijrt}, and that the error term ϵ_{ijrt} follows the extreme value distributional assumption of a nested logit model, the probability that farmer i chooses product j is derived:

$$\mathrm{s}_{ijrt}(\boldsymbol{\delta}_{rt}, \Pi) = \frac{\exp((\delta_{jrt} + \nu_{ijrt}(\Pi))/(1-\rho))}{\exp(I_{ig}/(1-\rho))} \frac{\exp(I_{ig})}{\exp(I_i)}$$

where δ_{jrt} is the mean utility of product j, $\nu_{ijrt}(\Pi)$ is the random part of farmer-specific valuations, I_{ig} and I_i are the group-specific and total inclusive values defined by:

$$\begin{aligned}
\delta_{jrt} &= \boldsymbol{x_j'}\boldsymbol{\beta} - \alpha \ln p_{jrt} + \phi_b + \phi_r + \phi_t + \xi_{jrt} \\
\nu_{ijrt}(\Pi) &= (\boldsymbol{x}_j', \ln p_{jrt}) * \Pi D_{irt} \\
I_{ig} &= (1-\rho) \ln \sum_{k \in \Omega_f} \exp((\delta_{krt} + \nu_{ikrt})/(1-\rho)) \\
I_i &= \ln \left(1 + \sum_{g=1}^{G} \exp(I_{gi}) \right)
\end{aligned}$$

Where Ω_f is a set of products provided by firm f.

The nesting parameter ρ captures the correlation of preferences across products in the same group. We define nests ($g = 1, ..., G$) as subsets of products provided by each firm. The parameter ρ should satisfy $0 \leq \rho \leq 1$. When ρ takes a higher value, the preference correlation in the same nest is stronger. If $\rho = 0$, the model reduces to a simple logit.

To derive the demand for product j, we apply Roy's identity to the indirect utility function in equation (1), which gives $d_{ijrt} = y_{irt}/p_{jrt}$. This is the conditional demand given that farmer i chooses product j. Then, the expected demand for product j by farmer i is:

$$q_{ijrt}(\boldsymbol{p}_{rt}, y_{irt}) = E_\epsilon[q_{ijrt}|\boldsymbol{p}_{rt}] = s_{ijrt}(\boldsymbol{\delta}_{rt}, \Pi) \frac{y_{irt}}{p_{jrt}}$$

[7] Although we do not include parameters related to unobserved heterogeneity, the model can be seen as a special case of the random coefficient logit model based on the discussion by Berry and Jia (2010).

This expected demand indicates that farmer i chooses one of the products and purchases multiple units of it.[8]

By aggregating the expected demand for product j over all farmers ($i = 1, ..., I_{rt}$), we derive the market demand for product j in region r and year t:

$$q_{jrt}(\boldsymbol{p}_{rt}, Y_{rt}) = \mathrm{s}_{jrt}(\boldsymbol{\delta}_{rt}, \Pi)\frac{Y_{rt}}{p_{jrt}} \tag{2}$$

$$\mathrm{s}_{jrt}(\boldsymbol{\delta}_{rt}, \Pi) = \sum_{i=1}^{I_{rt}} w_{irt}\frac{\exp((\delta_{jrt} + \nu_{ijrt}(\Pi))/(1-\rho))}{\exp(I_{ig}/(1-\rho))}\frac{\exp(I_{ig})}{\exp(I_i)} \tag{3}$$

where Y_{rt} is the aggregate expenditure, defined by $Y_{rt} = I_{rt}\sum_i w_{irt}y_{irt}$. w_{irt} is the share of farmers who have demographic variable D_{irt} in the population of region r and year t.

The market share in equation (3) follows the familiar form of the standard random coefficient nested logit model (Grigolon and Verboven, 2014). A notable difference is that here the price term enters logarithmically ($-\alpha \ln p_{jt}$), whereas it enters linearly ($-\alpha p_{jt}$) in the standard nested logit. Due to this specification, the market share is measured by value, not by quantity as determined from equation (2). Björnerstedt and Verboven (2016) discuss that this type of discrete choice model is a straightforward variant of the random coefficient logit demand model by Berry et al. (1995) and the same estimation technique, including contraction mapping, can be applied.

3.2 Supply models in the previous research

Our main innovation involves introducing a new supply framework that enalbes the estimation of firm-specific conduct parameters while maintaining empirical tractability even when the number of firms increases. To illustrate the advantages of our proposed model, we first demonstrate how to estimate firm conduct in the existing models and then discuss the challenges associated with in implementing such models.

In the supply side of structural models, the standard practice is to estimate marginal cost equations together with markup equations derived from solving first-order conditions of the profit maximization problem (Berry et al., 1995). We begin with the standard Bertrand price competition model.

There are F firms. Firm f produces a subset, Ω_f, of the $j = 1, ..., J$ differentiated products. For notational simplicity, we suppress the subscript of region r and year t. The profit maximization problem of firm f is:

$$\max_{\boldsymbol{p}_f} \quad \sum_{j\in\Omega_f}(p_j - c_j)q_j(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y) - FC_f$$

where $\boldsymbol{p}_f$ is a vector of prices of products produced by firm f; $\boldsymbol{p}_{-f}$ is a vector of prices of products produced by the other firms; c_j is the marginal cost of product j; FC_f is the fixed cost of firm f; and q_j is the demand function of product j obtained in equation (2).

Deriving the first-order conditions and stacking them in vector form, we have:

$$\boldsymbol{p} - \boldsymbol{c} = -\left[\left(\frac{\partial \boldsymbol{q}(\boldsymbol{p}, Y)}{\partial \boldsymbol{p}}\right)^T\right]^{-1}\boldsymbol{q}(\boldsymbol{p}, Y)$$

where $\boldsymbol{p}$, $\boldsymbol{c}$, and $\boldsymbol{q}$ are J by 1 vectors of prices, marginal costs, and quantities of all products, respectively. $\partial\boldsymbol{q}/\partial\boldsymbol{p}$ is a J by J Jacobian matrix of the demand function. The subscript T denotes the transpose of the matrix.

This is a vector of equilibrium markups under Nash-Bertrand price competition. Since only demand-side parameters need to be estimated, many papers rely on the assumption of this benchmark conduct to estimate markups (Hausman and Leonard, 2007; Nakamura and Zerom, 2010; Nevo, 2000).

[8] Dubé (2019) notes that observed consumer behavior often involves multiple purchases in many industries. In the case of corn seed, it is likely that farmers determine the purchase quantity based on the size of their farmland.

Nevo (1998) demonstrates how to introduce conduct parameters concerning competition between multiproduct firms. The marginal cost is specified as a linear function, $\boldsymbol{c} = \gamma\boldsymbol{\omega} + \boldsymbol{\zeta}$, where γ is a marginal cost parameter, $\boldsymbol{\omega}$ is a vector of observed cost shifters, and $\boldsymbol{\zeta}$ is a vector of unobserved cost shifters. Substituting this marginal cost function in the first-order conditions and introducing a matrix of conduct parameters, we have:

$$\boldsymbol{p} = \gamma\boldsymbol{\omega} - \left[\Theta * \left(\frac{\partial \boldsymbol{q}(\boldsymbol{p}, Y)}{\partial \boldsymbol{p}}\right)^T\right]^{-1} \boldsymbol{q}(\boldsymbol{p}, Y) + \boldsymbol{\zeta} \tag{4}$$

where $*$ denotes element-wise multiplication, and Θ is a J by J matrix of conduct parameters defined by:

$$\Theta = \begin{bmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1J} \\ \theta_{21} & \ddots & \cdots & \theta_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{J1} & \theta_{J2} & \cdots & \theta_{JJ} \end{bmatrix}$$

The matrix Θ measures the degree of internalization for a pair of products when firms solve their profit maximization problems. For instance, consider a situation where firm f produces product j and firm g produces product k. If θ_{jk} takes a positive value, it indicates that firm f internalizes the profit of product k when it chooses a price of product j. Within this framework, different models of competition can be nested depending on values of Θ; a single-product Nash-Bertrand pricing model corresponds to an identity matrix, a multiproduct Nash-Bertrand pricing model corresponds to a block diagonal matrix, and a full collusive model corresponds to a matrix of one. Therefore, this formulation allows for flexible estimation of firm conduct.

Nevo (1998) argues that a downside of this formulation is the presence of J^2 numbers of conduct parameters, which requires the same number of excluded instruments because markups are inherently correlated with unobserved marginal costs through firms' price decisions. Since finding such a large number of instruments is hard in practice, he suggests using testing-based approaches for a menu of pre-specified models, which is less demanding in terms of the number of excluded instruments (Backus et al., 2021; Magnolfi and Sullivan, 2022; Duarte et al., 2024).

Several papers estimate conduct parameters by imposing additional assumptions on a matrix of Θ to reduce the dimension of the parameters, including Sudhir (2001), Ciliberto and Williams (2014), Miller and Weinberg (2017), and Michel et al. (2023).

First, these papers focus on firm-level conduct rather than product-level conduct by specifying the same values of parameters for all products produced by the same firm. This decreases the number of conduct parameters from J^2 to F^2. Second, they reduce the number of firms that are subject to estimation. For instance, Sudhir (2001) focuses on competition between two stores (firms), which makes the number of parameters 4 ($= 2 \times 2$). Kadiyali et al. (2001) point out that, in many studies, the focus has been on the largest two or three firms in an industry. Third, most of the papers set diagonal elements of the parameter matrix to one (Ciliberto and Williams, 2014; Miller and Weinberg, 2017; Michel et al., 2023). In this formulation, conduct parameters measure deviation from the benchmark Bertrand pricing. This reduces the number of parameters from F^2 to $F(F-1)$.

In addition to these assumptions, Miller and Weinberg (2017) further assume symmetric coordination between a subset of firms. Specifically, their matrix of conduct parameters Θ for four firms (Anheuser-Busch InBev (ABI), MillerCoors, Modelo, and Heineken) in the beer industry is specified as follows:

$$\Theta_{Miller} = \begin{bmatrix} 1 & \theta & 0 & 0 \\ \theta & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

As you can see from the matrix, they assume symmetric coordination between ABI and MillerCoors and no coordination for any other combinations of the firms. This specification is based on their

interest in the effects of the merger between Miller and Coors on the coordination between ABI and MillerCoors. The number of conduct parameters is reduced to 1.

The other papers also reduce the number of conduct parameters to 1 or 2. Michel et al. (2023) estimate conduct parameters of firms in the US cereal industry using two specifications. In the first specification, all conduct parameters take the same value, resulting in a single conduct parameter. In the second specification, they assume group-specific conduct for two groups: the largest two firms (Kellogg's and General Mills) and the other firms.[9] Ciliberto and Williams (2014) take another approach, which specifies conduct parameters as functions of exogenous variables of multi-market contact between a pair of firms in the US airline industry. Under this functional assumption, the number of conduct parameters is reduced to 2 in their application. This approach is useful when it is possible to find exogenous variables that directly determine the conduct of firms in industries.

We then discuss how to apply this framework to the US corn seed industry. There are five major players (Monsanto, Dupont, Syngenta, Dow AgroSciencies, and AgReliant). To estimate the conduct of the five firms, possible specifications of a matrix of Θ are:

$$\Theta^1 = \begin{bmatrix} 1 & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} \\ \theta_{21} & 1 & \theta_{23} & \theta_{24} & \theta_{25} \\ \theta_{31} & \theta_{32} & 1 & \theta_{34} & \theta_{35} \\ \theta_{41} & \theta_{42} & \theta_{43} & 1 & \theta_{45} \\ \theta_{51} & \theta_{52} & \theta_{53} & \theta_{54} & 1 \end{bmatrix}, \Theta^2 = \begin{bmatrix} 1 & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} \\ \theta_{12} & 1 & \theta_{23} & \theta_{24} & \theta_{25} \\ \theta_{13} & \theta_{23} & 1 & \theta_{34} & \theta_{35} \\ \theta_{14} & \theta_{24} & \theta_{34} & 1 & \theta_{45} \\ \theta_{15} & \theta_{25} & \theta_{35} & \theta_{45} & 1 \end{bmatrix}, \Theta^3 = \begin{bmatrix} 1 & \theta_1 & \theta_1 & \theta_1 & \theta_1 \\ \theta_2 & 1 & \theta_2 & \theta_2 & \theta_2 \\ \theta_3 & \theta_3 & 1 & \theta_3 & \theta_3 \\ \theta_4 & \theta_4 & \theta_4 & 1 & \theta_4 \\ \theta_5 & \theta_5 & \theta_5 & \theta_5 & 1 \end{bmatrix} \quad (5)$$

The first specification Θ^1 is the most flexible, in which any pair of firms can interact asymmetrically. The number of parameters is 20. The second specification Θ^2 assumes symmetry of interactions between firms. The number of parameters is reduced to 10. The third specification Θ^3 assumes that each firm internalizes the profits of other firms by the same degree, resulting in the five conduct parameters. All of these specifications can provide valuable insights about firm conduct, but finding five or more excluded instruments is difficult in practice.

Furthermore, deriving estimation equations involves an inversion of a matrix of conduct parameters, which makes the markup term a complicated function of derivatives of demand functions and conduct parameters. To highlight this issue, we illustrate a simpler case in which there are three single-product firms. With the same assumption of the third specification Θ^3, estimation equations are derived as:

$$\begin{aligned} p_1 &= \boldsymbol{\omega}_1'\boldsymbol{\gamma} - \frac{(q_{22}q_{33} - \theta_2\theta_3 q_{23}q_{32})q_1 + (\theta_1\theta_3 q_{13}q_{32} - \theta_1 q_{12}q_{33})q_2 + (\theta_1\theta_2 q_{12}q_{23} - \theta_1 q_{13}q_{22})q_3}{D} + \zeta_{1rt} \\ p_2 &= \boldsymbol{\omega}_2'\boldsymbol{\gamma} - \frac{(\theta_2\theta_3 q_{23}q_{31} - \theta_2 q_{21}q_{33})q_1 + (q_{11}q_{33} - \theta_1\theta_3 q_{13}q_{31})q_2 + (\theta_1\theta_2 q_{13}q_{21} - \theta_2 q_{11}q_{23})q_3}{D} + \zeta_{2rt} \\ p_3 &= \boldsymbol{\omega}_3'\boldsymbol{\gamma} - \frac{(\theta_2\theta_3 q_{21}q_{32} - \theta_3 q_{22}q_{31})q_1 + (\theta_1\theta_3 q_{12}q_{31} - \theta_3 q_{11}q_{32})q_2 + (q_{11}q_{22} - \theta_1\theta_2 q_{12}q_{21})q_3}{D} + \zeta_{3rt} \end{aligned} \quad (6)$$

where $d_{jk} = \frac{\partial q_j}{\partial p_k}$ and D is a denominator of the inverse matrix in equation (4) given by:

$$D = q_{11}q_{22}q_{33} + \theta_1\theta_2\theta_3 q_{12}q_{23}q_{31} + \theta_1\theta_2\theta_3 q_{13}q_{21}q_{32} - \theta_1\theta_3 q_{13}q_{22}q_{31} - \theta_2\theta_3 q_{11}q_{23}q_{32} - \theta_1\theta_2 q_{12}q_{33}q_{21}$$

These estimation equations have highly nonlinear markup terms. They are already intractable even when the number of firms is three, and it becomes more complicated when the number of firms increases. In the end, it is impractically difficult to estimate conduct parameters for five firms in the existing framework. This motivates us to introduce a new supply framework that provides more tractable equations.

