Essays on Firm Conduct under Imperfect Competition

by

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Introduction

One of the central questions in industrial organization is whether firms compete or collude in oligopolistic markets, given the significant implications of collusion for market outcomes and competition policy. An extensive body of literature has emerged, focusing on empirically analyzing the degree of collusion and measuring its impact on welfare. However, this task is challenging because observed higher prices may be attributed to various factors such as a high degree of collusion, increased product differentiation, or higher marginal costs—all of which are unobserved.

The standard approach to this difficult task is to rely on structural modeling that consists of demand and cost primitives (Berry and Haile 2014). Over the decades, a body of the literature, initially referred to as the "New Empirical Industrial Organization (NEIO)", has provided structural frameworks for estimating conduct parameters. These parameters serve as a continuous measure of the degree of competition, ranging between perfect competition and collusion in the case of homogeneous products markets (Bresnahan 1989; Kadiyali, Sudhir, and Rao 2001; Sexton and Lavoie 2001; Sexton and Xia 2018). The method is often referred to as the conjectural variation model since its theoretical foundation is based on the canonical model presented by Bowley (1924). While this approach allows for the flexible estimation of the degree of competition, concerns about its theoretical validity and the reliability of inference have been raised (Friedman 1983; Corts 1999; Reiss and Wolak 2007).

Additionally, although the model can be theoretically extended to accommodate product differentiation, its practical application is hindered by the curse of dimensionality problem due to a large number of parameters (Nevo 1998). This issue remains unsolved, and the literature tends to restrict the level of competition to predetermined conduct such as Bertrand-Nash price competition (Goeree 2008; Nakamura and Zerom 2010; Miravete, Moral, and Thurk 2018). Given this situation, Schmalensee (2012) suggests a direction for future research, saying "the best way forward may be to attempt to develop and employ parsimonious parameterizations in the spirit of the "conjectural variations" approach that can provide reliable reduced-form estimates of the location of conduct."

In this dissertation, I propose a new structural model of demand and supply that enables the flexible estimation of firm conduct as continuous conduct parameters in differentiated products markets. A significant advantage of the framework is its empirical tractability, even when our focus is on the conduct of a large number of firms. This innovation is achieved through my unique setup of the supply-side modeling. Unlike the previous studies, I construct the supply side of the model using an oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007). Their model captures competition among firms in two dimensions: one is competition for market share and the other is competition for market size. This dichotomous characterization reduces the number of conduct parameters, making the estimation feasible for a larger number of firms. Importantly, the model retains flexibility on the degree of competition from monopolistic competition to collusion. Since d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) is a purely theoretical analysis and no other research has explored its empirical application, this study is the first attempt to use this oligopolistic model for estimating the conduct of firms.

In the first chapter, I demonstrate how to introduce the theoretical model by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) into an empirical structural framework and discuss its advantages compared with the previous approach. A key benefit of the proposed model is its reduced number of parameters and simpler functional form. Given the challenge in identifying conduct parameters, mainly due to the difficulty in finding valid instruments, my approach significantly extends its applicability to many situations where the existing models cannot be applied.

In the second chapter, I apply the proposed structural model to the US retail market for ground coffee, utilizing scanner data provided by Information Resources, Inc (IRI). To implement the empirical analysis, I use a multistage demand system following Hausman, Leonard, and Zona (1994) and Hausman, Pakes, and Rosston (1997). In the US retail coffee market, the two largest national brands (Folgers and Maxwell House) have more than 50% market share while there exist many regional brands with smaller market shares. I estimate conduct parameters of these two firms and the results show that the conduct of these firms is close to collusion and Nash-Bertrand pricing conduct is rejected. This application demonstrates the applicability of my proposed framework in assessing competition in retail pricing using the standard scanner datasets.

In the third chapter, I apply the model to analyze the US corn seed industry using a proprietary dataset on farm-level transactions for genetically modified seeds. Despite concerns regarding the ramifications of the growing market power of large biotech firms, there is limited understanding of whether firms compete or collude in their pricing strategies. On the supply side of the model, I extend the proposed framework to allow for multiproduct firms, while d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) rely on a restrictive assumption of single-product firms. On the demand side of the model, I choose the discrete/continuous demand system because it allows for recovering utility and expenditure functions of a representative consumer generated from the population of heterogeneous consumers (Anderson, De Palma, and Thisse 1987; Dubé, Joo, and Kim 2023). This integrability property ensures a theoretical consistency between the demand and supply model, allowing for welfare analysis based on the structural model. My estimation results show that the five largest firms are all engaged in imperfect collusion, and I reject benchmark conduct such as price and quantity competition. The low degree of competition translates into high price-cost margins, which I estimate at approximately 38%-51%. The results of counterfactual simulations indicate that seed companies extract substantial rent from farmers through non-competitive pricing, and total welfare loss is measured at $3.65 billion over the period 2008-2014.

This dissertation contributes to the literature by providing a new empirical strategy for estimating continuous conduct parameters in an empirically tractable way. In this context, the most closely related papers are Ciliberto and Williams (2014), Miller and Weinberg (2017), Sullivan (2017), and Michel, Manuel Paz y Mino, and Weiergraeber (2023), which estimate similar conduct parameters. Furthermore, it offers a valuable alternative to the testing-based approach employed in studies such as Rivers and Vuong (2002), Villas-Boas (2007), Backus, Conlon, and Sinkinson (2021), and Duarte et al. (2023) for identifying firms' conduct.

Chapter 1

The New Structural Framework for Estimating Firm Conduct

1.1 Introduction

This chapter demonstrates a theoretical framework for estimating conduct parameters in differentiated products markets. My approach is in line with the standard structural modeling that consists of demand and supply primitives (Berry, Levinsohn, and Pakes 1995; Nevo 2001; Berry and Haile 2014). Unlike the existing papers, I use an oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) as the theoretical model on the supply side. In this chapter, I first explain their model and demonstrate how to incorporate it into an empirical structural framework. Then, I discuss its advantages and disadvantages in terms of empirical applications.

1.2 Theoretical framework

In this section, I explain the oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007). My motivation of using this framework is that it provides a tractable equilibrium markup formula while keeping theoretical validity and flexibility on firm conduct with a single continuous parameter per firm.[1] The following explanation is basically based on d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007), whereas I put detailed derivations of equations and additional interpretations for readers' convenience.

1.2.1 Demand model

First, the demand side of the model is discussed. d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) consider an industry that provides J differentiated products by produced by J firms. Assume a representative consumer has a weakly separable preference between the differentiated products and all the other products.[2]

$$U = U(Q(\boldsymbol{q}), z)$$

where U and Q are continuously, twice differentiable, increasing, and strictly quasi-concave functions. $\boldsymbol{q}$ is a vector of the differentiated products and z represents the composite good of all other products. Here, the sub-utility function $Q(\boldsymbol{q})$ is interpreted as a composite product or quantity aggregator of the differentiated products. Assume that $Q(\boldsymbol{q})$ is homogeneous degree one in its arguments, which ensures the existence of a price aggregator corresponding to the quantity aggregator $Q(\boldsymbol{q})$. With this assumption, the utility function U is homothetically separable.

Since the utility function is weakly separable, the utility maximization can be solved in two stages.[3] The representative consumer first decides how much should be spent on the differentiated products and then decides expenditure allocation between J differentiated

[1] d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) refer the conduct parameters as competitive toughness of firm conduct.

[2] This setting is the same as one introduced Dixit and Stiglitz (1977) and later widely used in the field of international trade and macroeconomic analysis. Also, much of the literature in industrial organization usually focuses on a particular industry of interest by assuming quasi-linear preference, which implies weakly separable preference (See Vives 1999).

[3] Gorman (1959) shows that the existence of group price indices, such that group expenditures are functions only of these price indices, holds if and only if the utility function is homothetically separable or additively separable.

products. A utility maximization problem in the first stage allocation is formulated as follows:

$$\max_{Q,z} \quad U(Q,z)$$
$$\text{subject to} \quad PQ + z \leq Y$$

where $P = P(\boldsymbol{p})$ is the price aggregator of J differentiated products and $\boldsymbol{p}$ is a vector of prices of the J differentiated products. The price of z is normalized to 1. Y is the representative consumer's income. By solving this problem, the demand function of the composite good Q is derived as a function of the price aggregator and income.

$$Q = D(P(\boldsymbol{p}), Y) \tag{1.1}$$

Next, an expenditure minimization problem in the second stage allocation is formulated as follows:

$$\min_{\boldsymbol{q}} \quad \sum_{j=1}^{J} p_j q_j$$
$$\text{subject to} \quad Q(\boldsymbol{q}) \geq \underline{\mathrm{Q}}$$

Solving this minimization problem gives the following expenditure function. The functional form is multiplicative of the price and quantity aggregator as it is a general feature of homothetic utility functions.

$$e(\boldsymbol{p}, Q) = P(\boldsymbol{p})Q$$

By Shepard's lemma, the demand function conditional on the quantity aggregator Q is derived:

$$h_j(\boldsymbol{p}, Q) = \frac{\partial P(\boldsymbol{p})}{\partial p_j} Q \quad j = 1, ..., J \tag{1.2}$$

From the first order conditions, it is shown that the price of product j also has a multiplicative form as the dual representation of equation (1.2).

$$p_j = \lambda_D \frac{\partial Q(\boldsymbol{q})}{\partial q_i} = \frac{\partial e(\boldsymbol{p}, Q)}{\partial Q} \frac{\partial Q(\boldsymbol{q})}{\partial q_j} = P(\boldsymbol{p}) \frac{\partial Q(\boldsymbol{q})}{\partial q_j} \quad j = 1, ..., J$$

where λ_D is the Lagrange multiplier.

By substituting equation (1.1) into equation (1.2), the unconditional demand function of product j is given:

$$d_j(\boldsymbol{p}, Y) = \frac{\partial P(\boldsymbol{p})}{\partial p_j} D(P(\boldsymbol{p}), Y) \quad j = 1, ..., J$$

The two-stage budgeting under separable preference has important implications for competition between firms. In the first stage of optimization, the market size of J differentiated products is determined by the industry's level price, while in the second stage of optimization, the demand for each product is determined by the relative prices of the products. Firms must consider how both the demand for the industry and the demand for their own product respond to their decisions, which can be measured by relevant demand elasticities. In this model, the intra-sectoral and inter-sectoral elasticities of substitution are crucial determinants for understanding the degree of competition for each firm. The equilibrium markup equations can be expressed as a function of these two elasticities, as we will see later.[4]

Intra-sectoral elasticity of substitution

The intra-sectoral elasticity of substitution of product j for the composite good Q is defined as the absolute value of the elasticity of the ratio $q_j/Q(\boldsymbol{q})$ with respect to the corresponding price ratio $p_j/P(\boldsymbol{p})$. This elasticity of substitution measures substitutability between product j and the composite product within the industry, without considering a change in the total

[4]This is analogous to the case of Bertrand-Nash price competition in which an equilibrium markup is expressed as a reciprocal of own price elasticity of demand.

demand of the industry.[5]

$$\eta_j \equiv -\frac{d(q_j/Q)}{d(p_j/P(\boldsymbol{p}))}\bigg|_{q_j=h_j(\boldsymbol{p},Q)} \frac{p_j/P(\boldsymbol{p})}{q_j/Q} = -\frac{\dfrac{\partial \ln h_j(\boldsymbol{p},Q)}{\partial \ln p_j}}{1-\dfrac{\partial \ln P(\boldsymbol{p})}{\partial \ln p_j}} \quad j=1,...,J$$

(See Appendix 1.A for derivations).

Inter-sectoral elasticity of substitution

The inter-sectoral elasticity of substitution is defined as the absolute value of the elasticity of the ratio q_j/Y with respect to the corresponding price ratio $p_j/1$. This elasticity measures substitutability between product j and all other products, with implicitly considering a change in the total demand to the industry.

$$\sigma_j \equiv -\frac{d(q_j/Y)}{dp_j}\bigg|_{Q(\boldsymbol{q})=D(P(\boldsymbol{p}),Y)} \frac{p_j}{q_j/Y} = -\frac{\partial \ln D(P(\boldsymbol{p}),Y)}{\partial \ln P} \quad j=1,...,J$$

(See Appendix 1.A for derivations).

1.2.2 Supply model

Assume that each firm maximizes its own profit given other firms' choices under two demand constraints: 1) market share constraint and 2) market size constraint. A profit maximization problem of firm j is formulated as follows:

$$\max_{p_j,q_j} \quad (p_j - c_j)q_j$$
$$\text{subject to} \quad q_j \leq h_j((p_j,\boldsymbol{p}_{-j}),Q(q_j,\boldsymbol{q}_{-j}))$$
$$\text{and} \quad Q(q_j,\boldsymbol{q}_{-j}) \leq D(P(p_j,\boldsymbol{p}_{-j}),Y)$$

[5]The intra-sectoral elasticity is different from the elasticity of substitution between two products (q_i, q_j). If the sub-utility function Q is symmetric like CES preference, both elasticities coincide.

where c_j is the marginal cost of firm j, and $(\boldsymbol{q}_{-j}, \boldsymbol{p}_{-j})$ are vectors of quantities and prices of the firms other than firm j. h_j is the demand function of product j in equation (1.2) and D is the demand function of the composite good in equation (1.1).

By substituting the second constraint into the first constraint, we obtain:

$$q_j \leq h_j((p_j, \boldsymbol{p}_{-j}), D(p_j, \boldsymbol{p}_{-j}, Y)) = d_j(p_j, \boldsymbol{p}_{-j}, Y)$$

This equation is exactly the same as a constraint in the Bertrand price competition. Thus, the formulation with two demand constraints allows for a wider range of firms' decisions than the price competition.

The first constraint, referred to as the market share constraint, governs firms' choices of prices and quantities in terms of their own demand (market share) within the market. The Hicksian demand function h_j considers substitution between J differentiated products conditional on Q. Under this constraint, firms compete to obtain higher market shares by lowering their prices.

The second constraint, referred to as the market size constraint, governs firms' choices of prices and quantities in terms of the aggregate demand for the J differentiated products. The Marshallian demand function D considers substitution between J differentiated products and all other products. An increase in the market-level price prompts consumers to increase the purchased quantity of other products outside the industry. Thus, the constraint on market size captures their common interest as a sector, while the constraint on market share captures the conflictual side of competition between the firms.

To see how these constraints are connected to the two elasticities of substitution, I define two implicit functions from the two constraints: $f(\boldsymbol{q}, \boldsymbol{p}) = q_j - h_j((p_j, \boldsymbol{p}_{-j}), Q(q_j, \boldsymbol{q}_{-j}))$ and $g(\boldsymbol{q}, \boldsymbol{p}, Y) = Q(q_i, \boldsymbol{q}_{-j}) - D(p_j, \boldsymbol{p}_{-j}, Y)$. By taking a total derivative with respect to (q_j, p_j)

and letting $df = dg = 0$,

$$\left.\frac{d\ln q_j}{d\ln p_j}\right|_{q_j=h_j((p_j,\boldsymbol{p}_{-j}),Q(q_j,\boldsymbol{q}_{-j}))} = \frac{\dfrac{\partial \ln h_j(\boldsymbol{p},Q)}{\partial \ln p_j}}{1-\dfrac{\partial \ln h_j(\boldsymbol{p},Q)}{\partial \ln Q}\dfrac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j}} = -\eta_j \tag{1.3}$$

$$\left.\frac{d\ln q_j}{d\ln p_j}\right|_{Q(q_j,\boldsymbol{q}_{-j})=D(p_j,\boldsymbol{p}_{-j},Y)} = \frac{\dfrac{\partial \ln D(\boldsymbol{p},Y)}{\partial \ln p_j}}{\dfrac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j}} = -\sigma_j \tag{1.4}$$

Equation (1.3) indicates that the absolute value of the own price elasticity along the market share constraint is equal to the intra-sectoral elasticity of substitution η_j. Similarly, equation (1.4) shows that the inter-sectoral elasticity of substitution σ_j is equal to the absolute value of the elasticity along the market size constraint. These relationships between the constraints and elasticities are crucial for understanding firms' market power.

The fundamental source of firms' market power lies in their downward residual demand function. If the demand for an individual firm is not perfectly elastic, the firm has an incentive to reduce a quantity and raise its price to earn a positive markup. In the standard oligopoly problem, the markup is obtained as an inverse of the own price elasticity. Therefore, the more inelastic the demand, the higher the markup the firm can earn. In this model, the two constraints have different slopes, and how firms address these constraints has important implications for their market power.

1.2.3 Market equilibrium

Assuming the existence of a pure-strategy Nash equilibrium, a market equilibrium is defined as $(q_j^*, p_j^*)_{j=1,...,J} \in \mathbb{R}_+^J$ such that for all j,

$$\begin{aligned}(q_j^*, p_j^*) = \max_{p_j, q_j} \quad & (p_j - c_j)q_j \\ \text{subject to} \quad & q_j \leq h_j((p_i, \boldsymbol{p}_{-j}^*), Q(q_j, \boldsymbol{q}_{-j}^*)) \\ \text{and} \quad & Q(q_j, \boldsymbol{q}_{-j}^*) \leq D(p_j, \boldsymbol{p}_{-j}^*, Y)\end{aligned} \tag{1.5}$$

At the equilibrium $(\boldsymbol{p^*}, \boldsymbol{q^*})$, each firm maximizes its own profit given the other firms' decisions. d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) show that the markup at the equilibrium is expressed as the weighted harmonic mean of the reciprocals of the two elasticities of substitution η_j and σ_j. To derive the equilibrium markup, define the Lagrangian of this profit maximization problem as follows:

$$\mathcal{L} = (p_j - c_j)q_j + \lambda_j \left(1 - \frac{q_j}{h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}\right) + v_j \left(1 - \frac{Q(\boldsymbol{q})}{D(P(\boldsymbol{p}), Y)}\right) \quad j = 1, ..., J$$

where λ_j and v_j are the Lagrange multipliers for the market share and market size constraint respectively.