[9] Michel et al. (2023) add further flexibility to estimate separate parameters for three periods: pre-merger, post-merger, and price war period. Their main objective is to propose new instruments using promotion data, which can be constructed from the standard data set.

3.3 Proposed supply model

In the supply side of our structural model, we formulate firms' profit maximization problems based on the oligopolistic model developed by d'Aspremont et al. (2007). The model captures competition between firms along two dimensions: competition for market share and competition for market size. Oligopolistic firms compete with each other to obtain higher market shares by lowering prices. At the same time, they share a common interest in coordinating total market supply to maintain higher prices, effectively competing against products outside the market.The relative attitude toward these two kinds of competition determines the degree of competition for each firm. d'Aspremont et al. (2007) show that different degrees of competition, from monopolistic competition to collusion, can emerge as an oligopolistic equilibrium in their theoretical framework.

We demonstrate how to incorporate this model into an empirical structural model using a discrete/continuous nested logit demand model. This approach significantly reduces the number of dimensions of interactions between firms while maintaining flexibility for the degree of competition. Specifically, a single conduct parameter per firm characterizes the degree of collusion and the optimal markup for each firm. To construct the model, we extend the theoretical model of d'Aspremont et al. (2007) to accommodate multiproduct firms, as their assumption of single-product firms is restrictive in many applications.[10] For simplicity, we suppress the subscript of region r and year t in the meantime.

There are F firms. Firm f produces a subset, Ω_f, of the $j = 1, ..., J$ differentiated products. Following d'Aspremont et al. (2007), firm f maximizes its profit given other firms' choices under two demand constraints. A profit maximization problem of firm f is formulated as:

$$\begin{aligned} \max_{\boldsymbol{p}_f, \boldsymbol{q}_f} \quad & \sum_{j \in \Omega_f} (p_j - c_j) q_j - FC_f \\ & \text{subject to} \quad Q_f(\boldsymbol{q}_f) \leq H_f(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f})) \\ & \text{and} \quad Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f}) \leq D(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y) \end{aligned} \tag{7}$$

where p_j is the price of product j, c_j is the marginal cost, q_j is the quantity, FC_f is the fixed cost of firm f. $\boldsymbol{p}_f$ is a vector of prices of products produced by firm f, and $\boldsymbol{q}_f$ is a vector of the corresponding quantities. $\boldsymbol{p}_{-f}$ and $\boldsymbol{q}_{-f}$ are vectors of prices and quantities of all other products produced by the other firms. $Q_f(\boldsymbol{q}_f)$ is the quantity aggregator of firm f's products and H_f is its Hicksian demand function. $Q(\boldsymbol{q})$ is the quantity aggregator of all inside products and D is its Marshallian demand function. Y is the total expenditure. The integrability property of the discrete/continuous demand ensures the existence of these quantity aggregators (see Appendix A.1 for further details).

The first constraint is called the market share constraint. The Hicksian demand function H_f determines the firm-level demand conditional on the total quantity Q. Unlike d'Aspremont et al. (2007), we construct the market share constraint using a firm-level demand function rather than a product-level demand, allowing firms to internalize the profits from their own products.[11] This formulation ensures compatibility with multiproduct firms.

The second constraint is called the market size constraint. The Marshallian demand function D determines the market-level demand, which accounts for substitution between inside products and the outside product. As prices for inside products increase, consumers tend to purchase more of the outside product. While the constraint on market share reflects the competitive conflict between firms, the market size constraint is related to their common interest within the sector.

In models of oligopolistic competition with differentiated products, profit-maximizing firms charge positive markups based on perceived demand elasticities. For instance, a single-product firm sets a higher markup as demand becomes more inelastic.[12] In this sense, perceived demand elasticities

[10] Sakamoto and Stiegert (2018) incorporate the oligopolistic model by d'Aspremont et al. (2007) into a structural model with the almost ideal demand system by Deaton and Muellbauer (1980), and estimate conduct parameters for two firms in the U.S. retail coffee market. The results show that the conduct of these firms is close to collusion, rejecting the Nash-Bertrand pricing conduct.

[11] When firm f is a single-product firm, the market share constraint is $q_f \leq H_f(p_f, p_{-f}, Q(q_f, q_{-f}))$, which reduces to the same equation as one used in d'Aspremont et al. (2007).

[12] For single-product firms in price competition, the optimal markup is determined by a so-called inverse elasticity rule, $\mu = 1/(\frac{\partial \ln q_j}{\partial \ln p_j})$ (See, for instance, Tirole (1988)).

summarize necessary information for profit maximization. The same principle applies to the profit maximization problem given in equation (7), but perceived elasticities must be defined consistently with the market share and size constraints. By totally differentiating the two constraints respectively, we define the relevant elasticities.

$$\eta_j \equiv \frac{d\ln q_j}{d\ln p_j}\Big|_{Q_f(\boldsymbol{q}_f)=H_f(\boldsymbol{p},Q(\boldsymbol{q}))} = \frac{\dfrac{\partial \ln H_f}{\partial \ln p_j}}{\dfrac{\partial \ln Q_f}{\partial \ln q_j} - \dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f$$

$$\sigma_j \equiv \frac{d\ln q_j}{d\ln p_j}\Big|_{Q(\boldsymbol{q})=D(\boldsymbol{p},Y)} = \frac{\dfrac{\partial \ln D}{\partial \ln p_j}}{\dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f$$

The elasticity η_j is the firm-level elasticity of substitution of product j. Intuitively, because it is derived as the curvature of the firm-level demand function, it measures how the firm's demand changes when the firm changes the price of product j. This feature reflects the strategic nature of multiproduct firms, which internalize the demand of all of their own products when maximizing profits. In contrast, the elasticity σ_j is the market-level elasticity of substitution of product j. It is derived as the curvature of the market-level demand function and measures how the market-level demand changes when the firm changes the price of product j. In many cases involving substitutable products, the firm-level elasticity is typically larger in absolute value than the market-level elasticity; that is, we expect $|\eta_j| > |\sigma_j|$.[13]

With our demand specification, these elasticities of substitutions are given by:

$$\eta_j = -\frac{1}{S_{f|in}(s_{j|f} - s_{j|in})} \sum_{i=1}^{I} \alpha_i s_{ij|in}(1 - S_{if|in}) - 1 \quad \text{for j} \in \Omega_f \tag{8}$$

$$\sigma_j = -\frac{1}{(1-s_0)s_{j|in}} \sum_{i=1}^{I} \alpha_i s_{ij} s_{i0} - 1 \quad \text{for j} \in \Omega_f \tag{9}$$

(see Appendix A.2 for details on derivations)

To solve the maximization problem for firm f, we derive the Lagrangian as:

$$\mathcal{L}_f = \sum_{j\in\Omega_f} (p_j - c_j)q_j - FC_f + \lambda_f \left(1 - \frac{Q_f(\boldsymbol{q}_f)}{H_f(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f}))}\right) + v_f \left(1 - \frac{Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f})}{D(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y)}\right)$$

where λ_f and v_f are the Lagrange multipliers for the market share and size constraint, respectively.

Solving the first-order conditions of the profit maximization problem for firm f, we have the following equilibrium markup of product j supplied by firm f.
(see Appendix A.3 for details on derivations)

$$\mu_j^* = \frac{p_j - c_j}{p_j} = \frac{\theta_f(1 - S_{f|in}) + (1-\theta_f)S_{f|in}}{\theta_f(1 - S_{f|in})|\eta_j| + (1-\theta_f)S_{f|in}|\sigma_j|} \quad \text{for j} \in \Omega_f \tag{10}$$

where $S_{f|in}$ is the market share of firm f's products within the inside products (subscript in denotes the inside products hereafter). Specifically, $S_{f|in} = \sum_{j\in\Omega_f} s_{j|in}$, with $s_{j|in}$ being the market share of product j produced by firm f within the inside products.

The parameter θ_f denotes the conduct parameter for firm f, which measures the degree of collusion. It is defined as the ratio of two Lagrange multipliers: $\theta_f = \lambda_f/(\lambda_f + v_f)$. This ratio reflects the relative

[13] These elasticities correspond to the intra- and inter- elasticities of substitution defined in d'Aspremont et al. (2007) in the case of single product firms.

weight given to the firm-level demand (market share constraint) versus the market-level demand (market size constraint), when firms set their prices.

Equation (10) indicates that the optimal markup depends on the firm market share, the two elasticities of substitution, and the conduct parameter. To better understand the relationship among these factors, we express the markup equation as a weighted harmonic mean of the two elasticities of substitution.

$$\mu_j^* = \frac{1}{(1-w_f)|\eta_j| + w_f|\sigma_j|} \tag{11}$$

where the weight w_f is given by:

$$w_f = \frac{(1-\theta_f)S_{f|in}}{\theta_f(1-S_{f|in}) + (1-\theta_f)S_{f|in}} \tag{12}$$

From equation (11), the markup μ_j increases as the weight w_f increases when $|\eta_j| > |\sigma_j|$. Equation (12) shows that the weight w_f is an increasing function of the firm share $S_{f|in}$ and is a decreasing function of the conduct parameter θ_f. Consequently, the markup is higher with a larger market share and a lower conduct parameter, ceteris paribus. For instance, if $S_{f|in} = 1$, which is a monopoly case, the weight is zero and the markup equals to $1/|\sigma_j|$. Similarly, if $\theta_f = 0$, the markup attains the monopoly level even if $S_{f|in} < 1$. The specific values of θ_f correspond to the benchmark conduct as follows:

$$\mu_j^* = \begin{cases} \frac{1}{|\sigma_j|} & \text{if } \theta_f = 0 \quad \text{(Collusion)}, \\ \frac{1-S_{f|in}}{|\eta_j|} + \frac{S_{f|in}}{|\sigma_j|} & \text{if } \theta_f = \frac{1}{1+|\eta_j|/|\sigma_j|} \quad \text{(Cournot quantity competition)}, \\ \frac{1}{(1-S_{f|in})|\eta_j| + S_{f|in}|\sigma_j|} & \text{if } \theta_f = 1/2 \quad \text{(Bertrand price competition)}, \\ \frac{1}{|\eta_j|} & \text{if } \theta_f = 1 \quad \text{(Monopolistic competition)}. \end{cases}$$

(see Appendix B for details on derivations)

To illustrate the model, we present a simple example in which two firms each produce two products. We set $\eta_j = 6$ and $\sigma_j = 2$ for two elasticities of substitution. The market share of each product is set to $s_j = 0.2$ for $j = 1, ..., 4$, so $S_{f|in} = 0.5 (= (0.2 \times 2)/(0.2 \times 4))$ for $f = 1, 2$. Prices of all products and total expenditure are set to 1. These values are consistent with the simple discrete/continuous logit. Then, we calculate markups by using equation (10) for values of θ_f from 0 to 1.

Figure 5 shows the results of the calculations. The markup increases as θ_f decreases from 1 to 0. The highest value of the markup is attained when $\theta_f = 0$ (=collusion), while the lowest value is attained when $\theta_f = 1$ (=monopolistic competition). The markups under quantity competition and price competition are between these two extremes and the markup under quantity competition is larger than price competition (see Appendix C for further details).

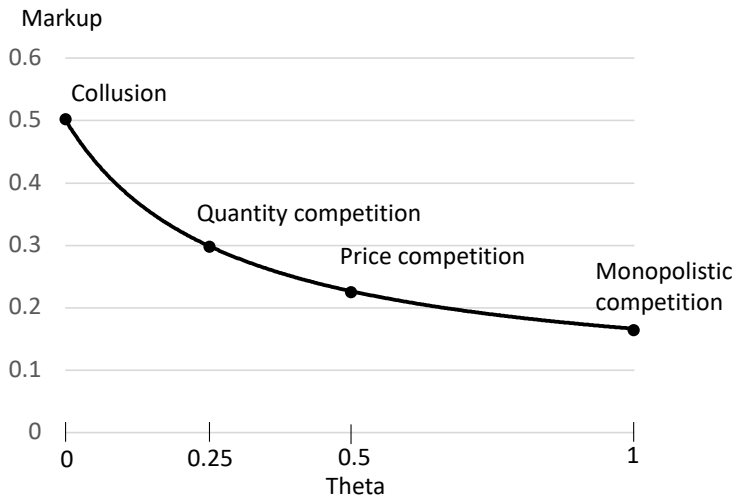


Figure 5: Relationship between markup ($\mu_j = (p_j - c_j)/p_j$) and conduct parameter (θ_f)
Note: Author's computations. We set $\eta_j = 6, \sigma_j = 2, S_{f|1} = 0.5$ and calculate the equilibrium markups for values of conduct parameters from 0 to 1. See Appendix C for further details.

As a final step in deriving estimation equations, we assume that the marginal cost of product j in region r and year t is linear in both parameters and in the observed cost shifters.

$$c_{jrt} = \boldsymbol{\omega}'_{jrt}\boldsymbol{\gamma} + \phi_r + \zeta_{jrt}$$

where $\boldsymbol{\omega}_{jrt}$ is a vector of observed cost shifters of product j and $\boldsymbol{\gamma}$ is a vector of parameters. The observed cost shifters include the previous year's future corn price and dummy variables indicating the presence of licensing on GM traits. The term ϕ_r is the region fixed effects that are expected to absorb region-specific costs such as distributional and marketing costs, and ζ_{jrt} is an unobserved cost shifter left as a structural error.

Substituting this marginal cost equation into the equilibrium markup equation (10), we have the following estimation equations.

$$\zeta_{jrt} = p_{jrt}\left(1 - \frac{\theta_f(1 - S_{frt|in}) + (1-\theta_f)S_{frt|in}}{\theta_f(1 - S_{frt|in})|\eta(\alpha_i)_{jrt}| + (1-\theta_f)S_{frt|in}|\sigma(\alpha_i)_{jrt}|}\right) - \boldsymbol{\omega}'_{jrt}\boldsymbol{\gamma} \quad \text{for j} \in \Omega_f \quad f = 1, ..., F \tag{13}$$

In equation (13), the estimated parameters include marginal cost parameters ($\boldsymbol{\gamma}$) and firm conduct parameters $\boldsymbol{\Theta} = (\theta_1, ..., \theta_F)$.[14] The markup term is endogenous because it is necessarily correlated with the unobserved costs. This correlation arises because firms consider unobserved marginal costs when setting their prices, and markups depend on the prices of all products in the market. This endogeneity requires excluded instruments for $\boldsymbol{\Theta} = (\theta_1, ..., \theta_F)$. Our identification strategy for conduct parameters is discussed in Section 4.

3.4 Comparison of the proposed model with the previous approach

Here, we discuss the advantages and disadvantages of the proposed model compared to the previous approach.

First, the proposed model maintains its tractability even with a large number of firms. From equation (13), the markup term takes a much simpler functional form and is determined by only one conduct parameter, θ_f. This structure ensures that the estimation equations remain tractable even as

[14] Corts (1999) notes that inference of conduct parameters is invalid if researchers do not formulate "the true nature of the behavior underlying the observed equilibrium." This critique does not apply here, as we assume that the observed equilibrium is generated from firms' static profit-maximization behavior with true values of conduct parameters. Under this assumption, our conduct parameters have structural interpretations. This argument is borrowed from Ciliberto and Williams (2014) and Magnolfi and Sullivan (2022).

the number of firms increases. Furthermore, a single excluded instrument can suffice for estimating all conduct parameters $\Theta = (\theta_1, ..., \theta_F)$, provided there is sufficient variation within-firm in the data. In the following application, we use one instrumental variable in interaction with firm-dummy variables to estimate firm-specific conduct parameters. This contrasts with the existing model, which, in principle, requires as many instruments as there are conduct parameters.

Second, the proposed model does not impose restrictions on the degree of collusion. Each value of the conduct parameters specifies the level of collusion of each firm, ranging from monopolistic competition to perfect collusion. For instance, some firms may be engaged in imperfect collusion while others may engage in Bertrand price competition. Consequnetly, the model can generate a rich set of equilibrium markups depending on firm-specific conduct parameters.

A disadvantage of the proposed model is its inability to estimate the degree of coordination between pairs of firms. The existing model can perform such an estimation, but only when the number of parameters is sufficiently small. Table 1 summarizes the number of conduct parameters for both approaches. In the existing model, the number of parameters increases more than the number of firms for asymmetric specifications (labeled (a) in the table) and symmetric specifications (b). As a result, the estimation becomes infeasible as the number of firms increases. In contrast, firm-specific specifications (c) have the same number of parameters in the existing model and the proposed model. However, the proposed model offers greater tractability due to the structure of its estimation equations. Therefore, while the existing model is suitable when researchers have an interest in the conduct of a small subset of firms, the proposed model is more effective for estimating firm-specific conduct for many firms.

Table 1: The number of conduct parameters

Number of firms	Number of conduct parameters			
	Existing model based on Nevo (1998)			Proposed model
	(a) asymmetric	(b) symmetric	(c) firm-specific	
1	1	1	1	1
2	2	1	2	2
3	6	3	3	3
4	12	6	4	4
5	20	10	5	5
⋮	⋮	⋮	⋮	⋮
n	$n(n-1)$	$\frac{n(n-1)}{2}$	n	n

Note: In the existing model, column (a) refers to a model in which asymmetric coordination is allowed for any pair of firms, column (b) refers to a model that assumes symmetry of a matrix of conduct parameters, and column (c) refers to a model that assumes firm-specific conduct parameters. See specifications given in equation (5). The proposed model refers to the model developed in this paper.

4 Data and Identification

In this section, we present the data and identification strategy for the application of the proposed structural model to the US corn seed industry.

4.1 Data Sources

Our primary data source is the corn TraitTrak data set, collected by GfK Kynetec, a major market research organization specializing in agriculture-related industries. The data set is constructed from a stratified sample of US corn growers surveyed annually from 1995 to 2014. It records expenditure, quantity, brands, parent companies, types of genetically modified traits, and product names for individual transactions between seed firms and farmers. The data are supposed to represent each crop

reporting district (CRD) of the US Department of Agriculture.[15] The data set includes 407,801 observations across 254 CRDs in 47 states over 1995-2014. On average, about 5,000 farmers are sampled per year, with approximately 25% of these farmers being retained in the subsequent year.

We focus on the core region of the Corn Belt in the midwestern US. The market share of the Corn Belt accounts for approximately 64% of the total corn seed market, and the share of the core region accounts for roughly 70% of the Corn Belt. Our definition of the core region includes 26 CRDs in six states: Illinois, Indiana, Iowa, Minnesota, North Dakota, and South Dakota.[16] The selected regions share relatively similar agro-economic conditions, such as soil fertility and rainfall. We refer to CRDs as regions hereafter.

We focus on the years 2005-2014, a period that seems to undergo fewer structural changes in both demand and supply. On the demand side, as Figure 1 shows, the introduction of triple-stacked traits in 2005 drastically changed the market situation. We expect that farmer preference remained relatively stable after the introduction of the triple-stacked traits. On the supply side, most acquisitions and mergers by major biotech firms were completed by the mid-2000s. Thus, the industry's structure did not undergo significant changes during the selected years, which is important for obtaining reliable estimates of firm conduct parameters. There are 104,057 observations in 260 markets (year-region combinations).

We define products as combinations of brand and GM traits, following previous papers that estimate discrete choice demand using the same dataset (Ciliberto et al., 2019; Luo et al., 2023). Corn farmers perceive the product qualities of corn seeds through brands and types of GM traits. In the sample, there are numerous brands sold by large seed firms or local/regional seed companies. We select brands with market shares greater than 1% over the entire period. Smaller brands are aggregated under one brand for each company: Monsanto, Dupont, Syngenta, Dow AgroSciences, AgReliant, and Regional (other regional companies).

Regarding GM traits, while Ciliberto et al. (2019) and Luo et al. (2023) categorize them as CB (corn borer resistance), RW (rootworm resistance), GT (glyphosate tolerance), double-stacked (CB_RW, CB_GT, RW_GT), and triple-stacked (CB_RW_GT), we further refine this categorization by utilizing the information on the specific traits developed by different firms. For instance, Monsanto initially introduced YieldGard CB for corn borer resistance in the early years of the sample and later developed YieldGard VT PRO, which also targets corn borer but uses more advanced technology. As seed prices vary based on the traits contained in the products, farmers are likely to perceive differences in the characteristics of these traits. Because the corn TraitTrak dataset contains the names of specific seed products such as SmartStack and AcreMax, we supplement it with technical documentation that is available on company websites to infer which GM traits are incorporated in the products. Table 2 provides the definitions of GM traits used for aggregation in the estimation.[17]

Based on the discussion above, we aggregate the data to year-region-product level, where products are defined as brands and GM traits combinations.[18] Table 3 shows the market shares calculated by brands. The market shares are measured in value, not quantity. The table shows that Dekalb, owned by Monsanto, and Pioneer, owned by Dupont, dominate the market, together holding more than a 50% market share. These brands maintain a significant presence in the seed market, possibly due to brand loyalty and long-term relationships with customers.

[15] CRDs consist of multiple counties as defined by the National Agricultural Statistics Service (NASS) of the USDA.

[16] We follow Stiegert et al. (2011) for the definition of the core region with a slight adjustment to reflect the trend of corn acreage in our estimation period. The CRDs we include are 17010, 17020, 17030, 17040, 17060, 17070, 18010, 18040, 18070, 19010, 19020, 19030, 19040, 19050, 19060, 27070, 27080, 27090, 31030, 31060, 31090, 38090, 46030, 46060, and 46090.

[17] We do not treat Liberty Link as a separate trait because it is usually considered a marker gene. See the discussion by Ciliberto et al., 2019.

[18] We drop products with a single RW trait or other herbicide tolerance (e.g., Clearfield developed by BASF) because there are very few observations, and their market shares are less than 0.1% during the estimation years.

Table 2: Definition of GM traits

Variable	Trait name	Attribute	Patent company
YGCB	YieldGard CB	corn borer resistance	Monsanto
YGRW	YieldGard RW	rootworm resistance	Monsanto
YGVTCB	YieldGard VT PRO	corn borer resistance	Monsanto
YGVTRW	YieldGard VT RW	rootworm resistance	Monsanto
RR	RoundupReady/RoundupReady2	glyphosate tolerance	Monsanto
AGCB	Agrisure CB	corn borer resistance	Syngenta
AGRW	Agrisure RW	rootworm resistance	Syngenta
AGGT	Agrisure GT	glyphosate tolerance	Syngenta
AGVP	Agrisure Viptera	corn borer resistance	Syngenta
HXCB	Herculex CB	glyphosate tolerance	Dow-Dupont
HXRW	Herculex RW	rootworm resistance	Dow-Dupont

Table 3: Market shares (%) by Brands

Parent company	Brand	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014
Monsanto	Dekalb	23.27	31.11	32.41	32.24	28.00
	Channel	-	-	2.83	5.28	4.94
	Kruger Seed	0.85	1.32	1.15	1.30	0.99
	Others	5.67	10.49	7.73	3.72	2.90
Dupont	Pioneer	29.28	24.42	24.70	26.30	29.57
	Others	0.58	0.38	0.50	1.40	2.23
Syngenta	Golden Harvest	3.78	2.13	4.10	5.06	5.13
	NK Seeds	3.83	1.92	1.12	1.23	1.20
	Others	3.84	1.89	0.84	0.00	0.21
Dow AgroSciences	Mycogen	2.59	1.82	1.82	1.86	1.88
	Others	-	-	0.55	0.77	1.44
AgReliant	Agrigold	2.35	3.82	3.44	4.54	3.52
	LG Seeds	1.51	1.81	1.72	2.19	2.54
	Producer Hybrids	0.95	0.83	1.20	1.15	1.56
	Others	0.90	1.26	1.23	1.02	1.15
Regional	Myfeels Hybrids	1.96	1.77	2.39	1.61	2.13
	Croplan Genetics	1.31	1.96	1.66	1.29	1.55
	Beck's Hybrids	0.75	1.15	1.44	1.35	1.57
	Others	16.56	11.93	9.20	7.68	7.49
Total		100	100	100	100	100

Note: In the estimation, Kruger Seed is treated as Monsanto's brand only after 2007 because it was purchased by Monsanto in 2006. Authors' calculation using GfK Kynetec data.

Table 4: Market shares(%) by GM traits

Type	Contained GM traits	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014
CB	YGCB	15.12	2.87	0.50	0.20	0.21
	HXCB	7.60	4.81	1.07	0.43	0.10
	AGCB	4.53	2.29	0.71	0.12	0.09
GT	RR	11.46	12.55	13.86	12.30	6.01
	AGGT	0.26	0.42	0.78	1.14	1.06
CB_GT	YGCB_RR	16.70	10.71	2.14	0.67	0.27
	AGCB_AGGT	0.20	0.46	0.68	0.36	0.19
	HXCB_RR	0.81	4.67	7.25	8.36	5.88
	YGVTCB_RR	-	-	0.06	1.84	7.40
	YGCB_HXCB_RR	-	-	-	0.51	5.58
CB_RW	YGCB_YGRW	2.71	1.26	0.31	0.05	0.01
	HXCB_HXRW	0.32	1.74	0.82	0.22	0.10
	AGCB_AGRW	-	0.74	0.83	0.17	0.12
RW_GT	YGRW_RR	2.98	1.65	0.23	0.14	0.07
	HXRW_RR	0.09	0.15	0.05	0.84	0.59
CB_RW_GT	YGCB_YGRW_RR	6.67	16.75	2.27	0.32	0.27
	HXCB_HXRW_RR	0.34	7.69	14.07	13.21	8.40
	AGCB_AGRW_AGGT	-	0.35	3.61	4.92	3.12
	YGCB_YGVTRW_RR	-	21.81	44.46	28.19	4.21
	YGVTCB_YGVTRW_RR	-	-	0.34	9.14	18.00
	AGCB_AGRW_AGGT_AGVP	-	-	-	1.48	3.12
	YGCB_HXCB_HXRW_RR	-	-	-	0.71	6.82
	YGCB_HXCB_AGRW_RR	-	-	-	0.08	1.41
	YGVTCB_YGVTRW_HXCB_HXRW_RR	-	-	1.75	10.08	22.62
Non-GM		30.22	9.10	4.23	4.52	4.35
	Total	100	100	100	100	100

Note: Authors' calculation using GfK Kynetec data. See Table 2 for the definition of GM traits.

Table 4 shows the market shares calculated by GM traits. First, the shares of seed products with single CB traits (e.g., YGCB, HXCB, AGCB) decreased over the years as stacked trait products became more widespread. Although the shares of RR (single GT) also declined, it remained above 6% even in 2013-2014. Among double-stacked types, CB_RW and RW_GT did not gain as much popularity as CB_GT. Lastly, the share of CB_RW_GT increased rapidly after its introduction in 2005. Additionally, biotech firms introduced numerous new products with more advanced GM traits, often stacking more than three traits. For example, the Smartstax series, developed by Monsanto and Dow, contains five GM traits ($YGVTCB_YGVTRW_HXCB_HXRW_RR$). The table shows that farmers aggressively adopted these new products.

The outside option is purchasing soybean seeds. We calculate the market size as the sum of total expenditure on both corn seeds and soybean seeds. Data on soybean seeds is also obtained from the GfK Kynetec dataset. The share of the outside option corresponds to the propotion ofexpenditure on soybean seeds. The price of each product is calculated by dividing the expenditure by the purchase quantity (number of bags). Similarly, the price of the outside option is also calculated by dividing the soybean expenditure by the purchase quantity. In the estimation, the price of each product is divided by the price of the outside option.

In the demand estimation, we include the log of price and dummy variables for each GM trait in the mean utility. We also construct farmer demographics from the TraitTrak data to incorporate preference heterogeneity as follows. First, we calculate the corn-planted acreage of farmers as a measure of farm size. The logarithm of this variable is used to account for different price sensitivity parameters across different-sized farms. Second, we construct two indicator variables for different size categories: medium-size (250-499 acres) and large-size (500 acres or more). The variable medium-size takes the value of 1 when a farmer' size falls within the range of 250 to 499 acres, and large-size takes the value of 1 when a farmer' size is 500 acres or more. These dummy variables are used to allow the parameters on attribute types of GM traits (CB, GT, CB_GT,CB_RW_GT) to vary depending on the size categories.[19] Summary statistics of the variables used for demand estimation are presented

[19]While it is possible to use the same dummy variables for GM traits as those used in the mean utility (e.g., YGCB,

in Table 5.

Table 5: Summary statistics of variables for demand estimation

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev
YGCB	0.050	0.218	AGCB_AGRW	0.010	0.102
HXCB	0.036	0.186	YGRW_RR	0.027	0.162
AGCB	0.030	0.172	HXRW_RR	0.008	0.087
RR	0.154	0.361	YGCB_YGRW_RR	0.057	0.231
AGGT	0.030	0.171	HXCB_HXRW_RR	0.037	0.190
YGCB_RR	0.071	0.257	AGCB_AGRW_AGGT	0.034	0.181
AGCB_AGGT	0.016	0.125	YGCB_YGVTRW_RR	0.093	0.291
HXCB_RR	0.030	0.171	YGVTCB_YGVTRW_RR	0.047	0.212
YGVTCB_RR	0.027	0.161	AGCB_AGRW_AGGT_AGVP	0.012	0.108
YGCB_HXCB_RR	0.008	0.087	YGCB_HXCB_HXRW_RR	0.009	0.093
YGCB_YGRW	0.026	0.158	YGCB_HXCB_AGRW_RR	0.005	0.067
HXCB_HXRW	0.017	0.128	YGVTCB_YGVTRW_HXCB_HXRW_RR	0.050	0.219
log(price)	1.554	0.205	CB	0.112	0.316
product share	0.012	0.024	GT	0.184	0.387
outside share	0.322	0.075	CB_GT	0.152	0.359
Number of products per market	61.68	14.25	CB_RW_GT	0.344	0.475
Number of own products per market	12.41	5.15			
Number of rivals' products per market	49.27	12.56			
log (farm size(acre))	6.00	0.96			
medium-size (250-499 acres)	0.25	0.43			
large-size (500 acres or more)	0.26	0.44			

Note: Authors' calculation using GfK Kynetec data. See Table 2 for the definition of GM traits. Farm size is a continuous variable of the corn-planted acreage of an individual farm. medium-size and large-size are indicator variables for the corresponding size categories. Number of observations for the year-region-product level aggregation is 15,045. Number of observations for the farm size variables is 65,236.

On the supply side, we construct variables for marginal cost parameters. First, the expected price of corn influences the marginal costs for seed production. Seed firms sign contracts with farmers to produce commercial seeds in year $t-1$ for sale in year t (Fernandez-Cornejo, 2004). Under these contracts, seed companies must pay farmers at least what they could have earned if they had sold their own corn. Following Kim and Moschini (2018) and Luo et al. (2023), we use the previous year's future corn price as a proxy for the expected price of corn, which serves as the observed marginal cost shifter. To construct this variable, we collect corn futures price data from Barchart.com. Using futures prices with a December delivery month, we average the daily closing prices from January to March, the periods before the planting season.