Solving this maximization problem, the equilibrium markup of firm j is derived as follows (See Appendix 1.B for detailed derivations).

$$\mu_j = \frac{p_j - c_j}{p_j} = \frac{\theta_i(1 - b_j) + (1 - \theta_j)b_j}{\theta_j(1 - b_j)\eta_j + (1 - \theta_j)b_j\sigma_j} \quad j = 1, ..., J$$

where b_j is the budget share of product j within the industry and θ_j is defined as:

$$\theta_j = \frac{\lambda_j}{\lambda_j + v_j} = \begin{cases} 1 \quad \text{if} \quad v_j = 0, \lambda_j > 0 \\ (0,1) \quad \text{if} \quad \lambda_j, v_j > 0 \\ 0 \quad \text{if} \quad \lambda_j = 0, v_j > 0 \end{cases}$$

The parameter θ_j measures the degree of competition of firm j. Defined as the ratio of the two Lagrange multipliers, θ_j takes values from zero to one. This parameter represents the relative attitude toward market share and market size constraints. When $\theta_j = 1$, firm j maximizes its profit as if it competes solely for market share, as the shadow value of the market size constraint is zero at the equilibrium. In this case, the degree of competition of firm j is the highest. Conversely, when $\theta_j = 0$, firm j competes exclusively for market size, resulting in the lowest degree of competition. Standard price competition and quantity competition always fall between these two extremes. Additionally, if $\eta_i > \sigma_j$, indicating higher substitutability within the industry than against outside the industry, θ_j is lower, and μ_j is higher for Cournot quantity competition than for Bertrand price competition. To summarize, the equilibrium markup and firm conduct are related as follows:

$$\mu_j = \begin{cases} \frac{1}{\sigma_j} & \text{if } \theta_j = 0 \quad \text{(Collusion)}, \\ \frac{1-b_j}{\eta_j} + \frac{b_j}{\sigma_j} & \text{if } \theta_j = \frac{1}{1+\eta_j/\sigma_j} \quad \text{(Cournot quantity competition)}, \\ \frac{1}{(1-b_j)\eta_j + b_j\sigma_j} & \text{if } \theta_j = 1/2 \quad \text{(Bertrand price competition)}, \\ \frac{1}{\eta_j} & \text{if } \theta_j = 1 \quad \text{(Monopolistic competition)}. \end{cases}$$

It is worth emphasizing that each firm can take different values of θ_j, so it may be possible some firms take the conduct of price competition and others take the conduct of quantity competition. Therefore, the vector $\boldsymbol{\theta} = (\theta_1, ..., \theta_J)$ characterizes the degree of competition in the differentiated industry, which is translated into the level of markups.

1.3 Empirical structural model

In this section, I demonstrate how to incorporate the oligopolistic model by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) into an empirical structural framework.

1.3.1 Estimation equations

In empirical applications, there are J_t differentiated products produced by J_t firms at market t. I assume that observed prices and market shares of products at each market are equilibria generated from the theoretical model. Specifically, the markup equation provides relationships between prices, market shares, elasticities of substitutions, marginal costs, and conduct parameters at each market.

$$\mu_{jt} = \frac{p_{jt} - c_{jt}}{p_{jt}} = \frac{\theta_j(1 - b_{jt}) + (1 - \theta_j)b_{jt}}{\theta_j(1 - b_{jt})\eta_{jt} + b_{jt}(1 - \theta_j)\sigma_{jt}} \quad j = 1, ..., J_t \tag{1.6}$$

where μ_{jt} is the markup of product j at market t, p_{jt} is the price, c_{jt} is the marginal cost, θ_j is the conduct parameter, b_{jt} is the market share in value, η_{jt} is the intra-sectoral elasticity of substitution, and σ_{jt} is the inter-sectoral elasticity of substitution.

Identification of conduct parameters is straightforward if marginal costs are observed, because they are calculated directly from the data by solving (1.6) for θ_j given the identification of demand elasticities. However, since marginal costs are rarely observed due to the discrepancy with accounting costs (Fisher and McGowan 1983), inferring marginal costs becomes necessary. This introduces complexity into the identification of conduct parameters as it requires a joint estimation with marginal costs.

To derive estimation equations, the marginal cost function is specified as follows. Estimating the marginal cost using firms' first-order conditions is a standard practice in the empirical industrial organization field, first conducted by Rosse (1970) to infer monopoly power.

$$c_{jt} = \boldsymbol{\omega}'_{jt}\boldsymbol{\gamma} + \zeta_{jt} \tag{1.7}$$

where $\boldsymbol{\omega}_{jt}$ is a vector of observed cost shifters, $\boldsymbol{\gamma}$ is a vector of estimated parameters and ζ_{jt} is the unobserved cost shifter.

Substituting (1.7) in (1.6), the estimation equations on the supply side are obtained.

$$p_{jt} = \boldsymbol{\omega}'_{jt}\boldsymbol{\gamma} + \frac{\theta_j(1-b_{jt}) + (1-\theta_j)b_{jt}}{\theta_j(1-b_{jt})\eta_{jt} + b_{jt}(1-\theta_j)\sigma_{jt}} p_{jt} + \zeta_{jt} \quad j = 1, ..., J_t \tag{1.8}$$

To estimate equation (1.8), obtaining two elasticities of substitution, η_{jt} and σ_{jt}, is necessary. There are two dominant approaches to estimating demand for differentiated products: 1) multistage demand models (Hausman, Leonard, and Zona 1994) and 2) discrete choice models (Berry, Levinsohn, and Pakes 1995). Several authors have compared these two demand models, discussing their advantages and disadvantages (Bajari, Benkard, et al. 2003; Hausman and Leonard 2005; Hausman and Leonard 2007; Reiss and Wolak 2007; Huang, Rojas, and Bass 2008; Weinberg and Hosken 2013).

The proposed structural model is applicable to both types of demand models. First, the theoretical model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) assumes the weakly separable utility function, generating two demand functions: the demand function of each product conditional on the sub-utility function $h_{jt}(\boldsymbol{p}_t, Q_t)$ and the unconditional demand function of the aggregate product $D_t(\boldsymbol{p}_t, Y)$. One approach to recover these two demand functions is to estimate them separately, motivating the use of multi-stage demand systems (Hausman, Leonard, and Zona 1994). In Chapter 2, I demonstrate how to implement this approach.

Another approach is to estimate an unconditional demand system and recover the conditional demand from it. Discrete choice demand models, such as random coefficient logit, are recognized as good tools for estimating demand for differentiated products since Berry, Levinsohn, and Pakes (1995). However, it is not immediately clear whether these models are consistent with the theoretical model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007), which assumes the existence of a representative consumer. In Chapter 3, I illustrate how to ensure such consistency using discrete/continuous choice models.

1.3.2 Identification

In this section, I discuss how to identify conduct parameters $\boldsymbol{\theta} = (\theta_1, ..., \theta_J)$ from equation (1.8). In the theoretical model, conduct parameters are defined as a ratio of Lagrange multipliers on two constraints in firms' profit maximization problems. This implies that these parameters take different values at different equilibria. However, it is impossible to make an inference if θ_j takes different values at each observation. Therefore, the following assumption is imposed.

Assumption 1: A competitive parameter θ_j is constant across some observations for each firm j.

The assumption of constant conduct is common in the previous research.[6] One way to justify this assumption is to consider firms' choices in two stages; In the first stage, firms choose conduct θ_j, and in the second stage, the firms maximize their own profits under the given conduct. That is, the first assumption is equivalent to saying that firms do not change their conduct in the short run.

Since the estimation equations (1.8) are nonlinear in parameters, nonlinear regressions need to be employed. Nonlinear least squares (NLLS) is a candidate for an estimator in this context. However, it cannot provide consistent estimates due to the correlation between the markup term (the second term in eq. (1.8)) and the unobserved cost shifter. This endogeneity inevitably leads to the inconsistency of estimates from NLLS. Therefore, instrumental variables are required to identify parameters.

Assumption 2: There exists a set of instruments $\boldsymbol{Z}_{jt}$ such that $E[\zeta_{jt}|\boldsymbol{Z}_{jt}] = 0]$.

This assumption requires that the instrument $\boldsymbol{Z}_{jt}$ is mean-independent of the unobserved

[6] Sullivan (2017) also introduces conduct parameters derived from Lagrange multipliers on firms' maximization problems. He theoretically justifies the same conduct parameters among cross-sectional observations, pooling relevant constraints. However, he still needs to assume that conduct parameters are constant across time-series observations in the empirical application.

cost shifter ζ_{jt}. Under this mean independent restriction, a generalized method of moments (GMM) estimator generates consistent estimates (Hansen 1982) . A GMM estimator $(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\gamma}})$ is defined as follows.

$$(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\gamma}}) = \min_{\boldsymbol{\theta}, \boldsymbol{\gamma}} \zeta(\boldsymbol{\theta}, \boldsymbol{\gamma})' \boldsymbol{Z} W \boldsymbol{Z}' \zeta(\boldsymbol{\theta}, \boldsymbol{\gamma})$$

where $\zeta(\boldsymbol{\theta}, \boldsymbol{\gamma})' = (\zeta_1', ..., \zeta_J')$, $\zeta_{jt} = p_{jt} \left(1 - \frac{\theta_(1 - b_{jt}) + (1 - \theta_j) b_{jt}}{\theta_j (1 - b_{jt}) \eta_{jt} + b_{jt} (1 - \theta_j) \sigma_{jt}}\right) - \boldsymbol{\omega}_{jt}' \boldsymbol{\gamma}$, W is a weight matrix for the GMM estimator.

In estimations, valid instruments should exogenously shift the markup while keeping the unobserved marginal costs constant. This shift in the markup is then reflected in the equilibrium price. Different types of conduct lead to distinct reactions of equilibrium prices to changes in the exogenous instruments, enabling the identification of conduct parameters. In the applications in Chapters 2 and 3, I follow the identification strategy offered by Bresnahan (1982) and generalized by Berry and Haile (2014). However. finding appropriate instruments is challenging in practice. Thus, the more parameters need to be estimated, the more challenging the identification is. In this context, the proposed structural model has great advantages for practical applications. I discuss them in the following section.

1.4 Comparison of the proposed model with the previous approach

In this section, I discuss advantages of the proposed structural model compared with the existing models.

1.4.1 Supply models in the previous research

My main innovation is related to the introduction of a new supply framework that allows for estimation of conduct parameters and maintains empirical tractability even when the number of firms increases. To highlight the advantages of my proposed model, I first demonstrate how to estimate firm conduct in the existing models and then discuss what is the difficulty in implementing such models.

I start from the standard Bertrand price competition model (see for instance, Berry, Levinsohn, and Pakes 1995).

There are F firms. Firm f produces a subset, Ω_f, of the $j = 1, ..., J$ differentiated products. Here, I suppress the subscript of market t for notational simplicity. 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.

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. Subscript T denotes the transpose of the matrix.

This is a vector of the equilibrium markups under Nash-Bertrand price competition. Because only demand-side parameters need to be estimated, many papers rely on the assumption of this benchmark conduct to estimate markups (Nevo 2000; Hausman and Leonard 2007; Goeree 2008; Nakamura and Zerom 2010).

Nevo (1998) shows how to introduce conduct parameters concerning competition between multiproduct firms. The marginal cost is specified as a linear function, $\boldsymbol{c} = \gamma \boldsymbol{\omega} + \boldsymbol{\epsilon}$, 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:

$$\boldsymbol{p} = \gamma\boldsymbol{\omega} - \left[\Theta * \left(\frac{\partial \boldsymbol{q}(\boldsymbol{p}, Y)}{\partial \boldsymbol{p}}\right)^T\right]^{-1} \boldsymbol{q}(\boldsymbol{p}, Y) + \boldsymbol{\zeta} \tag{1.9}$$

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 a 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 collusive model corresponds to a matrix of one. Therefore, this formulation allows for flexible estimation of firm conduct.

Nevo (1998) also argues that a downside of this formulation is that there are J^2 numbers of conduct parameters and thus it requires the same number of excluded instruments because the markups are necessarily 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, Conlon, and Sinkinson 2021; Magnolfi and Sullivan 2022; Duarte et al. 2023).

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, Manuel Paz y Mino, and Weiergraeber (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, Sudhir, and Rao (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, Manuel Paz y Mino, and Weiergraeber 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, Manuel Paz y Mino, and Weiergraeber (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.[7] 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.

To illustrate the challenges of applying this framework, consider the case of five firms, as examined in my application to the US corn seed industry in Chapter 3. To estimate the conduct of the five firms, possible specifications of a matrix of Θ are:

$$\Theta^1 = \begin{bmatrix} 1 & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} \\ \theta_{21} & 1 & \theta_{23} & \theta_{24} & \theta_{25} \\ \theta_{31} & \theta_{32} & 1 & \theta_{34} & \theta_{35} \\ \theta_{41} & \theta_{42} & \theta_{43} & 1 & \theta_{45} \\ \theta_{51} & \theta_{52} & \theta_{53} & \theta_{54} & 1 \end{bmatrix}, \Theta^2 = \begin{bmatrix} 1 & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} \\ \theta_{12} & 1 & \theta_{23} & \theta_{24} & \theta_{25} \\ \theta_{13} & \theta_{23} & 1 & \theta_{34} & \theta_{35} \\ \theta_{14} & \theta_{24} & \theta_{34} & 1 & \theta_{45} \\ \theta_{15} & \theta_{25} & \theta_{35} & \theta_{45} & 1 \end{bmatrix}, \Theta^3 = \begin{bmatrix} 1 & \theta_1 & \theta_1 & \theta_1 & \theta_1 \\ \theta_2 & 1 & \theta_2 & \theta_2 & \theta_2 \\ \theta_3 & \theta_3 & 1 & \theta_3 & \theta_3 \\ \theta_4 & \theta_4 & \theta_4 & 1 & \theta_4 \\ \theta_5 & \theta_5 & \theta_5 & \theta_5 & 1 \end{bmatrix} \tag{1.10}$$

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

[7] Michel, Manuel Paz y Mino, and Weiergraeber (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.

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, I 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:

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

where $d_{jk} = \frac{\partial q_j}{\partial p_k}$ and D is a denominator of the inverse matrix in equation (1.9) 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 me to introduce a new supply framework that provides more tractable equations.

1.4.2 Discussion

As a final remark of this chapter, I discuss advantages and disadvantages of the proposed model compared with the previous approach.

First, the proposed model maintains its tractability even for a large number of firms. From equation (1.8), the markup term takes a much simpler functional form; more importantly, it is determined by only one conduct parameter θ_f. This structure ensures that the estimation equations do not lose tractability even for a large number of firms. Furthermore, a single excluded instrument can be enough to estimate all conduct parameters $\Theta = (\theta_1, ..., \theta_F)$ if the data exhibits within-firm variations. In the following application, I interact one instrument with firm-dummy variables to estimate five conduct parameters. This is in contrast with the existing model, in which – in principle – it requires the same number of instruments as the number of conduct parameters in more complicated estimation equations.

Second, the proposed model does not restrict the degree of collusion. Each value of the conduct parameters determines the degree of collusion of each firm, which can be at any level from monopolistic competition to collusion. For instance, some firms may be engaged in imperfect collusion while others are engaged in price competition. Therefore, the model can generate a rich set of equilibrium markups depending on firm-specific conduct parameters.

A disadvantage of the proposed model is that it cannot estimate the degree of coordination of a pair of firms. The existing model allows for such an estimation, but only when the number of parameters is small enough. Table 1.1 summarizes the number of conduct parameters in 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). Thus, the estimation becomes infeasible very quickly as the number of firms increases. On the other hand, firm-specific specifications (c) have the same number of parameters in the existing model and the proposed model. However, the tractability is much higher for the proposed model due to the structure of the 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 serves to estimate firm-specific conduct for many firms.

Table 1.1: Comparisons of 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 (1.10). The proposed model refers to the model developed in this paper.