We assume that firms using GM traits licensed from other firms must pay licensing fees. For instance, Dupont's product AcreMax Xtreme contains Monsanto's YieldGard CB and Roundup Ready, Syngenta's Agrisure RW, Dow-Dupont's Herculex CB/RW for insect resistance, and Bayer's LibertyLink for herbicide tolerance. In this case, Dupont is supposed to pay certain royalty fees to Monsanto, Syngenta, and Bayer for utilizating their patented traits. We construct dummy variables that take the value 1 if the product contains the corresponding licensed trait. For instance, if a product contains Monsanto's traits and the seller is not Monsanto, the corresponding dummy variable takes the value 1. See Table 2 for patent companies for each GM trait.

The licensing dummy variables explain differences in how seed firms use licensed GM traits from other companies. Monsanto primarily utilizes its own patented technologies: the Roundup Ready and YieldGard traits. Dupont and Dow rely heavily on Monsanto's traits; more than 65% of their observations incorporate Roundup Ready. Additionally, they use Bayer's Liberty Link trait about half of their observations. In contrast, Syngenta does not use Monsanto's traits as extensively as the other firms. Syngenta primarily utilizes its own patented trait, Agrisure, and also incorporate Bayer's trait. Lastly, AgReliant, which does not own any patented GM traits, extensively utilizes Monsanto's traits. More than 70% of its observations use Monsanto's Roundup Ready, while the utilization rate

YGCB_YGVTRW_RR), this approach introduces computational challenges due to a large number of non-linear parameters.

of other firms' traits is fairly low. To summarize, the extent to which firms rely on licensed traits varies distinctly among them. These differences might affect marginal costs through licensing fees, leading to Monsanto and Syngenta being expected to be cost-efficient firms, while the marginal costs of Dupont, Dow, and AgReliant may be higher due to licensing fees.

Table 6 shows the summary statistics of the variables for supply estimation.

Table 6: Summary statistics of variables for supply estimation

Variable	Full sample		Means by firm					
	Mean	Std. Dev	Monsanto	Dupont	Syngenta	Dow	AgReliant	Regional
License_YGCB	0.219	0.414	0.000	0.279	0.105	0.211	0.405	0.338
License_YGRW	0.070	0.255	0.000	0.063	0.066	0.049	0.111	0.123
License_RR	0.437	0.496	0.000	0.667	0.162	0.678	0.732	0.605
License_YGVTCB	0.068	0.252	0.000	0.000	0.000	0.143	0.184	0.117
License_YGVTRW	0.113	0.317	0.000	0.010	0.000	0.220	0.301	0.196
License_AGCB	0.025	0.157	0.000	0.019	0.000	0.024	0.006	0.078
License_AGRW	0.021	0.143	0.000	0.037	0.000	0.022	0.006	0.050
License_AGGT	0.027	0.162	0.000	0.016	0.000	0.033	0.010	0.081
License_AGVP	0.003	0.051	0.000	0.001	0.000	0.000	0.000	0.010
License_HXCB	0.084	0.278	0.111	0.000	0.031	0.000	0.056	0.181
License_HXRW	0.059	0.235	0.096	0.000	0.000	0.000	0.048	0.115
License_LL	0.291	0.453	0.111	0.537	0.489	0.470	0.063	0.284
Product price	184.023	62,439	195.436	188.276	162.542	186.351	185.216	181.263
Firm share	0.203	0.155	0.391	0.293	0.082	0.031	0.085	0.165
Corn future price	424.123	130.479						

Note: Author's computations from Kynetec data. License variables are dummy variables that take the value 1 if a firm uses the corresponding trait owned by the other firms. LL stands for Liberty Link owned by Beyer. See Table 2 for the definition of the other GM traits.

4.2 Identification

We discuss our identification strategy for estimating the parameters of the demand and supply models. On the demand side, the key identification issue is the endogeneity of seed prices, which arises because oligopolistic firms set prices by taking into account the unobserved demand shifter that is unknown to researchers. The inclusion of multiple fixed effects is expected to alleviate the price endogeneity. However, it is still necessary to use instruments to obtain valid estimates, because the OLS estimate of the price coefficient remains positive even after controlling brand, region and year fixed effects.

We rely on the commonly used identification assumption that the product characteristics are uncorrelated with the error term (Berry et al., 1995). This assumption appears reasonable in the seed industry, as discussed in Ciliberto et al. (2019), who estimate the nested logit demand models for the U.S. corn and soybean seeds market. They argue that the introduction of new products is predetermined and is largely exogenous to pricing decisions because introducing GM seeds to the market requires a lengthy and complex process, including extensive molecular and agronomic testing, repeated breeding with elite germplasm, and clearing GM regulatory hurdles.

We count the number of rival firms' products that share the same GM trait (e.g., YBCB, YGVTCB_RR) in each market, following the approach used by Ciliberto et al. (2019). We expect the presence of products sharing the same GM trait to affect prices through firms' pricing decisions more than products with different GM traits. Our sample includes non-GM seeds, so we also construct the same variable for non-GM seeds. As a result, 25 instrumental variables (24 for GM traits and 1 for non-GM) for the price coefficient are constructed. Regarding the instrument for the nesting parameter, we follow the standard approach discussed in the literature (Conlon and Gortmaker, 2020). Specifically, we count the number of products within the nest in each market.

It is also necessary to construct instruments for the demographic interaction parameters. Since our dataset records individual transaction information, we construct micro moments targeting the demographic parameters, following the approach discussed in Petrin (2002), Berry et al. (2004), and

Conlon and Gortmaker (2023). We construct the following micro-moments.

$$\text{Cov}(\log(\text{price})_{jt}, \log(\text{farmsize})_{it} \mid j \neq 0)$$

$$E(\text{CB}_{jt} \mid \text{medium-size}_{it} = 1)$$

$$E(\text{CB}_{jt} \mid \text{large-size}_{it} = 1)$$

$$E(\text{GT}_{jt} \mid \text{medium-size}_{it} = 1)$$

$$E(\text{GT}_{jt} \mid \text{large-size}_{it} = 1)$$

$$E(\text{CB_GT}_{jt} \mid \text{medium-size}_{it} = 1)$$

$$E(\text{CB_GT}_{jt} \mid \text{large-size}_{it} = 1)$$

$$E(\text{CB_RW_GT}_{jt} \mid \text{medium-size}_{it} = 1)$$

$$E(\text{CB_RW_GT}_{jt} \mid \text{large-size}_{it} = 1)$$

In the first micro moment, we match the covariance between the log of price and the log of farm size to identify the interaction parameter between these variables. In the remaining micro moments, we match the probability that farmers in the medium-size or large-size categories purchase products with the corresponding type of GM traits. In the estimation, the values directly calculated from the data are matched with the fitted values predicted by the model.

To estimate the demand-side parameters $\theta^D = (\alpha, \rho, \boldsymbol{\beta}, \Pi)$, we construct aggregate moment conditions $g^A(\theta^D) = \frac{1}{N}\sum_{j,r,t} \xi'_{jrt} Z^D_{jrt}$ where N is the number of observations, ξ_{jrt} is the structural error in equation (1), and Z^D_{jrt} is a set of instruments. We combine these aggregate moments with micro-moments $g^M(\theta^D) = [\overline{f_m} - f_m(\theta^D)]$ where $\overline{f_m}$ is the observed values of the moment directly calculated by the data, and $f_m(\theta^D)$ represents the corresponding fitted values predicted by the model. Using these moment conditions, we define a GMM (generalized method of moments) estimator as follows:

$$\hat{\theta}^D = \arg\min_{\theta^D} \hat{g}'^D(\hat{\theta}^D)\hat{W}^D\hat{g}^D(\hat{\theta}^D), \quad \hat{g}^D(\theta^D) = \begin{bmatrix} \hat{g}^A(\theta^D) \\ \hat{g}^M(\theta^D) \end{bmatrix}, \quad \hat{g}^M(\theta^D) = \begin{bmatrix} \overline{f_1} - f_1(\theta^D) \\ \vdots \\ \overline{f_m} - f_m(\theta^D) \end{bmatrix}$$

where W^D is a weighting matrix for GMM estimation.

On the supply side, we construct instruments for conduct parameters. In supply-side estimation, it is necessary to address the endogeneity of the markups, which are correlated with unobserved marginal costs. Markups are functions of firm-level market share and two demand elasticities (firm-level and market-level demand), all of which are influenced by unobserved marginal costs through endogenous prices. To obtain consistent estimates of conduct parameters, we need to find excluded instruments that are correlated with the markups but uncorrelated with the unobserved marginal costs. Berry and Haile (2014) suggest that effective instruments should provide variation in market conditions that rotate the marginal revenue curve, including variables like the number of competing firms, the set of competing products, characteristics of competing products, or the costs of competing firms. Following this argument, we use the number of rival firms' products as an instrument for the conduct parameter. The number of rivals' products is expected to influence substitution among products and firms' market shares, thereby shifting optimal markups. To identify firm-specific conduct parameters, I interact this variable with firm dummy variables. The key identification assumption is that the instrument is uncorrelated with unobserved marginal costs, which seems reasonable in the seed industry, where the marginal cost of seed production is unlikely to be correlated with the number of rival products.

To estimate the supply-side parameters $\theta^S = (\boldsymbol{\gamma}, \theta_1, ..., \theta_F)$, we construct a GMM estimator as:

$$\hat{\theta}^S = \arg\min_{\theta^S} \hat{g}'^S(\hat{\theta}^S, \hat{\theta}^D)\hat{W}^S\hat{g}^S(\hat{\theta}^S, \hat{\theta}^D) \quad g^S(\theta^S, \theta^D) = \frac{1}{N}\sum_{j,r,t} \zeta'_{jrt} Z^S_{jrt}$$

where N is the number of observations, ζ_{jrt} is the structural error in equation (13), and Z^S_{jrt} is a set of instruments, and W^S is a weighting matrix for GMM estimation.

5 Empirical results

5.1 Demand estimates

Table 7 presents the results of the demand estimation. Model (1) shows the nested logit model without demographic interaction parameters, and Model (2) includes demographic interaction parameters. We estimate the models using a two-step GMM estimator. Both models include brand and market (year-region) fixed effects.[20] We use the pyBLP package developed by Conlon and Gortmaker (2020) for the estimations.

The estimated parameters have the expected signs. First, the price coefficient is negative and statistically significant at the 1% level. When we estimate the nested logit demand using OLS, the price coefficient is positive and statistically significant, suggesting that prices are indeed endogenous. The results of GMM estimation indicate that our excluded instruments reduce the upward bias on the price coefficient, leading to the negative price sensitivity.

The nesting parameters are 0.263 for Model (1) and 0.489 for Model (2). As expected, they take values between 0 and 1. The values are statistically significant at the 1% level, indicating that preferences are correlated across products within the same nest. We define nests as groups of products provided by each firm. These results suggest that farmers are influenced by the company supplying the corn seeds, potentially due to long-term relationships, the quality of germplasm, or the specific GM technologies.

Almost all the coefficients for GM traits in the mean utility are positive. Since we do not include an indicator variable for non-GM seeds, these parameters can be interpreted as the additional utility derived from GM traits compared to non-GM seeds. The positive coefficients indicate that farmers derive more utility from GM seeds than non-GM seeds. Additionally, the values of the parameters tend to increase as the product contains more stacked traits: however, the differences between these values are not always statistically significant.

In Model (2), we include demographic interaction parameters to account for farmer heterogeneity in corn seed preferences. Most of the coefficients are precisely estimated. First, the parameter for the interaction between log(price) and log(farm size) is positive and statistically significant at the 5% level. The positive coefficient indicates that larger farms are less sensitive to price increases. Figure 6 shows the estimated distribution of the price coefficients. The shape of the distribution reflects the distribution of farm sizes in the sample. The validity of the estimates is supported by the fact that none of the farmers exhibit positive price sensitivity.

Regarding the parameters for the interaction between size category dummies and GM traits, the coefficients are positive except for CB. Since these parameters represent the utility difference compared to small-size farmers (less than 249 acres), medium and large-size farmers derive more utility from GT, CB_GT, and CB_RW_GT but less utility from CB. As these parameters are identified by the micro moments, we report the values of micro moments in Table 8. The Table shows that the model fits the data well for most of these moments, although the moment for the covariance of log(price) and log(farm size) is not well-fitted compared to the other moments.

The mean of the estimated own-price elasticities is $(-4.909, -4.464)$ for Model (1) and (2), respectively. The results show that product-level demand is quite elastic.[21] The mean of the cross-price elasticities are (0.117, 0.163) for products within the same nest, and (0.046, 0.043) for products across nests. The former takes greater values than the latter, reflecting the preference correlation within the nest. Farmers are more likely to substitute toward products by the same firm when the price increases.

The average values of estimated firm-level demand elasticities of substitution are (-3.986, -2.916) for Model (1) and (2), respectively. Additionally, the average of estimated market-level demand elasticities of substitution are (-1.961, -1.606) for Model (1) and (2), respectively. As expected, the former exhibits more elastic response to price increases than the latter. As we use these estimate

[20] We also estimate the models with brand, region, and year fixed effects. While most of the parameters have the same signs, the price coefficient ($|\alpha|$) takes a smaller value than the results with market fixed effects. Based on these findings, we judge that market fixed effects are more effective for addressing the price endgeneity.

[21] Ciliberto et al. (2019) estimate the nested logit demand model for corn and soybean seed in the U.S. over 1996-2011 and report an own price elasticity of -6.990. While we cannot directly compare their estimates with ours, both results show the elastic demand for seeds at the product-level.

for supply-side estimation, we show the distribution of the estimates in the sample in Figure 7. The figure indicates that there is decent variation across the observations, reflecting farmer preferences and market conditions such as product availability.

Overall, we find the results of the demand estimation to be reasonable and economically meaningful. We use the results of Model (2) for the subsequent supply-side estimation.