Appendix

1.A Derivations of elasticities of substitution

The intra-sectoral elasticity of substitution of product j for the composite good Q is defined as the absolute value of the elasticity of the ratio $q_j/Q(\boldsymbol{q})$ with respect to the corresponding price ratio $p_j/P(\boldsymbol{p})$. This elasticity of substitution measures substitutability between product j and the composite product within the industry, without considering a change in the total demand of the industry.

$$\eta_j \equiv -\frac{d(q_j/Q)}{d(p_j/P(\boldsymbol{p}))}\bigg|_{q_j=h_j(\boldsymbol{p},Q)} \frac{p_j/P(\boldsymbol{p})}{q_j/Q} \quad j = 1, ..., J$$

By substituting $q_j = h_j(\boldsymbol{p}, Q)$ and differentiating $(h_j(\boldsymbol{p}, Q)/Q)$ and $(p_j/P(\boldsymbol{p}))$ with respect to p_j, we have:

$$\begin{aligned}
\eta_j &= -\frac{\dfrac{\partial h_j(\boldsymbol{p},Q)}{\partial p_j}\dfrac{1}{Q}\dfrac{p_j}{P(\boldsymbol{p})}}{\left(\dfrac{1}{P(\boldsymbol{p})} - \dfrac{p_j}{P^2(\boldsymbol{p})}\dfrac{\partial P(\boldsymbol{p})}{\partial p_j}\right)\dfrac{h_j(\boldsymbol{p},Q)}{Q}} \\
&= -\frac{\dfrac{\partial h_j(\boldsymbol{p},Q)}{\partial p_j}\dfrac{p_j}{h_j(\boldsymbol{p},Q)}}{1 - \dfrac{p_j}{P(\boldsymbol{p})}\dfrac{\partial P(\boldsymbol{p})}{\partial p_j}} = -\frac{\dfrac{\partial \ln h_j(\boldsymbol{p},Q)}{\partial \ln p_j}}{1 - \dfrac{\partial \ln P(\boldsymbol{p})}{\partial \ln p_j}} = \frac{\eta_{jj}^H}{1-b_j} \quad j = 1, ..., J
\end{aligned}$$

where η_{jj}^{H} is the own price elasticity of demand $h_j(\boldsymbol{p}, Q)$. Under homothetic preference, $\partial \ln Q(\boldsymbol{q})/\partial \ln q_j = \partial \ln P(\boldsymbol{p})/\partial \ln p_j = q_j p_j / PQ = b_j$. Here, b_j is the budget share of product j within the differentiated products industry.

$$\sigma_j \equiv -\frac{d(q_j/Y)}{dp_j}\bigg|_{Q(\boldsymbol{q})=D(P(\boldsymbol{p}),Y)} \frac{p_j}{q_j/Y} = -\frac{\partial \ln D(P(\boldsymbol{p}),Y)}{\partial \ln P} = \sigma \quad j = 1, ..., J$$

By totally differentiating $Q(\boldsymbol{q}) = D(P(\boldsymbol{p}), Y)$ with respect to p_j and q_j[8] and substituting dq_j/dp_j, we have:

$$\begin{aligned}
\sigma_j &= -\frac{\dfrac{\partial D(P(\boldsymbol{p}),Y)}{\partial P}\dfrac{\partial P(\boldsymbol{p})}{\partial p_j}}{\dfrac{\partial Q(\boldsymbol{q})}{\partial q_j}} \frac{p_j}{q_j} \\
&= -\frac{\dfrac{\partial D(P(\boldsymbol{p}),Y)}{\partial P}\dfrac{P(\boldsymbol{p})}{D(P(\boldsymbol{p}),Y)}\dfrac{\partial P(\boldsymbol{p})}{\partial p_j}\dfrac{p_j}{P(\boldsymbol{p})}}{\dfrac{\partial Q(\boldsymbol{q})}{\partial q_j}\dfrac{q_j}{Q(\boldsymbol{q})}} \\
&= -\frac{\partial \ln D(P(\boldsymbol{p}),Y)}{\partial \ln P} \quad j = 1, ..., J
\end{aligned} \tag{1.11}$$

where the third equality holds because $\partial \ln Q(\boldsymbol{q})/\partial \ln q_j = \partial \ln P(\boldsymbol{p})/\partial \ln p_j$. This means that the inter-sectoral elasticity of substitution is equal to the price elasticity of the demand for the composite good with respect to the industry price index under homothetic preference.

1.B Derivations of equilibrium markup

The Lagrangian of the profit maximization problem is as follows:

$$\mathcal{L} = (p_j - c_j)q_j + \lambda_j \left(1 - \frac{q_j}{h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}\right) + v_j \left(1 - \frac{Q(\boldsymbol{q})}{D(P(\boldsymbol{p}),Y)}\right) \quad j = 1, ..., J$$

[8]Since the relation between p_j and q_j are implicitly controlled by $Q(\boldsymbol{q}) = D(P(\boldsymbol{p}), Y)$, it is necessary to totally differentiate it.

where λ_j and v_j are the Lagrange multipliers for the market share and market size constraints, respectively.

By differentiating the Lagrangian with respect to p_j and q_j, the first-order conditions are derived.

$$\frac{\partial \mathcal{L}}{\partial p_j} = q_j + \lambda_j \left(\frac{q_j}{h_j^2(\boldsymbol{p}, Q(\boldsymbol{q}))} \frac{\partial h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}{\partial p_j} \right) + v_j \left(\frac{Q(\boldsymbol{q})}{D^2(P(\boldsymbol{p}), Y)} \frac{\partial D(P(\boldsymbol{p}), Y)}{\partial P} \frac{\partial P(\boldsymbol{p})}{\partial p_j} \right) = 0$$

$$\begin{aligned}
&\Leftrightarrow q_j = \lambda_j \left(-\frac{1}{h_j(\boldsymbol{p}, Q(\boldsymbol{q})} \frac{\partial h_j(\boldsymbol{p}, Q(\boldsymbol{q})}{\partial p_j} \right) + v_j \left(-\frac{1}{D(P(\boldsymbol{p}), Y)} \frac{\partial D(P(\boldsymbol{p}), Y)}{\partial P} \frac{\partial P(\boldsymbol{p})}{\partial p_j} \right) \\
&\Leftrightarrow q_j = \frac{\lambda_j}{p_j} \left(-\frac{\partial \ln h_j(\boldsymbol{p}, Q(\boldsymbol{q})}{\partial \ln p_j} \right) + \frac{v_j}{p_j} \left(-\frac{\partial \ln D(P(\boldsymbol{p}), Y)}{\partial \ln P} \frac{\partial \ln P(\boldsymbol{p})}{\partial \ln p_j} \right) \\
&\Leftrightarrow q_j = \frac{\lambda_j}{p_j}(1 - b_j)\eta_j + \frac{v_j}{p_j} b_j \sigma_j
\end{aligned} \tag{1.12}$$

$$\frac{\partial \mathcal{L}}{\partial q_j} = p_j - c_j + \lambda_j \left(-\frac{1}{h_j(\boldsymbol{p}, Q(\boldsymbol{q}))} + \frac{q_j}{h_j^2(\boldsymbol{p}, Q(\boldsymbol{q}))} \frac{\partial h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}{\partial Q} \frac{\partial Q(\boldsymbol{q}))}{\partial q_j} \right) + v_j \left(-\frac{1}{D(P(\boldsymbol{p}), Y)} \frac{\partial Q(\boldsymbol{q})}{\partial q_j} \right)$$

$$\begin{aligned}
&\Leftrightarrow p_j - c_j = \lambda_j \left(\frac{1}{q_j} - \frac{1}{q_j} \frac{\partial h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}{\partial Q} \frac{\partial Q(\boldsymbol{q})}{\partial q_j} \right) + v_j \left(\frac{1}{D(P(\boldsymbol{p}), Y)} \frac{\partial Q(\boldsymbol{q})}{\partial q_j} \right) \\
&\Leftrightarrow p_j - c_j = \frac{\lambda_j}{q_j} \left(1 - \frac{\partial \ln h_j(\boldsymbol{p}, Q(\boldsymbol{q}))}{\partial \ln Q} \frac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j} \right) + \frac{v_j}{q_j} \left(\frac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j} \right) \\
&\Leftrightarrow p_j - c_j = \frac{\lambda_j}{q_j} \left(1 - \frac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j} \right) + \frac{v_j}{q_j} \left(\frac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j} \right) \\
&\Leftrightarrow p_j - c_j = \frac{\lambda_j}{q_j}(1 - b_j) + \frac{v_j}{q_j} b_j
\end{aligned} \tag{1.13}$$

where the two constraints hold as equality at the equilibrium and $\partial \ln h(\cdot)/\partial \ln Q = 1$ under homothetic preference. Remember b_j is the budget share of product j within the industry.

Dividing both sides of equation (1.13) by equation (1.12) and multiplying (q_j/p_j) gives:

$$\frac{p_j - c_j}{p_j} = \frac{\lambda_j(1-b_j) + v_j b_j}{\lambda_j(1-b_j)\eta_j + v_j b_j \sigma_j}$$

By dividing both the denominator and numerator of the right-hand side by $(\lambda_j + v_j)$ and defining $\theta_j = \lambda_j/(\lambda_j + v_j)$, the equilibrium markup formula is derived as follows:

$$\mu_j = \frac{p_j - c_j}{p_j} = \frac{\theta_j(1-b_j) + (1-\theta_j)b_j}{\theta_j(1-b_j)\eta_j + (1-\theta_j)b_j\sigma_j}$$

Chapter 2

Comparing Competitive Toughness to Benchmark outcomes in Retail Oligopoly Pricing: The Case of the US Ground Coffee Market

2.1 Introduction

d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) and d'Aspremont and Dos Santos Ferreira (2016) discuss the Cournot-Bertrand dichotomy,[1] and develop oligopolistic models based on the shadow values of market share and market size constraints leading to a measure they dub 'competitive toughness'. The primary purpose of this chapter is to empirically implement this oligopolistic framework for measuring firm conduct under product differentiation in consumer goods.

The so-called New Empirical Industrial Organization (NEIO) (Bresnahan 1989) framework

[1] Literature on mixed Cournot-Bertrand (dubbed 'differentiated oligopolies') recognizes that not all firms maintain the same strategic variable(s) at the same time in the same industry (Häckner 2000; Zanchettin 2006, Arya, Mittendorf, and Sappington 2008; Tremblay and Tremblay 2011).

measures firm conduct for a homogeneous goods industry using a continuous conjectural variations parameter in a range between perfect competition and collusion. While its use in empirical industrial organization research has been quite popular (see surveys by Bresnahan 1989; Kadiyali, Sudhir, and Rao 2001; Sexton and Lavoie 2001), its reliance on a static measure for what is conceptually a dynamic behavior has led to much resistance and declining acceptance in the industrial organization field. A common alternative relies on non-nested tests to select the best-fitted benchmark outcome from a menu of possible benchmark solutions (i.e. Cournot, Stackelberg, Bertrand, Collusion) (See for instance, Bresnahan 1987; Gasmi, Laffont, and Vuong 1992). Although this approach can be applicable to many industries, it has an essential drawback ascribed to Bain (1968). He closely observes many industries in the US and concludes that much of the observed market conduct lies somewhere between competitive and collusive one. This implies that the benchmark models in the menu approach may fail to capture the true conduct. My approach avoids most of these pitfalls. It estimates firm conduct using a theoretically valid continuous conduct parameter (competitive toughness) in a range between monopolistic competition and collusion using an empirically tractable framework that is parsimonious in the parameter space.

I apply the proposed structural model to sales data to examine its performance. I use U.S. retail scanner data provided by Information Resources, Inc (IRI) for the ground coffee category. The two largest national brands (Folgers and Maxwell House) have more than 50% market share while there exist other brands with various market shares. Using pretests to determine which brands belong to the dominant subgroup and which belong to the fringe, I find that Folgers and Maxwell House are the only two dominant brands. As such, the main focus of my empirical application is to evaluate the conduct of these two national brands.

To derive the required demand elasticities for estimating the developed structural model, I employ a multistage demand system, as employed by Hausman, Leonard, and Zona (1994) and Hausman, Pakes, and Rosston (1997). This approach exploits the fact that consumers' budget allocation can be decomposed into multiple stages under weakly separable preferences. Under this assumption, the number of products in each group becomes empirically manageable. While substitution patterns of products in different groups are restricted to some extent, the substitution patterns in the same group remain flexible.

The rest of the chapter is organized as follows. The next section presents a brief discussion of the theoretical model. Sections 2.3 and 2.4 contain a discussion of the constructed empirical model, data, and identification strategies. The results and conclusions are presented in sections 2.5 and 2.6, respectively.

2.2 Theoretical framework

In this section, the oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) and d'Aspremont and Dos Santos Ferreira (2016) is demonstrated as a basic framework.[2] Consider a single industry where J single-product firms produce J differentiated products $\boldsymbol{q} = (q_1, ..., q_J)'$. All other products are aggregated as a numéraire good z.

2.2.1 Utility maximization under separable preference

Assume a representative consumer with preferences characterized by a separable utility function $U(\boldsymbol{q}, z) = U(Q(\boldsymbol{q}), z)$, where $Q(\boldsymbol{q})$ is a sub-utility function. Because of the separability assumption, J differentiated products $\boldsymbol{q}$ can be aggregated into one composite good Q. The representative consumer maximizes his/her utility under the budget constraint $\boldsymbol{p}'\boldsymbol{q} + z \leq Y$ where Y is income, $\boldsymbol{p} = (p_1, ..., p_J)'$ is a vector of prices of $\boldsymbol{q}$ and the price of z is normalized to one.

Since the utility function is weakly separable, utility maximization is solved in two stages. First, the consumer allocates his/her income to the composite good Q and the numéraire z, and then the consumer chooses the quantity demanded of q_j for all j given the first-stage

[2] d'Aspremont and Dos Santos Ferreira (2016) extends the model by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) to allow for a non-homothetic utility function.

decision. By solving the consumer's optimization problem, we obtain the following demand functions.

$$q_j = h_j(\boldsymbol{p}, Q) \quad j = 1, ..., J \tag{2.1}$$

$$Q = D(\boldsymbol{p}, Y) \tag{2.2}$$

where $h_j(\boldsymbol{p}, Q)$ is the demand function for product j conditioned on Q. $D(\boldsymbol{p}, Y)$ is the demand function for the composite good Q and can be interpreted as the aggregate demand function to the industry.

This oligopolistic model defines the intra-sectoral elasticity of substitution η_j as

$$\eta_j \equiv -\frac{d\ln(q_j/Q)}{d\ln(\partial Q/\partial q_j)} = -\frac{d\ln(q_j/Q)}{d\ln(p_j/P)} \quad j = 1, ..., J \tag{2.3}$$

where P is the price index of the composite good Q. The second equality holds because of the first-order condition of the consumer's utility maximization problem. This elasticity measures substitutability of product j against the composite good Q. That is, it provides information about how each firm's market share responds to price changes inside the industry.

In the first stage of the utility maximization problem, the representative consumer allocates his/her budget between Q and z. Each firm's pricing strategy impacts the size of the market, which is governed by the inter-sectoral elasticity of substitution σ_j given by:

$$\sigma_j \equiv -\frac{d\ln(q_j/Y)}{d\ln p_j}\bigg|_{Q(\boldsymbol{q})=D(\boldsymbol{p},Y)} \quad j = 1, ..., J \tag{2.4}$$

This elasticity measures substitutability of product j against the numéraire taking into account how the aggregate demand to the industry responds to a change of p_j.

2.2.2 Firms' competition and Market equilibrium

Firm j chooses quantity and price of its product (q_j, p_j) to maximize its own profit given the other firms' decisions $(\boldsymbol{x}_{-j}, \boldsymbol{p}_{-j})$, where c_j is a marginal cost of producing q_j. Assuming the existence of a pure-strategy Nash equilibrium, a market equilibrium is defined as $(\boldsymbol{q}^*, \boldsymbol{p}^*) = (q_1^*, ..., q_J^*, p_1^*, ..., p_J^*)$ such that for all j,

$$\begin{aligned}(q_j^*, p_j^*) = \max_{q_j, p_j} \quad & (p_j - c_j)q_j \\ & \text{subject to} \quad q_j \leq h_j((p_j, \boldsymbol{p}_{-j}^*), Q(q_j, \boldsymbol{q}_{-j}^*)) \\ & \text{and} \quad Q(q_j, \boldsymbol{q}_{-j}^*) \leq D(p_j, \boldsymbol{p}_{-j}^*, Y)\end{aligned} \tag{2.5}$$

where $h_j(\boldsymbol{p}, Q)$ and $D(\boldsymbol{p}, Y)$ are the demand functions defined by (2.1) and (2.2), respectively. The first constraint (market share constraint) limits the market share of firm j while the second constraint (market size constraint) bounds the market size of the industry. The Lagrangian of firm j's profit maximization is as follows:

$$\mathcal{L}_j = (p_j - c_j)q_j + \lambda_j(h_j(\boldsymbol{p}, Q) - q_j) + v_j(D(\boldsymbol{p}, Y) - Q(\boldsymbol{q})) \quad j = 1, ..., J \tag{2.6}$$

where λ_j and v_j are the Lagrange multipliers for the market share and market size constraints, respectively. d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) and d'Aspremont and Dos Santos Ferreira (2016) define competitive toughness for each firm as a "normalized Lagrange Multiplier" given by:

$$\theta_j = \frac{\lambda_j}{\lambda_j + v_j} \quad j = 1, ..., J \tag{2.7}$$

The concept of competitive toughness is best seen through the interpretation of each Lagrange multiplier. In a highly competitive setting (i.e. with competitively tough firms), the shadow value of the market size constraint is close to zero: the firm increases the supply of a differentiated product without regard to the market impacts of increased supply of the composite good. A low value of v_j might be due to a highly unconcentrated industry in which firms cannot control the quantity of the composite good. This could also be the case of concentrated industries with a significant threat of new entry or in an industry with an aggressive culture that yields competitive outcomes. As discussed further below, competitive toughness depends critically on the ability of industry participants to constrain the output of the composite good. On the other hand, the market share constraint focuses on competition among the firms in the industry. A low value of λ_j would be consistent with a firm having a product that is highly differentiated or a product with strong brand loyalty.