Table 7: Demand estimates

Model		(1)Nested Logit		(2)RC Nested Logit	
log(price) (-α)		-2.988***	(1.016)	-3.198***	(0.798)
Nesting Parameter(ρ: nests=firms)		0.263***	(0.035)	0.489***	(0.032)
GM traits(β)					
CB	YGCB	0.288*	(0.176)	0.290***	(0.128)
	HXCB	0.447**	(0.189)	0.384***	(0.138)
	AGCB	0.190	(0.149)	0.273**	(0.113)
GT	RR	0.929***	(0.252)	0.354**	(0.171)
	AGGT	0.214	(0.229)	-0.205	(0.157)
CB_GT	YGCB_RR	0.893***	(0.303)	0.430**	(0.212)
	AGCB_AGGT	0.446	(0.300)	0.056	(0.210)
	HXCB_RR	1.175***	(0.341)	0.619**	(0.238)
	YGVTCB_RR	1.324***	(0.393)	0.718***	(0.273)
	YGCB_HXCB_RR	1.370***	(0.386)	0.763***	(0.269)
CB_RW	YGCB_YGRW	0.424	(0.336)	0.193	(0.225)
	HXCB_HXRW	0.545*	(0.310)	0.247	(0.209)
	AGCB_AGRW	0.772**	(0.317)	0.424*	(0.219)
RW_GT	YGRW_RR	0.499	(0.354)	0.247	(0.238)
	HXRW_RR	0.382	(0.367)	0.168	(0.246)
CB_RW_GT	YGCB_YGRW_RR	1.195***	(0.410)	0.468*	(0.284)
	HXCB_HXRW_RR	1.916***	(0.453)	0.930***	(0.314)
	AGCB_AGRW_AGGT	1.531***	(0.436)	0.659**	(0.303)
	YGCB_YGVTRW_RR	2.289***	(0.493)	1.249***	(0.342)
	YGVTCB_YGVTRW_RR	2.000***	(0.509)	1.050***	(0.349)
	AGCB_AGRW_AGGT_VP	1.678***	(0.468)	0.743**	(0.327)
	YGCB_HXCB_HXRW_RR	1.814***	(0.478)	0.887***	(0.330)
	YGCB_HXCB_AGRW_RR	1.036**	(0.429)	0.349	(0.298)
	YGVTCB_YGVTRW_HXCB_HXRW_RR	2.192***	(0.551)	1.168***	(0.377)
Demographics interaction(Π)					
log(price) × log(farmsize)				0.237**	(0.098)
CB × medium-size(250-499 Acres)				-0.156***	(0.050)
CB × large-size(500 Acres-)				-0.268***	(0.060)
GT × medium-size(250-499 Acres)				0.456***	(0.051)
GT × large-size(500 Acres-)				0.289***	(0.050)
CB_GT × medium-size(250-499 Acres)				0.279***	(0.052)
CB_GT × large-size(500 Acres-)				0.100	(0.068)
CB_RW_GT × medium-size(250-499 Acres)				0.551***	(0.056)
CB_RW_GT × large-size(500 Acres-)				0.320***	(0.078)
Price Elasticities					
Product demand					
Own		-4.909		-4.464	
Cross:within nest		0.117		0.163	
Cross:across nests		0.046		0.043	
Firm-level demand		-3.988		- 2.916	
Market-level demand		-1.961		- 1.606	
Fixed Effects		Brand+Year×Region		Brand+Year×Region	
Number of observations		15,045		15,045	

Notes: See Table 2 for the definition of GM traits. Standard errors are robust standard errors. Elasticities are the average values in the sample. $*$, $**$, $***$ denote significance of the test statistic at the 10%, 5%, and 1% level, respectively.

Table 8: Micro Moment Values

	Data	Estimated	Difference
$\text{Cov}(\log(\text{price})_{jt}, \log(\text{farm size})_{it} \mid j \neq 0)$	0.017	0.004	0.013
$E(\text{CB}_{jt} \mid \text{medium-size}_{it} = 1)$	0.062	0.063	-0.001
$E(\text{CB}_{jt} \mid \text{large-size}_{it} = 1)$	0.064	0.064	-0.001
$E(\text{GT}_{jt} \mid \text{medium-size}_{it} = 1)$	0.124	0.125	-0.001
$E(\text{GT}_{jt} \mid \text{large-size}_{it} = 1)$	0.134	0.135	-0.001
$E(\text{CB_GT}_{jt} \mid \text{medium-size}_{it} = 1)$	0.148	0.148	-0.001
$E(\text{CB_GT}_{jt} \mid \text{large-size}_{it} = 1)$	0.147	0.147	-0.0003
$E(\text{CB_RW_GT}_{jt} \mid \text{medium-size}_{it} = 1)$	0.561	0.556	0.005
$E(\text{CB_RW_GT}_{jt} \mid \text{large-size}_{it} = 1)$	0.512	0.508	0.004

Notes: This table reports values for the micro moments for the data and the estimated model. Firm size is a continuous variable representing the size of farmers in acres. medium-size$_{it}$ is an indicator variable that takes the value 1 when farmer i's size falls within the range of 250 to 499 acres. large-size$_{it}$ is an indicator variable that takes the value 1 when farmer i's size is greater than or equal to 500 acres. Source: Authors' computations.

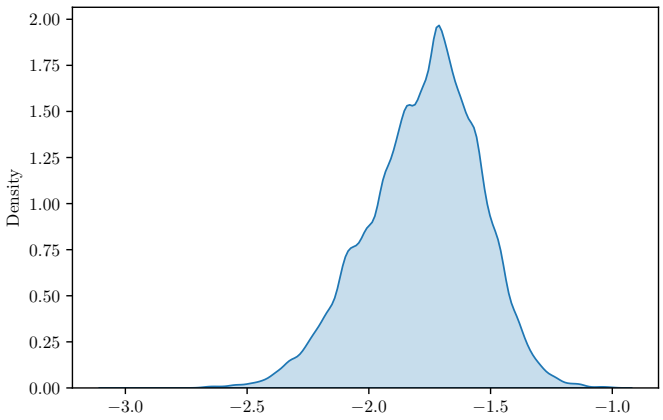


Figure 6: Estimaetd distribution of price coefficients(-α_i) among farmers in all markets

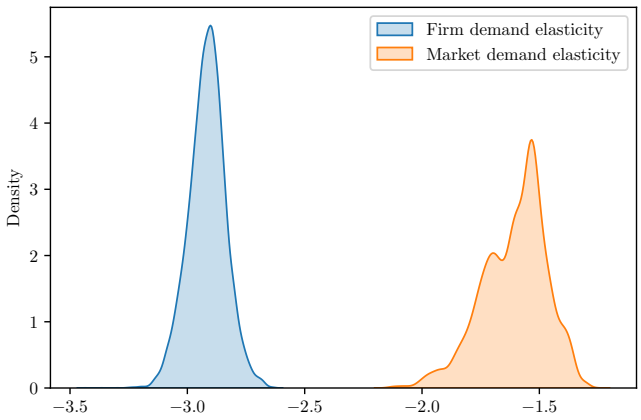


Figure 7: Estimated distribution of firm-level and market-level demand elasticities in all markets

5.2 Supply estimates

On the supply side, we estimate parameters of firm conduct and marginal cost given the estimated demand-side parameters. This two-step estimation is computationally less demanding and has been applied in past research (Michel et al., 2023; Miller and Weinberg, 2017). However, in two-step estimation, it is important to account for the estimation errors of the demand parameters. To address this issue, we calculate standard errors through bootstrapping.[22] In the estimation, we use OLS to concentrate the linear marginal cost parameters and fixed effects out of the optimization problem. This procedure reduces the dimensionality of the nonlinear search to only six conduct parameters, which significantly simplifies the estimation process. Table 9 presents the results of the supply-side parameters using a two-step GMM estimator. Below, we discuss the results of Model (1) in Table 9.

The conduct parameters for the six firms are precisely estimated and take values from 0 to 1, as required by the theoretical model. The results indicate that the conduct of the four firms (Monsanto: 0.145, Syngenta: 0.100, Dow: 0.164, AgReliant: 0.261) is imperfect collusion, with the estimated conduct parameters falling between perfect collusion ($\theta_f = 0$) and quantity competition ($\theta_f = 0.36$).[23] The low values of the conduct parameters may reflect coordination between firms, internalization by the licensing firms, or both. In the seed industry, the licensing firms can earn additional profits from sales made by the licensed firms, providing them with additional incentives to sustain higher prices. On the other hand, Dupont's conduct parameter is 0.509, which is close to Bertrand price competition.

Table 10 indicates the results of hypothesis testing on the benchmark conduct. The testing results indicate that all benchmark conduct hypotheses are rejected for Monsanto, Syngenta, Dow and, AgReliant. Among these firms, the hypothesis of perfect collusion for Monsanto has the smallest value of t-statistics. On the other hand, the hypotheses of Bertrand price competition for Dupont and Regional are not rejected at the 10% significance level. Dupont was the largest seed firm in the early 2000s, but its market share declined by 2009 as Monsanto introduced new GM traits and expanded its market presence (see Figure 3). Additionally, Dupont faced cost disadvantages due to its reliance on Monsanto's patented traits (see Table 6 for licensing dummies for Dupont). The competitive conduct of Dupont might reflect its strategy to retain market share by lowering prices in this challenging environment.

Back to Table 9, most of the marginal cost parameters are positive, as expected. The positive coefficient on the corn future price implies that seed firms must pay more to corn farmers when corn prices are expected to increase. The positive parameters on the dummy variables for licensed GM traits indicate that the utilization of licensed traits increases marginal costs. This result is consistent with the fact that, through licensing agreements, firms are supposed to pay licensing fees to licensors when they incorporate patented traits. [24]

To further investigate these estimates, we calculate marginal costs and markups for these firms. The results are shown in Table 11. The average marginal costs are lower for Monsanto ($91 per bag) and Syngenta ($94 per bag), while the other three firms have higher marginal costs ($113-118 per bag). The ownership structure of patented traits explains these differences. Monsanto and Syngenta mainly use their own patented GM traits, but Syngenta also uses Bayer's trait for about 50% of their products, while Monsanto uses it for only 10% of their products (see Table 6). This makes Monsanto more cost-efficient than Syngenta. On the other hand, Dupont, Dow, and AgReliant heavily rely on Monsanto's GM traits, leading to additional licensing costs. To better illustrate this tendency, we present a kernel density of estimated marginal costs in all markets for Monsanto, Syngenta, and

[22] The bootstrap is conducted as follows. Among the demand parameters, only the price coefficient α and its interaction with farm size (Π_α) appear in the supply estimation equations through the firm-level and market-level demand elasticities. To account for the estimation errors in the demand side, we simulate 200 distinct sets of parameters for $(\alpha, \Pi_\alpha$ using the estimated covariance matrix of the demand parameters. We then estimate the supply model for each of these 200 simulated parameter sets. Based on these simulated results, we calculate the bootstrapped standard errors for the supply parameters.

[23] In the case of quantity competition, $\theta_f = 1/(1 + \eta_j/\sigma_j)$, where (η_j, σ_j) are the firm-level and market-level demand elasticities of substitution. We calculate this value using the average of the elasticities in the sample.

[24] The estimates of License_AGCB and HXCB are negative, which contradicts with our expectation. As Table 6 shows, the market shares of the products with these licensed trait are fairly small. This limited avairablity may have led to invalid estimates.

Table 9: Supply estimates

Model		(1)		(2)	
Conduct parameters (θ_f)					
	Monsanto	0.145***	(0.053)	0.155***	(0.051)
	Dupont	0.509***	(0.025)	0.480***	(0.022)
	Syngenta	0.100***	(0.012)	0.086***	(0.011)
	Dow AgroSciencies	0.164***	(0.017)	0.126***	(0.018)
	AgReliant	0.261***	(0.010)	0.234***	(0.006)
	Regional	0.493***	(0.014)	0.429***	(0.015)
Marginal cost parameters (γ)					
License_Monsanto	License_YGCB	4.906***	(1.384)	6.430***	(1.691)
	License_YGRW	6.807***	(1.261)	8.852***	(1.598)
	License_RR	17.976***	(2.659)	16.000***	(2.356)
	License_YGVTCB	12.488***	(2.713)	8.545***	(2.168)
	License_YGVTRW	23.447***	(3.669)	21.043***	(3.248)
License_Syngenta	License_AGCB	-12.230***	(1.559)	-7.862***	(0.926)
	License_AGRW	17.220***	(2.395)	11.651***	(1.606)
	License_AGGT	22.053***	(3.162)	16.585***	(2.279)
	License_AGVP	32.695***	(5.337)	30.700***	(4.955)
License_DowDupont	License_HXCB	-11.471***	(1.564)	-8.584***	(1.100)
	License_HXRW	15.701***	(2.003)	10.961***	(1.245)
License_Bayer	License_LL	18.005***	(3.494)	15.888***	(3.279)
	Corn future price	0.168***	(0.028)		
Fixed Effects		Region		Year,Region	

Notes: LL stands for Liberty Link owned by Beyer. See Table 2 for the definition of the other GM traits. Standard errors are bootstrapped standard errors using 200 simulated sets of the demand parameters. $***$ denotes significance of the test statistic at the 1%-level.

Dupont in Figure 8. It shows that Dupont has higher marginal costs than Monsanto and Syngenta.

The estimates of markups are also shown in Table 11. Monsanto charges the highest markup, while the other firms have relatively similar ranges for their markups. The average relative markup ($= (p-mc)/p$) is 53% for Monsanto and $36-42$% for the other four firms. Although Dupont's conduct is more competitive compared to Syngenta, Dow, and AgReliant, its average markup is close to theirs. This is primarily because Dupont has a larger market share, which makes it easier to exert its market power. Figure 9 shows the estimated distribution of markups for Monsanto, Syngenta, and Dupont. It indicates that Monsanto tends to change higher markups than the other two firms.

In the estimation of Model (1) in Table 9, we control marginal costs using the future corn price, licensing dummy variables, and region fixed effects. The region fixed effects are expected to capture region-specific costs such as distribution costs, but there might exist year-specific unobserved common costs which are not accounted for by the future corn price. To check the robustness of our estimates, we include year-fixed effects so that unobserved costs are more flexibly captured. The results are shown as Model (2) in Table 9.[25] The estimates of conduct and marginal cost parameters have the same sign and fall within similar ranges for the most part.

[25]We drop the future corn price as it is colinear with year fixed effects.

Table 10: Hypothesis testing on benchmark conduct

Null Hypothesis	Perfect Collusion $\theta_f = 0$	Cournot Quantity competition $\theta_f = 0.36$	Bertrand Price competition $\theta_f = 0.5$	Monopolistic competition $\theta_f = 1$
t-statistics				
Monsanto	2.762***	3.981***	6.744***	16.250***
Dupont	20.168***	6.035***	0.348	19.472***
Syngenta	8.290***	21.201***	33.024***	74.339***
Dow AgroSciencies	9.500***	11.096***	19.454***	48.408***
AgReliant	27.498***	9.672***	25.094***	77.686***
Regional	35.181***	9.865***	0.506	36.193***

Notes: The table reports the t-statistics associated with the associated hypothesis. In the case of quantity competition, $\theta_f = 1/(1 + \eta_j/\sigma_j)$, where (η_j, σ_j) are the firm-level- and market-level elasticities of substitution. We calculate this value using the average of the elasticities, which is 0.36. $*$, $**$, $***$ denote significance of the test statistic at the 10%, 5%, and 1% level, respectively.

Table 11: Estimates of marginal costs and markups

	Average Price (in \$) p (observed)	Marginal cost (in \$) mc (estimated)	Markup (in \$) $p - mc$ (estimated)	Relative markup $(p - mc)/p$ (estimated)
Monsanto	195.44	90.66	104.78	53.04%
[95% CI]		[81.24, 100.08]	[95.36, 114.19]	[48.29, 57.78]
Dupont	188.28	113.50	74.77	39.55%
[95% CI]		[111.87, 115.13]	[73.14, 76.40]	[38.71, 40.40]
Syngenta	162.54	94.22	68.32	42.13%
[95% CI]		[91.80, 96,65]	[65.89, 70.74]	[40.64, 43.62]
Dow AgroSciencies	186.35	118.24	68.11	36.42%
[95% CI]		[117.32, 119.16]	[67.19, 69.02]	[35.94, 36.89]
AgReliant	185.22	114.81	70.40	37.78%
[95% CI]		[114.27, 115.36]	[69.86, 70.95]	[37.49, 38.06]

Notes: The price, marginal cost, and markup are US dollars per bag. 95% confidence intervals are calculated by parametric bootstrap using the asymptotic distribution of the estimated parameters. The number of simulation draws is 500.

5.3 Counterfactual simulations

To quantify the impact of the firm conduct, we conduct counterfactual simulations to explore how changes in firm conduct would affect market outcomes. We analyze two counterfactual scenarios: (1) Perfect collusion ($\theta_f = 0$ for all firms), (2) Bertrand price competition ($\theta_f = 0.5$ for all firms). To measure farmer surplus, we calculate the farmers' compensating variation resulting from the corresponding price change. In addition, to measure producer surplus, we calculate the change in the sum of firms' variable profits. We use the results of Model (1) for the following simulations.