Each θ_j takes a value from zero to one by definition. When $\theta_j = 1$ (or $v_j = 0$), the market size constraint is not binding. In other words, firm j maximizes profits as if it competes considering only the impact of its pricing strategy on its market share. In this case, the degree of competition of the firm is the highest: the firm is competitively tough. In other words, this is the point where the firm experiences little gain in limiting output. On the other hand, when $\theta_j = 0$ (or $\lambda_j = 0$), the market share constraint is not binding. Firm j competes considering only the impact of its pricing on the market size, so the degree of competition of firm j is at its lowest point. This would be consistent with joint profit maximization. The vector of $\boldsymbol{\theta} = (\theta_1, ..., \theta_J)$ describes the degree of competition of the industry. Therefore, the parameters of competitive toughness serve as conduct parameters.

d'Aspremont and Dos Santos Ferreira (2016) develop the relationship between the conduct parameters (competitive toughness), the intra- and inter-sectoral elasticities of substitution, and the Lerner Index of market power. By using the first order conditions of (2.5), the equilibrium markup μ_j^* is derived:

$$\begin{aligned}\mu_j^* \equiv \frac{p_j^* - c_j}{p_j^*} &= \frac{\theta_j^*(1-\alpha_j^*\beta_j^*) + (1-\theta_j^*)\alpha_j^*}{\theta_j^*(1-\alpha_j^*\beta_j^*)\eta_j^* + \alpha_j^*(1-\theta_j^*)\sigma_j^*} \\ &= \frac{1}{w_j^*(\theta_j^*)\eta_j^* + (1-w_j^*(\theta_j^*))\sigma_j^*} \quad j = 1, ..., J\end{aligned} \tag{2.8}$$

where $w_j(\theta_j) = \dfrac{\theta_j(1-\alpha_j\beta_j)}{\theta_j(1-\alpha_j\beta_j)+(1-\theta_j)\alpha_j}$, $\alpha_j = \dfrac{\partial \ln Q(\boldsymbol{q})}{\partial \ln q_j}$, $\beta_j = \dfrac{\partial \ln h_j(\boldsymbol{p}, Q)}{\partial \ln Q}$.

From equation (2.8), an equilibrium markup is expressed as a weighted harmonic mean of the reciprocal of the two elasticities of substitution defined in (2.3) and (2.4). By definition, the weight $w_j(\theta_j)$ goes to zero (one) as θ_j goes to zero (one). Thus, the conduct parameters θ_j^* determine the relative importance of the two elasticities of substitution for a level of the markup μ_j^*. For instance, the markup is $1/\sigma_j^*$ when $\theta_j^* = 0$ (the degree of competition is the lowest). This means only the substitutability between q_j and z measured by σ_j^* matters in determining the markup, which corresponds to joint profit maximization. On the other hand, when $\theta_j^* = 1$ (the degree of competition is the highest), the markup is $1/\eta_j^*$, so only the substitutability between $\boldsymbol{q}$ measured by η_j^* matters for the markup. In this case, the markup corresponds to the benchmark for free-entry monopolistic competition obtained by Dixit and Stiglitz (1977). Thus, the parameter θ_j^* is theoretically bound to any result from monopolistic competition to collusion which includes benchmarks such as Bertrand and Cournot competition. Table 2.1 contains a summary of common benchmarks for different values of θ_j

Table 2.1: Equilibrium markups

			Markup	
			Differentiated ($s_i < \infty$)	Homogeneous ($\eta_j = \infty$)
1	Collusion	$\theta_j^1 = 0$	$\mu_i^1 = \dfrac{1}{\sigma_j^*}$	-
2	Quantity competition	$\theta_j^2 = 1/(1+\eta_j^*/\sigma_j^*)$	$\mu_j^2 = \dfrac{(1-\alpha_j^*)}{\eta_j^*} + \dfrac{\alpha_j^*}{\sigma_j^*}$	$\mu_j^2 = \dfrac{\alpha_j^*}{\sigma_j^*}$
3	Price competition	$\theta_j^3 = 1/2$	$\mu_j^3 = \dfrac{1}{\eta_j^*(1-\alpha_j^*)+\sigma_j^*\alpha_j^*}$	$\mu_j^3 = 0$
4	Monopolistic competition (Perfect competition)	$\theta_j^4 = 1$	$\mu_j^4 = \dfrac{1}{\eta_j^*}$	$\mu_j^4 = 0$

Note: To make comparisons of markups easier, the sub-utility function is assumed to be homothetic.

In the following discussion, I consider the situation where the intra-sectoral elasticity is greater than the inter-sectoral elasticity, i.e., $s_j^* > \sigma_j^*$. Since substitutability among the differentiated products in the same industry is more likely higher than across industries, this situation is expected to be more relevant to empirical applications. Then, the markups and the degree of competition are ordered as follows. This ranking shows that the markup and the conduct parameter are negatively correlated.

Monopolistic competition		Price competition		Quantity competition		Collusion
μ_j^4	$<$	μ_j^3	$<$	μ_j^2	$<$	μ_j^1
θ_j^4	$>$	θ_j^3	$>$	θ_j^2	$>$	θ_j^1

I also compare markups under product differentiation and product homogeneity. As goods become highly substitutable, I observe the standard conditions that quantity competition is required to obtain economic profit and collusion cannot be sustained. However, when products are highly differentiated, firms are not rewarded with increased market share for lowering their prices, which is suggestive of a low degree of competition.

2.3 Empirical structural model

2.3.1 Demand model

On the demand side of the model, I use a multistage demand system.[3] The primary motivation for using a multistage demand system approach comes from the structure of the theoretical model by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007). Because this model assumes a separable utility function, it is necessary to estimate demand functions for different levels of consumer decisions. The multistage demand system approach allows us to estimate demand functions in each stage of the consumer's utility maximization, which enables the empirical analysis to be fully consistent with the model.

In the empirical analysis, I assume the industry to be divided into two segments: a dominant and a fringe segment. The dominant segment includes differentiated products produced by firms whose conduct is subject to estimation, while the fringe segment includes other products in the same industry.[4] This assumption is motivated by the need to exploit

[3] There are many applications of multistage demand systems (Chaudhuri, Goldberg, and Jia 2006; Rojas 2008; Weinberg and Hosken 2013).

[4] The words "dominant" and "fringe" come from the fact that this setting is similar to the dominant-firm model under which the industry is characterized by a dominant firm and many fringe firms (Suslow 1986; Salvo 2010).

the structure of the oligopolistic model for identifying conduct parameters. From equation (2.8), the markup in the model is expressed as a function of two elasticities of substitution. As discussed later, changes in the number of products in the fringe segment exogenously shift the inter-sectoral elasticity of substitution through changes in the competitive environment, but they are expected to be independent of the marginal cost. This characteristic renders the number of products in the fringe segment a suitable instrument for the conduct parameters.

In the following application, I utilize a three-stage demand system. The three budgeting decisions correspond to: 1) allocation between the industry of interest and all other industries represented by the numéraire (top level), 2) allocation between the dominant segment and the fringe segment (middle level), 3) allocation within the dominant segment (bottom level). The utility function of the representative consumer is given as follows:

$$\begin{aligned} U(\boldsymbol{q}) &= U(Q(\boldsymbol{q}), z) \\ &= U(Q(Q_D(\boldsymbol{q}_D), Q_F(\boldsymbol{q}_F)), z) \end{aligned}$$

where $\boldsymbol{q}' = (\boldsymbol{q}'_D, \boldsymbol{q}'_F)$, $\boldsymbol{q}_D$ is a vector of quantities of products in the dominant segment, $\boldsymbol{q}_F$ is a vector of quantities of products in the fringe segment (brands, goods, and products are used interchangeably hereafter), and z is the numéraire. U is the utility function for all goods, and (Q, Q_D, Q_F) are the sub-utility functions corresponding to different levels of consumer decisions. Under this specification, consumer preference is assumed to be weakly separable between $(\boldsymbol{q})$ and (z) and is also weakly separable between $(\boldsymbol{q}_D)$ and $(\boldsymbol{q}_F)$. Having separable preferences restricts the substitution patterns of goods at different levels.