Our simulations proceed as follows. In each simulation, we set the values of conduct parameters based on the scenario considered. Then, we generate new equilibria by solving the firms' first-order conditions with fixed-point iterations. The calculations are conducted separately for each market. We find that the fixed-point iterations converge within 200 iterations for all markets in every scenario. We assume that the price of outside products (soybean seeds) remains unchanged. Also, we assume that the marginal costs are fixed in the simulations.

Table 12 presents the results of counterfactual simulations. We report the changes in price, quantity, firm variable profit, farmer surplus, and total welfare. In CF1, in which the conduct is perfect

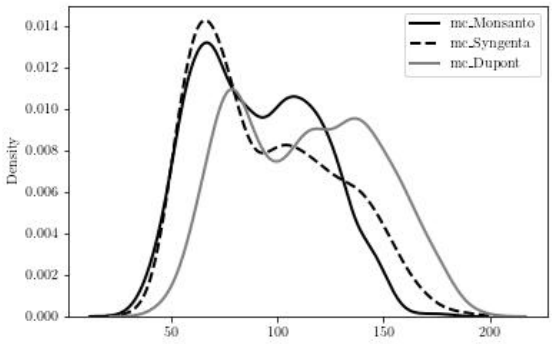


Figure 8: Estimated distribution of marginal costs (in $ per bag)

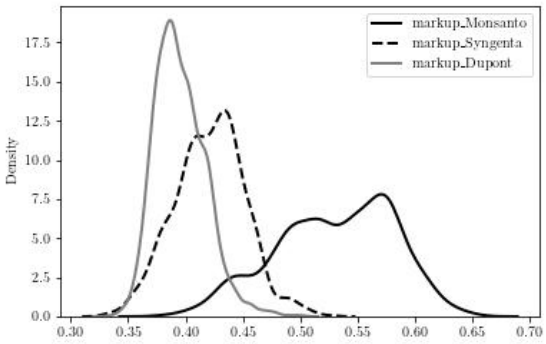


Figure 9: Estimated distribution of markups $(p - mc)$ (in $ per bag)

collusion for all firms, the average price increases by 37%, and firm profits increase by 1,217 million dollars. However, farmer surplus decreases by 5,244 million dollars. As a result, total welfare decreases by 4,027 million dollars. In contrast, in CF2, where the conduct is Bertrand price competition for all firms, the average price decreases by 6%, firm profits decrease by 509 million dollars, and farmer surplus increases by 1,622 million dollars. As a result, total welfare increases by 1,113 million dollars.

The counterfactual results indicate that seed firms can extract substantial surplus from farmers by setting prices above competitive levels, while more competitive behavior by the firms would lead to an increase in total welfare.

Table 12: Counterfactual simulations

	CF1	CF2
Hypothetical conduct	Perfect collusion	Bertrand Price competition
Simulation results		
Δ Average Price (in %)	36.68	-5.98
Δ Total Quantity (in %)	-29.21	15.12
Δ Firm variable profit (in million-USD)	1216.90	-508.93
Δ Farmer surplus (in million-USD)	-5243.55	1612.78
Δ Total welfare (in million-USD)	-4026.65	1112.85

Note: 'Perfect collusion' indicates the conduct parameter (θ_f) takes 0 for all firms and 'Bertrand price competition' indicates the conduct parameter (θ_f) takes 0.5 for all firms. The simulation results are changes of each variable from the base scenario in which the conduct parameters of all firms takes the estimated values. Price changes are averages over all markets. For quantity, firm profit, farmer surplus, and total welfare, we report the total changes aggregated over all years and all regions.

6 Conclusion

This paper develops a new structural model of demand and supply that is useful for the estimation of firm-specific conduct parameters in a differentiated products market. The proposed model allows for the flexible estimation of the degree of collusion and remains empirically tractable, even when estimating conduct parameters for many multiproduct firms. Thus, the model overcomes the limitations of the existing models that suffer from the curse of dimensionality. A key assumption of the model is that the firms' profit maximization problem can be formulated using two demand functions: firm-level demand and market-level demand. In this framework, a single conduct parameter determines the degree of collusion for each firm. We show that this formulation is compatible with the standard settings using the discrete/continuous demand models without requiring additional assumptions.

A limitation of the model is that it cannot identify pair-wise relationships of coordination. While existing methods are better suited for analyzing such pair-wise relationships, they are only applicable when the number of parameters is sufficiently reduced. In contrast, the proposed model is suitable for analyzing the degrees of collusion in industries where numerous major firms operate.

We apply the proposed model to the US corn seed industry, in which there are longstanding concerns about the negative impacts of growing market power on market outcomes, yet the related empirical evidence is limited. We estimate firm-specific conduct parameters for the five largest firms. Four of the five firms exhibit conduct of imperfect collusion, while one firm engages in Bertrand price competition. The estimated markups ranges from 38% to 53%, with the leading firm charging the highest markup. The results of the counterfactual simulations indicate that the degree of collusion would significantly impact firms' pricing strategies: prices would increase by 37% under perfect collusion and decrease by 6% under competitive conduct. This application proves the applicability of the model and provides new empirical evidence on the degree of collusion in the seed industry, which has been subject to numerous anti-trust regulations in many countries.

References

Anderson, S. P., De Palma, A., & Thisse, J.-F. (1987). "The ces is a discrete choice model". *Economics Letters*, *24*(2), 139–140.

Backus, M., Conlon, C., & Sinkinson, M. (2021). "Common ownership and competition in the ready-to-eat cereal industry". *NBER Working Paper*.

Berry, S., & Jia, P. (2010). "Tracing the woes: An empirical analysis of the airline industry". *American Economic Journal: Microeconomics*, *2*(3), 1–43.

Berry, S., Levinsohn, J., & Pakes, A. (1995). "Automobile prices in market equilibrium". *Econometrica*, *63*(4), 841–890.

Berry, S., Levinsohn, J., & Pakes, A. (2004). "Differentiated products demand systems from a combination of micro and macro data: The new car market". *Journal of political Economy*, *112*(1), 68–105.

Berry, S. T., & Haile, P. A. (2014). "Identification in differentiated products markets using market level data". *Econometrica*, *82*(5), 1749–1797.

Björnerstedt, J., & Verboven, F. (2016). "Does merger simulation work? evidence from the swedish analgesics market". *American Economic Journal: Applied Economics*, *8*(3), 125–64.

Bresnahan, T. F. (1982). "The oligopoly solution concept is identified". *Economics Letters*, *10*(1), 87–92.

Bresnahan, T. F. (1989). "Empirical studies of industries with market power". *Handbook of industrial organization*, *2*, 1011–1057.

Breustedt, G., Müller-Scheeßel, J., & Latacz-Lohmann, U. (2008). "Forecasting the adoption of gm oilseed rape: Evidence from a discrete choice experiment in germany". *Journal of Agricultural Economics*, *59*(2), 237–256.

Chavas, J.-p., Shi, G., & Stiegert, K. (2020). "Pricing and industry structure when demand elasticity changes". *Review of Industrial Organization*, *57*, 891–907.

Ciliberto, F., Moschini, G., & Perry, E. D. (2019). "Valuing product innovation: Genetically engineered varieties in us corn and soybeans". *The RAND Journal of Economics*, *50*(3), 615–644.

Ciliberto, F., & Williams, J. W. (2014). "Does multimarket contact facilitate tacit collusion? inference on conduct parameters in the airline industry". *The RAND Journal of Economics*, *45*(4), 764–791.

Clancy, M. S., & Moschini, G. (2017). "Intellectual property rights and the ascent of proprietary innovation in agriculture". *Annual Review of Resource Economics*, *9*, 53–74.

Conlon, C., & Gortmaker, J. (2020). "Best practices for differentiated products demand estimation with pyblp". *RAND Journal of Economics*, *51*(4), 1108–1161.

Conlon, C., & Gortmaker, J. (2023). "Incorporating micro data into differentiated products demand estimation with pyblp". *Working Paper*.

Corts, K. S. (1999). "Conduct parameters and the measurement of market power". *Journal of Econometrics*, *88*(2), 227–250.

d'Aspremont, C., Dos Santos Ferreira, R., & Gérard-Varet, L.-A. (2007). "Competition for market share or for market size: Oligopolistic equilibria with varying competitive toughness". *International Economic Review*, *48*(3), 761–784.

De Loecker, J., Eeckhout, J., & Unger, G. (2020). "The rise of market power and the macroeconomic implications". *The Quarterly Journal of Economics*, *135*(2), 561–644.

Deaton, A., & Muellbauer, J. (1980). "An almost ideal demand system". *The American Economic Review*, *70*(3), 312–326.

Deconinck, K. (2020). "Concentration in seed and biotech markets: Extent, causes, and impacts". *Annual Review of Resource Economics*, *12*, 129–147.

Döpper, H., MacKay, A., Miller, N., & Stiebale, J. (2023). "Rising markups and the role of consumer preferences". *NBER Working Paper*.

Duarte, M., Magnolfi, L., Sølvsten, M., & Sullivan, C. (2024). "Testing firm conduct". *Quantitative Economics*, *15*(3), 571–606.

Dubé, J.-P. (2019). "Microeconometric models of consumer demand". In *Handbook of the economics of marketing* (pp. 1–68, Vol. 1). Elsevier.

Dubé, J.-P. H., Joo, J., & Kim, K. (2023). "Discrete-choice models and representative consumer theory". *NBER Working Paper*.

Fernandez-Cornejo, J. (2004). *The seed industry in us agriculture: An exploration of data and information on crop seed markets, regulation, industry structure, and research and development* (tech. rep. No. Agricultural Information Bulletin no.786). US Department of Agriculture.

Graff, G. D., Rausser, G. C., & Small, A. A. (2003). "Agricultural biotechnology's complementary intellectual assets". *The Review of Economics and Statistics*, *85*(2), 349–363.

Grigolon, L., & Verboven, F. (2014). "Nested logit or random coefficients logit? a comparison of alternative discrete choice models of product differentiation". *Review of Economics and Statistics*, *96*(5), 916–935.

Hanemann, W. M. (1984). "Discrete/continuous models of consumer demand". *Econometrica*, *52*(3), 541–561.

Hausman, J. A., & Leonard, G. K. (2007). "Estimation of patent licensing value using a flexible demand specification". *Journal of econometrics*, *139*(2), 242–258.

Howard, P. H. (2009). "Visualizing consolidation in the global seed industry: 1996–2008". *Sustainability*, *1*(4), 1266–1287.

Howard, P. H. (2015). "Intellectual property and consolidation in the seed industry". *Crop Science*, *55*(6), 2489–2495.

Hubbell, B. J., Marra, M. C., & Carlson, G. A. (2000). "Estimating the demand for a new technology: Bt cotton and insecticide policies". *American Journal of Agricultural Economics*, *82*(1), 118–132.

Hurwicz, L., & Uzawa, H. (1971). "On the integrability of demand functions". In *Preferences, utility, and demand* (pp. 114–148). Harcourt Brace Jovanovich.

Kadiyali, V., Sudhir, K., & Rao, V. R. (2001). "Structural analysis of competitive behavior: New empirical industrial organization methods in marketing". *International Journal of Research in Marketing*, *18*(1), 161–186.

Kim, H., & Moschini, G. (2018). "The dynamics of supply: Us corn and soybeans in the biofuel era". *Land Economics*, *94*(4), 593–613.

Konovalov, A., & Sándor, Z. (2010). "On price equilibrium with multi-product firms". *Economic Theory*, *44*, 271–292.

Lee, S., & Moschini, G. (2022). "On the value of innovation and extension information: Scn-resistant soybean varieties". *American Journal of Agricultural Economics*, *104*(4), 1177–1202.

Luo, J., Moschini, G., & Perry, E. D. (2023). "Switching costs in the us seed industry: Technology adoption and welfare impacts". *International Journal of Industrial Organization*, *89*, 102977.

Magnolfi, L., & Sullivan, C. (2022). "A comparison of testing and estimation of firm conduct". *Economics Letters*, *212*.

Michel, C., y Mino, J. M. P., & Weiergraeber, S. (2023). "Estimating industry conduct using promotion data". *forthcoming at RAND Journal of Economics*.

Miller, N. H., & Weinberg, M. C. (2017). "Understanding the price effects of the millercoors joint venture". *Econometrica*, *85*(6), 1763–1791.

Moschini, G. (2008). "Biotechnology and the development of food markets: retrospect and prospects". *European Review of Agricultural Economics*, *35*(3), 331–355.

Moschini, G. (2010). "Competition issues in the seed industry and the role of intellectual property". *Choices*, *25*(2).

Nakamura, E., & Zerom, D. (2010). "Accounting for incomplete pass-through". *The Review of Economic Studies*, *77*(3), 1192–1230.

Nevo, A. (1998). "Identification of the oligopoly solution concept in a differentiated-products industry". *Economics Letters*, *59*(3), 391–395.

Nevo, A. (2000). "Mergers with differentiated products: The case of the ready-to-eat cereal industry". *The RAND Journal of Economics*, *31*(3), 395–421.

Nocke, V., & Schutz, N. (2018). "Multiproduct-firm oligopoly: An aggregative games approach". *Econometrica*, *86*(2), 523–557.

OECD. (2018). "Concentration in seed markets: Potential effects and policy responses". *OECD Publishing, Paris*.

Petrin, A. (2002). "Quantifying the benefits of new products: The case of the minivan". *Journal of Political Economy*, *110*(4), 705–729.

Qaim, M., & De Janvry, A. (2003). "Genetically modified crops, corporate pricing strategies, and farmers' adoption: The case of bt cotton in argentina". *American Journal of Agricultural Economics*, *85*(4), 814–828.

Rivers, D., & Vuong, Q. (2002). "Model selection tests for nonlinear dynamic models". *The Econometrics Journal*, *5*(1), 1–39.

Sakamoto, R., & Stiegert, K. (2018). "Comparing competitive toughness to benchmark outcomes in retail oligopoly pricing". *Agribusiness*, *34*(1), 44–60.

Shi, G., Chavas, J.-P., & Lauer, J. (2013). "Commercialized transgenic traits, maize productivity and yield risk". *Nature biotechnology*, *31*(2), 111–114.

Shi, G., Meloyan, A., & Kubo, K. (2023). "Two tigers in one mountain: Are there implicit collusions in the u.s. corn seed market?" *Working Paper*.

Stiegert, K. W., Shi, G., & Chavas, J.-P. (2011). "Spatial pricing of genetically modified hybrid corn seeds". In *Genetically modified food and global welfare* (pp. 149–171, Vol. 10). Emerald Group Publishing Limited.

Sudhir, K. (2001). "Structural analysis of manufacturer pricing in the presence of a strategic retailer". *Marketing Science*, *20*(3), 244–264.

Tirole, J. (1988). *The theory of industrial organization*. MIT press.

USDA. (2023). "More and better choices for farmers: Promoting fair competition and innovation in seeds and other agricultural inputs". *USDA Publishing Report*.

Villas-Boas, S. B. (2007). "Vertical relationships between manufacturers and retailers: Inference with limited data". *The Review of Economic Studies*, *74*(2), 625–652.

Appendix A Further details on derivations

A.1 Derivations of demand functions in market share and size constraint

We show how to derive firm-level Hicksian demand and market-level Marshallian demand functions in market share and market size constraints using a discrete/continuous logit demand model.[26] Two constraints are given as follows.

$$Q_f(\boldsymbol{q}_f) \leq H_f(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f})) \quad \text{(market share constraint)}$$

$$Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f}) \leq D(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y) \quad \text{(market size constraint)}$$

First, we derive the expected demand of product j conditional on choosing inside products ($j = 1, ..., J$).

$$q_{j|in}(\boldsymbol{p}, Y_{In}) = \frac{1}{I}\sum_{i=1}^{I} \frac{\exp(\delta_j + \nu_{ij}(\Pi))}{\sum_{k=1}^{J}\exp(\delta_k + \nu_i(\Pi))}\frac{Y_{in}}{p_j} = s_{j|in}(\boldsymbol{p})\frac{Y_{in}}{p_j} \tag{14}$$

where $s_{j|in}$ is the choice probability of product j conditional on choosing the inside products, $\delta_j = \boldsymbol{x_j'}\boldsymbol{\beta} - \alpha \ln p_j + \xi_j$ is the mean utility from product j. Y_{in} is the expenditure on the inside products. Notice that the denominator of this conditional choice probability does not include the mean utility of the outside product ($\exp(\delta_0) = 1$).

Dubé et al. (2023) show that the expected demand system derived from the discrete/continuous demand model is integral because it satisfies the necessary and sufficient conditions from Hurwicz and Uzawa (1971). This integrability ensures recovering an expenditure function of the representative consumer corresponding to the conditional demand system given in equation (14).

Following Dubé et al. (2023), we derive the expenditure function as:

$$e(\boldsymbol{p}, Q) = \exp\left(-\frac{1}{I}\sum_{i=1}^{I}\ln\left(\sum_{k=1}^{J}\exp(\delta_k + \nu_i(\Pi))\right)^{1/\alpha_i}\right) Q = P(\boldsymbol{p})Q \tag{15}$$

where P and Q are the price and quantity aggregators of all inside products.

Using this price aggregator, the Marshallian demand function D is:

$$D = \sum_{j=1}^{J} s_j \frac{Y}{P(\boldsymbol{p})} = S_{in}\frac{Y}{P(\boldsymbol{p})} \tag{16}$$

where S_{in} is the total market share of all inside products, $S_{in} = \sum_{j=1}^{J} s_j(\boldsymbol{\delta})$.

Similarly, we derive the expected demand of product j conditional on choosing products of firm f.

$$q_{j|f}(\boldsymbol{p}_f, Y_f) = \frac{1}{I}\sum_{i=1}^{I} \frac{\exp(\delta_j + \nu_{ij}(\Pi))}{\sum_{k\in\Omega_f}\exp(\delta_k + \nu_i(\Pi))}\frac{Y_f}{p_j} = s_{j|f}(\boldsymbol{p}_f)\frac{Y_f}{p_j} \tag{17}$$

where $s_{j|f}$ is the choice probability of product j conditional on choosing the products of firm f. Y_f is the expenditure on the products of firm f.

Using the same integrability result above, the expenditure function corresponding to the demand system given in equation (17) is

$$Y_f = e_f(\boldsymbol{p}_f, Q_f) = \exp\left(-\frac{1}{I}\sum_{i=1}^{I}\ln\left(\sum_{k\in\Omega_f}\exp(\delta_k + \nu_i(\Pi))\right)^{1/\alpha_i}\right) Q_f = P_f(\boldsymbol{p}_f)Q_f \tag{18}$$

where P_f and Q_f are the price and quantity aggregators of the products produced by firm f.

[26] We demonstrate the case of simple logit for illustration. The same argument applies to discrete/continuous nested logit demand models.

Using this firm-level price aggregator, the Hicksian demand function H_f is:

$$H_f = \sum_{j \in \Omega_f} s_{j|in} \frac{Y_{in}}{P_f(\boldsymbol{p}_f)} = S_{f|in} \frac{P(\boldsymbol{p})Q}{P_f(\boldsymbol{p}_f)} \tag{19}$$

where $s_{j|in}$ is the conditional market share of product j within the inside products. $S_{f|in}$ is the conditional market share of firm f's products, $S_{f|in} = \sum_{j \in \Omega_f} s_{j|in}$.

The discrete/continuous demand system has a homothetic preference as the expenditure function has a multiplicative form of the price aggregator and quantity aggregator (see equations (15) and (18)). The homotheticity generates the following useful properties.

$$\frac{\partial \ln Q}{\partial \ln q_j} = \frac{\partial \ln P}{\partial \ln p_j} = s_{j|in}, \quad \frac{\partial \ln Q_f}{\partial \ln q_j} = \frac{\partial \ln P_f}{\partial \ln p_j} = s_{j|f} \quad \frac{\partial \ln H_f}{\partial \ln Q} = 1 \tag{20}$$

where these equations are derived from the first-order conditions of the consumer expenditure minimization problem and the functional form of the expenditure functions.

Several remarks should be made. Formulating two constraints in the firms' profit maximization problem is key and discrete/continuous demand models are compatible with the formulation. On the other hand, the standard logit demand models are not necessarily consistent with this formulation because they may fail to satisfy the integrability property for some situations (Nocke and Schutz, 2018; Dubé et al., 2023). The failure of the integrability means that it is not possible to recover an expenditure function nor a utility function of a representative consumer. If these functions are not recovered, the existence of relevant price and quantity aggregators is not ensured. As a result, deriving demand functions in two constraints is not possible in general.

A.2 Derivations of firm-level- and market-level elasticity of substitution

We show how to derive firm-level- and market-level elasticities of substitution.

A.2.1 Firm-level elasticity of substitution

By totally differentiating the market share constraint with equality and setting $dp_k = dq_k = 0$ for $k \neq j$, we have

$$\frac{\partial Q_f}{\partial q_j} dq_j = \frac{\partial H_f}{\partial p_j} dp_j + \frac{\partial H_f}{\partial Q} \frac{\partial Q}{\partial q_j} dq_j \quad \text{for j} \in \Omega_f$$

By arranging the terms and dividing both sides by p_j/q_j, we have the firm-level elasticity of substitution of product j.

$$\left. \frac{d \ln q_j}{d \ln p_j} \right|_{Q_f(\boldsymbol{q}_f) = H_f(\boldsymbol{p}_f, Q(\boldsymbol{q}))} = \frac{\dfrac{\partial \ln H_f}{\partial \ln p_j}}{\dfrac{\partial \ln Q_f}{\partial \ln q_j} - \dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f \tag{21}$$

where $\dfrac{\partial \ln H_f}{\partial \ln Q} = 1$ due to homothetic preference.

This elasticity is calculated as a curvature of the market share constraint, so this is interpreted as a perceived demand elasticity of product j for firm f. Firm f takes into account the value of this elasticity when it maximizes profits under the market share constraint.

Next, we show that this elasticity equals the elasticity of Q_f/Q with respect to P_f/P, which is an analog to the definition of the intra-sectoral elasticity of substitution derived in d'Aspremont et al. (2007). The difference is that We use Q_f instead of q_j because the market share constraint is formulated for the firm-level share of multiproduct firms, so if firm f produces only one product, both definitions coincide.

$$-\frac{d(Q_f/Q)}{d(P_f/P)}\frac{P_f/P}{Q_f/Q} = -\frac{\dfrac{\partial H_f}{\partial p_j}\dfrac{P_f}{QP}}{\left(\dfrac{\partial P_f}{\partial p_j}\dfrac{1}{\partial P} - \dfrac{\partial P}{\partial p_j}\dfrac{P_f}{P^2}\right)\dfrac{Q_f}{Q}}$$

$$= -\frac{\dfrac{\partial \ln H_f}{\partial \ln p_j}}{\dfrac{\partial \ln P_f}{\partial \ln p_j} - \dfrac{\partial \ln P}{\partial \ln p_j}} = -\frac{\dfrac{\partial \ln H_f}{\partial \ln p_j}}{\dfrac{\partial \ln Q_f}{\partial \ln q_j} - \dfrac{\partial \ln Q}{\partial \ln q_j}} = |\eta_j|$$

where the first equality follows a differentiation with respect to p_j, and the second equality follows by arranging the terms. The third equality follows from equation (20).

Next. we show how to derive equation (8). By differentiating the Hicksian demand given in equation (19) and expressing the terms in elasticity forms, we have:

$$\frac{\partial \ln H_f}{\partial \ln p_j} = \frac{\partial \ln S_{f|in}}{\partial \ln p_j} + \frac{\partial \ln P}{\partial \ln p_j} - \frac{\partial \ln P_f}{\partial \ln p_j}$$

$$= -\frac{1}{S_{f|in}}\sum_{i}^{I}\alpha_i s_{ij|in}(1 - S_{if|in}) - (s_{j|f} - s_{j|in})$$

By substituting this into equation (21) and using equation (20), we have:

$$\eta_j = -\frac{1}{S_{f|in}(s_{j|f} - s_{j|in})}\sum_{i=1}^{I}\alpha_i s_{ij|in}(1 - S_{if|in}) - 1 \quad \text{for j} \in \Omega_f$$

In the case of a simple logit without any random coefficients, this elasticity is simplified to:

$$\eta_j = -\alpha - 1 \tag{22}$$

A.2.2 Market-level elasticity of substitution

By totally differentiating the market size constraint with equality and setting $dp_k = dq_k = 0$ for $k \neq j$, we have:

$$\frac{\partial Q}{\partial q_j}dq_j = \frac{\partial D}{\partial p_j}dp_j \quad \text{for j} \in \Omega_f$$

By arranging the terms and dividing both sides by p_j/q_j, we have the market-level elasticity of substitution of product j.

$$\sigma_j \equiv \frac{d\ln q_j}{d\ln p_j}\Big|_{Q(\boldsymbol{q})=D(\boldsymbol{p},Y)} = \frac{\dfrac{\partial \ln D}{\partial \ln p_j}}{\dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f \tag{23}$$

This elasticity is calculated as a curvature of the market size constraint, so firm f takes into account the value of this perceived demand elasticity when it maximizes profits under the market size constraint. Also, this elasticity coincides with the market-level elasticity of substitution defined in d'Aspremont et al. (2007).

Next. we show how to derive equation (9). By differentiating the Marshallian demand function given in equation (16) with respect to p_j and expressing the terms in elasticity forms, we have:

$$\frac{\partial \ln D}{\partial \ln p_j} = \frac{\partial \ln S_{in}}{\partial \ln p_j} - \frac{\partial \ln P}{\partial \ln p_j}$$
$$= -\frac{1}{1-s_0}\sum_{i}^{I} \alpha_i s_{ij} s_{i0} - s_{j|in}$$

By substituting this into equation (23) and using equation (20), we have:

$$\sigma_j = -\frac{1}{(1-s_0)s_{j|in}}\sum_{i=1}^{N} \alpha_i s_{ij} s_{i0} - 1 \tag{24}$$

In the case of a simple logit without any random coefficients, this elasticity is simplified to:

$$\sigma_j = -\alpha s_0 - 1 \tag{25}$$

A.3 Solving first-order conditions of profit maximization problem

We show how to solve the profit maximization problem of firm f given in equation (7). The Lagrangian for firm f is:

$$\mathcal{L}_f = \sum_{j\in\Omega_f}(p_j - c_j)q_j - FC_f + \lambda_f\left(1 - \frac{Q_f(\boldsymbol{q}_f)}{H_f(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f}))}\right) + v_f\left(1 - \frac{Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f})}{D(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y)}\right)$$

By differentiating this Lagrangian with respect to (p_j) and (q_j) for $j \in \Omega_f$, we have:

$$(p_j) \quad q_j + \lambda_f\left(\frac{Q_f}{H_f^2}\frac{\partial H_f}{\partial p_j}\right) + v_f\left(\frac{Q}{D^2}\frac{\partial D}{\partial p_j}\right) = 0 \quad \text{for j} \in \Omega_f$$

$$(q_j) \quad p_j - c_j + \lambda_f\left(-\frac{1}{H_f}\frac{\partial Q_f}{\partial q_j} + \frac{Q_f}{H_f^2}\frac{\partial H_f}{\partial Q}\frac{\partial Q}{\partial q_j}\right) + v_f\left(-\frac{1}{D}\frac{\partial Q}{\partial q_j}\right) = 0 \quad \text{for j} \in \Omega_f$$

Arranging the terms, we have:

$$(p_j) \quad q_j = \frac{\lambda_f}{p_j}\left(-\frac{\partial \ln H_f}{\partial \ln p_j}\right) + \frac{v_f}{p_j}\left(-\frac{\partial \ln D}{\partial \ln p_j}\right) \quad \text{for j} \in \Omega_f \tag{26}$$

$$(q_j) \quad p_j - c_j = \frac{\lambda_f}{q_j}\left(\frac{\partial \ln Q_f}{\partial \ln q_j} - \frac{\partial \ln H_f}{\partial \ln Q}\frac{\partial \ln Q}{\partial \ln q_j}\right) + \frac{v_f}{q_j}\frac{\partial \ln Q}{\partial \ln q_j} \quad \text{for j} \in \Omega_f \tag{27}$$

Dividing equation (27) by equation (26) and arranging the terms, we have:

$$\frac{p_j - c_j}{p_j} = \frac{\lambda_f(s_{j|f} - s_{j|in}) + v_f s_{j|in}}{\lambda_f(-\frac{\partial \ln H_f}{\partial \ln p_j}) + v_f(-\frac{\partial \ln D}{\partial \ln p_j})} \quad \text{for j} \in \Omega_f$$

where we use $\frac{\partial \ln Q_f}{\partial \ln q_j} = s_{j|f}$, $\frac{\partial \ln Q}{\partial \ln q_j} = s_{j|in}$, and $\frac{\partial \ln H_f}{\partial \ln Q} = 1$, all of which hold due to the homothetic preference.

Finally, defining $\theta_f = \lambda_f/(\lambda_f + v_f)$ and arranging the terms, the equilibrium relative markup is derived:

$$\mu_j^* = \frac{p_j - c_j}{p_j} = \frac{\theta_f(1 - S_{f|in}) + (1-\theta_f)S_{f|in}}{\theta_f(1 - S_{f|in})|\eta_j| + (1-\theta_f)S_{f|in}|\sigma_j|} \quad \text{for j} \in \Omega_f \tag{28}$$

where η_j and σ_j are the firm-level and market-level elasticities of substitution of product j.

Appendix B Relationship with benchmark competition models

We show how the specific values of θ_f generate the equilibrium markups that correspond to ones generated from benchmark models. We use a discrete/continuous logit demand without random coefficients because it allows us to obtain closed-form derivations.

The demand function of product j is given as:

$$q_j = s_j \frac{Y}{p_j} = \frac{\exp(v_j - \alpha \log p_j)}{1 + \sum_{k=1}^{J} \exp(v_k - \alpha \log p_k)} \frac{Y}{p_j}$$

where v_j is a product-specific valuation.

B.1 Price competition

In the case of multiproduct Bertrand price competition, a profit maximization problem of firm f is:

$$\max_{\boldsymbol{p}_f} \quad \pi_f = \sum_{j \in \Omega_f} (p_j - c_j) q_j(\boldsymbol{p}, Y)$$

The first-order condition for product j produced by firm f is given by:

$$\frac{\partial \pi_f}{\partial p_j} = q_j + \sum_{k \in \Omega_f} (p_k - c_k) \frac{\partial q_k}{\partial p_j} = 0$$

The derivatives of the demand function are given by:

$$\frac{\partial q_j}{\partial p_j} = \frac{\partial s_j}{\partial p_j} \frac{Y}{p_j} - \frac{s_j Y}{p_j^2} = \left(-\alpha \frac{s_j}{p_j} + \alpha \frac{s_j^2}{p_j} \right) \frac{Y}{p_j} - \frac{s_j Y}{p_j^2} = \alpha \frac{s_j^2 Y}{p_j^2} - (\alpha + 1) \frac{s_j Y}{p_j^2} \quad \text{for j} \in \Omega_f$$

$$\frac{\partial q_k}{\partial p_j} = \frac{\partial s_k}{\partial p_j} \frac{Y}{p_j} = \alpha \frac{s_j s_k Y}{p_j p_k} \quad \text{for } j, k \in \Omega_f \quad k \neq j$$

Substituting the derivatives into the first-order condition, we have:

$$q_j + \alpha \sum_{k \in \Omega_f} \frac{(p_k - c_k)}{p_k} s_k q_j - (\alpha + 1) \frac{(p_j - c_j)}{p_j} q_j = 0$$

As relative markups $(p_j - c_j)/p_j$ take the same values under the discrete/continuous logit (see Konovalov and Sándor (2010) and Nocke and Schutz (2018)), we set $\mu = (p_j - c_j)/p_j$ for all j. Rearranging the terms, we have:

$$\mu = \frac{p_j - c_j}{p_j} = \frac{1}{(1 - S_f)\alpha + 1} \tag{29}$$

where $S_f = \sum_{k \in \Omega_f} s_k$ is the market share of firm f.

This is the equilibrium markup under multiproduct price competition. The markups are higher for firms with higher market shares because multiproduct firms internalize their own products.

Next, we derive the equilibrium markup under the proposed model when $\theta_f = 0.5$, which is given as:

$$\frac{p_j - c_j}{p_j} = \frac{1}{(1 - S_{f|1})|\eta_j| + S_{f|1}|\sigma_j|}$$

Substituting $|\eta_j| = \alpha + 1$ and $|\sigma_j| = \alpha s_0 + 1$ from equations (22) and (25), we have:

$$\begin{aligned} \frac{p_j - c_j}{p_j} &= \frac{1}{(1 - S_{f|1})(\alpha + 1) + S_{f|1}(\alpha s_0 + 1)} \\ &= \frac{1}{(1 - S_{f|1} + S_{f|1}(1 - S_1))\alpha + 1} = \frac{1}{(1 - S_f)\alpha + 1} \end{aligned}$$

This markup equation is the same as equation (29). This result indicates that the markup under the proposed model with $\theta_f = 0.5$ takes the same value as the multiproduct price competition model.

B.2 Quantity competition

In the case of multiproduct Cournot quantity competition, a profit maximization problem of firm f is:

$$\max_{\boldsymbol{q}_f} \quad \pi_f = \sum_{j \in \Omega_f} (p_j(\boldsymbol{q}, Y) - c_j) q_j$$

where $p_j(\boldsymbol{q}, Y) = D^{-1}(Q(\boldsymbol{q}), Y) \dfrac{\partial Q}{\partial q_j}$ is the inverse demand function of product j. This inverse demand function is obtained from the first-order condition of the expenditure minimization problem and substitute $P = D^{-1}(Q(\boldsymbol{q}), Y)$.

The first-order condition for product j produced by firm f is given by:

$$\frac{\partial \pi_f}{\partial q_j} = p_j - c_j + \sum_{k \in \Omega_f} \frac{\partial p_k}{\partial q_j} q_k = 0$$

The derivatives of the inverse demand function are given by:

$$\frac{\partial p_j}{\partial q_k} = \frac{\partial D^{-1}}{\partial Q} \frac{\partial Q}{\partial q_j} \frac{\partial Q}{\partial q_k} + D^{-1} \frac{\partial^2 Q}{\partial q_j q_k} \quad \text{for } j, k \in \Omega_f$$

Substituting the derivatives into the first-order condition, we have:

$$0 = p_j - c_j + \sum_{k \in \Omega_f} \left(\frac{\partial D^{-1}}{\partial Q} \frac{\partial Q}{\partial q_j} \frac{\partial Q}{\partial q_k} + D^{-1} \frac{\partial^2 Q}{\partial q_j q_k} \right) q_k$$

$$p_j - c_j = -\frac{\partial D^{-1}}{\partial Q} \frac{\partial Q}{\partial q_j} \sum_{k \in \Omega_f} \frac{\partial Q}{\partial q_k} q_k - D^{-1} \sum_{k \in \Omega_f} \frac{\partial^2 Q}{\partial q_j q_k} q_k$$

$$\frac{p_j - c_j}{p_j} = -\frac{\partial \ln D^{-1}}{\partial \ln Q} \sum_{k \in \Omega_f} \frac{\partial \ln Q}{\partial \ln q_k} - \frac{1}{\dfrac{\partial Q}{\partial q_j}} \sum_{k \in \Omega_f} \frac{\partial^2 Q}{\partial q_j q_k} q_k \tag{30}$$

The first term in equation (30) is written by:

$$-\frac{\partial \ln D^{-1}}{\partial \ln Q} \sum_{k \in \Omega_f} \frac{\partial \ln Q}{\partial \ln q_k} = \frac{1}{\frac{\partial \ln D}{\partial \ln P}} \sum_{k \in \Omega_f} s_{k|1} = \frac{S_{f|1}}{\alpha s_0 + 1} \tag{31}$$

For the second term in equation (30), we recover the direct utility function corresponding to the expenditure function in equation (15) by exploiting the duality between the expenditure function and the direct utility function.

$$Q(\boldsymbol{q}) = \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}} \right)^{\frac{\alpha+1}{\alpha}}$$

where C_j is the product-specific constant of product j.

We calculate the derivatives of the utility function with respect to q_j as:

$$\frac{\partial Q}{\partial q_j} = C_j q_j^{\frac{-1}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}} \right)^{\frac{1}{\alpha}}$$

$$\frac{\partial^2 Q}{\partial q_j^2} = -\frac{C_j}{\alpha+1} q_j^{\frac{-\alpha-2}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1}{\alpha}} + \frac{C_j^2}{\alpha+1} q_j^{\frac{-2}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1-\alpha}{\alpha}}$$

$$\frac{\partial^2 Q}{\partial q_j q_k} = \frac{C_j C_k}{\alpha+1} q_j^{\frac{-1}{\alpha+1}} q_k^{\frac{-1}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1-\alpha}{\alpha}} \quad \text{for } k \neq j$$

Substituting these derivatives into the second term in equation (30), we have:

$$\begin{aligned}
-\frac{1}{\frac{\partial Q}{\partial q_j}} \sum_{k\in\Omega_f} \frac{\partial^2 Q}{\partial q_j q_k} q_k &= \frac{\frac{C_j}{\alpha+1} q_j^{\frac{-1}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1}{\alpha}} - \sum_{k\in\Omega_f} \left(\frac{C_j C_k}{\alpha+1} q_j^{\frac{-1}{\alpha+1}} q_k^{\frac{-1}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1-\alpha}{\alpha}} q_k\right)}{C_j q_j^{\frac{-1}{\alpha+1}} \left(\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1}{\alpha}}} \\
&= \frac{1}{\alpha+1} - \frac{1}{\alpha+1} \sum_{k\in\Omega_f} \frac{C_k q_k^{\frac{-1}{\alpha+1}}}{\sum_{j=1}^{J} C_j q_j^{\frac{\alpha}{\alpha+1}}} q_k \\
&= \frac{1}{\alpha+1} - \frac{1}{\alpha+1} \sum_{k\in\Omega_f} s_{k|in} = \frac{1 - S_{f|in}}{\alpha+1}
\end{aligned} \tag{32}$$

Substituting equations (31) and (32) into equation (30), we have the equilibrium markup under multiproduct quantity competition.

$$\frac{p_j - c_j}{p_j} = \frac{S_{f|in}}{\alpha s_0 + 1} + \frac{1 - S_{f|in}}{\alpha+1} \tag{33}$$

On the other hand, the equilibrium markup under the proposed model is given as follows when $\theta_f = 1/(1 + \eta_j/\sigma_j)$.

$$\frac{p_j - c_j}{p_j} = \frac{1 - S_{f|in}}{|\eta_j|} + \frac{S_{f|in}}{|\sigma_j|}$$

Substituting $|\eta_j| = \alpha + 1$ and $|\sigma_j| = \alpha s_0 + 1$ from equations (22) and (25) generates the same markup equation given in (33). This result indicates that the markup under the proposed model with $\theta_f = 1/(1 + \eta_j/\sigma_j)$ takes the same value as the multiproduct quantity competition model.

B.3 Collusion

In the case of collusion, firms maximize joint profits of all firms. A profit maximization problem of firm f is given as:[27]

$$\max_{\boldsymbol{p}_f} \quad \pi_f = \sum_{j=1}^{J} (p_j - c_j) q_j(\boldsymbol{p}, Y)$$

The first-order condition for product j produced by firm f is given by:

$$\frac{\partial \pi_f}{\partial p_j} = q_j + \sum_{k=1}^{J} (p_k - c_k) \frac{\partial q_k}{\partial p_j} = 0$$

Firms internalize all products in the market when maximizing their profits. Substituting the derivatives of the demand function into this equation, we have:

[27] It is also possible to formulate the problem using the inverse demand function and treat quantities as choice variables. The solutions in both formulations end up with the same collusive equilibrium.

$$q_j + \alpha \sum_{k=1}^{J} \frac{(p_k - c_k)}{p_k} s_k q_j - (\alpha + 1) \frac{(p_j - c_j)}{p_j} q_j = 0$$

Using the same markup property under the logit, we have:

$$\frac{p_j - c_j}{p_j} = \frac{1}{\alpha + 1 - \alpha S_{in}} = \frac{1}{\alpha s_0 + 1} \tag{34}$$

On the other hand, the equilibrium markup under the proposed model is given as follows when $\theta_f = 0$.

$$\frac{p_j - c_j}{p_j} = \frac{1}{|\sigma_j|} = \frac{1}{\alpha s_0 + 1}$$

This result indicates that the markup under the proposed model with $\theta_f = 0$ takes the same value as one when firms maximize joint profits.

B.4 Monopolistic competition

In the proposed model, the optimal markup with $\theta_f = 1$ is given by:

$$\frac{p_j - c_j}{p_j} = \frac{1}{|\eta_j|} = \frac{1}{\alpha + 1} \tag{35}$$

We show that this markup equals one when firms do not internalize any other products in the market. The first-order condition for product j produced by firm f is given by

$$\begin{aligned} \frac{\partial \pi_f}{\partial p_j} &= q_j + \sum_{k=1}^{J} (p_k - c_k) \frac{\partial q_k}{\partial p_j} \\ &= q_j + (p_j - c_j) \frac{\partial q_j}{\partial p_j} = 0 \end{aligned}$$

Rearranging the terms, we have:

$$\frac{p_j - c_j}{p_j} = -\frac{1}{\frac{\partial \ln q_j}{\partial \ln p_j}}$$

This equation indicates that the markup under monopolistic competition is a reciprocal of the own price elasticity. Here, this own price elasticity needs to be calculated by not taking into account its impact of price change on the denominator of the choice probability (see Nocke and Schutz (2018)). A simple calculation generates the following elasticity.

$$\frac{\partial \ln q_j}{\partial \ln p_j} = \left(-\alpha \frac{s_j Y}{p_j^2} - \frac{s_j Y}{p_j^2} \right) \frac{p_j}{q_j} = \alpha + 1$$

Rearranging the terms, we have:

$$\frac{p_j - c_j}{p_j} = \frac{1}{\alpha + 1} \tag{36}$$

Combining these facts indicates the equivalency between the proposed model with $\theta_f = 1$ and the monopolistic competition model.

Appendix C Illustration of the supply model in a simple case

We illustrate a simple example of the proposed supply model. There are four products, two firms $f_1 = \{1, 2\}$, $f_2 = \{3, 4\}$ selling two products each. There is an outside option ($j = 0$).

We use a discrete/continuous logit without any random coefficients. The demand function of product j is given as:

$$q_j = s_j \frac{Y}{p_j} = \frac{\exp(v_j - \alpha \log p_j)}{1 + \sum_{k=1}^{4} \exp(v_k - \alpha \log p_k)} \frac{Y}{p_j}$$

We suppose that we observe $Y = 1$, $\boldsymbol{s} = (0.2, 0.2, 0.2, 0.2)'$, $\boldsymbol{p} = (1, 1, 1, 1)'$, $\boldsymbol{q} = (0.2, 0.2, 0.2, 0.2)'$. We also assume $\alpha = 5$. With this setting, we can calculate that $\frac{\partial q_j}{\partial p_k} = -1$ if $j = k$, 0.2 otherwise.

The profit maximization problems of the two firms are given by :

$$\begin{aligned}
\max_{p_1, p_2, q_1, q_2} \quad & \pi_1 = (p_1 - c_1)q_1 + (p_2 - c_2)q_2 \\
& \text{subject to} \quad Q_1(q_1, q_2) \leq H_1(\boldsymbol{p}, Q(\boldsymbol{q})) \\
& \text{and} \quad Q(\boldsymbol{q}) \leq D(\boldsymbol{p}, Y) \\
\max_{p_3, p_4, q_3, q_4} \quad & \pi_2 = (p_3 - c_3)q_3 + (p_4 - c_4)q_4 \\
& \text{subject to} \quad Q_2(q_3, q_4) \leq H_2(\boldsymbol{p}, Q(\boldsymbol{q})) \\
& \text{and} \quad Q(\boldsymbol{q}) \leq D(\boldsymbol{p}, Y)
\end{aligned}$$

Solving the first-order conditions, we have the following equilibrium markups (see equation (10)).

$$\begin{aligned}
\frac{p_j - c_j}{p_j} &= \frac{\theta_1(1 - S_{1|in}) + (1 - \theta_1)S_{1|in}}{\theta_1(1 - S_{1|in})|\eta_j| + (1 - \theta_1)S_{1|in}|\sigma_j|} \quad \text{for j} = 1, 2 \\
\frac{p_j - c_j}{p_j} &= \frac{\theta_2(1 - S_{2|in}) + (1 - \theta_2)S_{2|in}}{\theta_2(1 - S_{2|in})|\eta_j| + (1 - \theta_2)S_{2|in}|\sigma_j|} \quad \text{for j} = 3, 4
\end{aligned}$$

From equations (22) and (25), the firm-level and market-level elasticities of substitution (η_j, σ_j) are calculated as $|\eta_j| = \alpha + 1 = 6$ and $|\sigma_j| = \alpha s_0 + 1 = 2$ for all j. Also, the firm-level shares within the inside products are $S_{1|1} = S_{2|1} = (0.2 * 2)/(0.2 * 4) = 0.5$.

The equilibrium markups are given as follows depending on the values of θ_f.

$$\frac{p - c}{p} = \begin{cases}
0.5 \ (= \frac{1}{\sigma_j}) & \text{if } \theta_f = 0 \quad \text{(Collusion)}, \\
0.33 \ (= \frac{1 - S_{f|1}}{\eta_j} + \frac{S_{f|1}}{\sigma_j}) & \text{if } \theta_f = 0.25 \ (= \frac{1}{1 + \eta_j/\sigma_j}) \quad \text{(Quantity competition)}, \\
0.25 \ (= \frac{1}{(1 - S_{f|1})\eta_j + S_{f|1}\sigma_j}) & \text{if } \theta_f = 0.5 \quad \text{(Price competition)}, \\
0.17 \ (= \frac{1}{\eta_j}) & \text{if } \theta_f = 1 \quad \text{(Monopolistic competition)}.
\end{cases}$$