The estimation equations for each of the three stages of the demand system are presented as follows:

$$w_{it}^B = \alpha_i^B + \sum_j \gamma_{ij}^B \ln p_{jt}^B + \beta_i^B \ln(Y_t^B / P_t^B) + \epsilon_{it}^B \quad i = 1, ..., J, t = 1, ..., T \tag{2.9}$$

$$w_{it}^M = \alpha_i^M + \sum_j \gamma_{ij}^M \ln P_{jt}^M + \beta_i^M \ln(Y_t^M/P_t^M) + \epsilon_{it}^M \quad i = D, F, t = 1, ..., T \tag{2.10}$$

$$\ln Q_t^T = \alpha^T + \gamma^T \ln P_t^T + \beta^T \ln Y_t^T + \epsilon_t^T \quad t = 1, ..., T \tag{2.11}$$

where superscript letters denote the bottom, the middle and the top stages of the demand system, respectively. Subscripts t denote markets and T is the number of markets.

Under the separability assumption, I specify demand for the bottom level (2.9), and the middle level (2.10) using a linearized version of the almost ideal demand system (LA/AIDS) proposed by Deaton and Muellbauer (1980). The LA/AIDS is known as a (locally) flexible demand specification and has been successful for various demand estimations. The theoretical restrictions and price and expenditure elasticities are well-known and thus are not presented here. For the top-level demand, a log-log model (2.11) is used. The same specification is used in Hausman, Leonard, and Zona (1994). They estimate a three-stage demand system for beer and specify demand using a LA/AIDS and a log-log model.

2.3.2 Supply model

Estimating an empirical counterpart of the markup equation derived in (2.8) requires demand-side estimates including two elasticities of substitutions. Although the conduct parameters are immediately identified if marginal costs are observable, they are rarely observed since observed accounting cost does not properly capture economic marginal costs (Fisher and McGowan 1983). Estimating equations for marginal cost are specified as follows:

$$c_{it} = \boldsymbol{\omega}_{it}' \boldsymbol{\gamma}_i + \zeta_{it} \quad i = 1, ..., J, t = 1, ..., T \tag{2.12}$$

where $\boldsymbol{\omega}_{it}$ is a vector of observed cost shifters, $\boldsymbol{\gamma}_i$ is a vector of estimated parameters and ζ_{it} is the unobserved cost shifter.

Rearranging the first-order condition of each firm and substituting the marginal cost function (2.12), estimation equations for the supply model are derived.[5]

$$p_{it} = \boldsymbol{\omega}'_{it}\boldsymbol{\gamma}_i + \frac{\theta_i(1-\alpha_{it}\beta_{it}) + (1-\theta_i)\alpha_{it}}{\theta_i(1-\alpha_{it}\beta_{it})s_{it} + \alpha_{it}(1-\theta_i)\sigma_{it}} p_{it} + \zeta_{it} \quad i = 1, ..., n, t = 1, ..., T \qquad (2.13)$$

In equation (2.13), estimated parameters are θ_i and $\boldsymbol{\gamma}_i$ while α_{it}, β_{it}, s_{it} and σ_{it} are inputs from the demand-side estimation. Since the conduct parameters take value from zero to one, I transform them to impose this theoretical restriction:

$$\theta_i = \frac{1}{1+\exp(\bar{\theta}_i)} \quad i = 1, ..., J \qquad (2.14)$$

2.4 Data and Estimation

2.4.1 IRI retail scanner data

The main data source is retail caffeinated ground coffee scanner data provided by Information Resources, Inc (IRI) available for academic studies (see Bronnenberg, Kruger, and Mela (2008) for further details). The data includes revenue and unit sales of coffee products in 48 demographic market areas (DMA) throughout the US from 2001-2004. Each DMA is a metropolitan region that includes major cities and all the adjacent counties and townships. The data is identified by its universal product code (UPC), retail store, and week. The caffeinated ground coffee category covers approximately 80% revenue share in the coffee category of the data. Coffee has been a focus of previous demand analysis (Draganska, Klapper, and Villas-Boas 2010; Nakamura and Zerom 2010; Bonnet et al. 2013). Narrowing

[5]Estimating the marginal cost from firms' first order conditions is the standard practice in the empirical industrial organization field since Rosse (1970).

the market category to caffeinated ground coffee allows us to simplify the cost side of the analysis. For example, instant coffee, whereas it consists of only a small share of the market, uses a very different production process that is more capital intensive and costly (Sutton 1991).[6]

The quantities of coffee are transformed into 16-ounce equivalent units. Prices are inferred from revenue and quantity sales. I aggregate the data from UPC level to brand level.[7] I also aggregate the data to month-DMA level. This aggregation helps to reduce the computational burden caused by the large number of observations. The data used in the estimations is at the product-month level in 48 DMAs from 2001 to 2004. Four products are used in the estimation: Folgers, Maxwell House, Starbucks, and Private label. These products have the largest national revenue shares in the dataset, while each of the other caffeinated ground coffee products has less than 3% national revenue share. Table 2.2 shows prices and revenue shares of these products. The number of observations is $2,304$ for each product.

Table 2.2: Prices and revenue shares

		Prices ($ per 16 ounce)				Revenue shares (%)			
	Brand	Mean	Std	Min	Max	Mean	Std	Min	Max
1	Folgers	2.55	0.33	1.46	4.32	32.04	11.41	8.24	71.07
2	Maxwell House	2.63	0.46	1.47	4.82	23.76	13.67	1.03	69.94
3	Private Label	2.38	0.57	1.41	5.26	9.27	4.83	0.61	31.37
4	Starbucks	9.84	0.71	6.20	12.43	8.70	3.84	0.36	25.05
5	All others	3.83	0.79	1.93	7.34	26.23	13.38	4.83	73.44

Notes: The table provides summary statistics of prices and revenue shares over 2001-2004.

The Stone price index is calculated as the fixed weight average of each product as it is considered superior to the original Stone index used by Deaton and Muellbauer (1980) (see Moschini (1995)). The per capita expenditure for each level is calculated by dividing the

[6]Note also that Nelson, Siegfried, and Howell (1992) and Nakamura and Zerom (2010) focus on only ground coffee in their analysis.

[7]For instance, there are numerous products within the Folgers brand at UPC levels. They differ in flavors, packaging, and sizes.

expenditure by population of each market. The data on population is collected from the US Census Bureau.

2.4.2 Cost data

The monthly import coffee prices are obtained by the International Coffee Organization for the varieties Colombian mild Arabica, other mild Arabica, Brazilian and other natural Arabicas, and Robusta. Following Nakamura and Zerom (2010), I construct a weighted average price of these four coffee varieties based on the US import quantity share obtained from Lewin, Giovannucci, and Varangis (2004). Wage data are Monthly Earning Extracts obtained from the US Current Population Survey provided by the National Bureau of Economic Research. Since this is an average county-level wage paid in the supermarket sector, I calculate a weighted average wage of each DMA using wages of all countries that compose the DMA. Following Miller and Weinberg (2017), I also construct a distance variable to capture transportation costs. First, I calculate driving miles from the roasting plant of Folgers and Maxwell House to the center of each city using Google map. Folgers is produced mainly in a plant in New Orleans and Maxwell House is produced in plants located in Jacksonville, Houston, and San Leandro (Leibtag et al. 2007). I assume that Maxwell House coffee is transported to each city from the nearest plant. Then, I multiply this driving distance (in miles) times diesel fuel prices which are obtained from the Energy Information Agency of the Department of Energy. The fuel prices have a monthly variation at the national level.

2.4.3 Estimation

The estimation is carried out in two sequential stages. First, I estimate the demand-side equations (2.9), (2.10) and (2.11) separately, using seemingly unrelated regressions (SUR) and generalized method of moments (GMM). Consistency is ensured regardless of the equations being estimated jointly or separately, although the joint estimation can be more efficient because of the possible correlations of the error terms in each equation. I conduct GMM estimation with the standard two-steps procedure, setting a weight matrix $W = (Z'Z)^{-1}$ in the first step where Z is a set of instruments and the optimal weight matrix in the second step. I proceed then to the supply-side estimation; the results of the demand model are used to calculate α_{it}, β_{it}, η_{it} and σ_{it}, substituting these values into (2.13).

Since the supply-side estimation equations are nonlinear in the parameter space, a nonlinear regression technique is required. A possible choice of an estimator is nonlinear least squares (NLLS). However, since the markup term is a function of price, it is necessarily correlated with unobserved cost shifters, and the endogeneity of price causes inconsistency in NLLS estimates. Therefore, I use GMM estimator. A GMM estimator $(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\gamma}})$ of the conduct parameters and marginal cost parameters are defined as follows:

$$(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\gamma}}) = \min_{\boldsymbol{\theta},\boldsymbol{\gamma}} \zeta(\boldsymbol{\theta}, \boldsymbol{\gamma})' \boldsymbol{Z} W \boldsymbol{Z}' \zeta(\boldsymbol{\theta}, \boldsymbol{\gamma}) \tag{2.15}$$

where $\zeta(\boldsymbol{\theta}, \boldsymbol{\gamma})' = (\zeta_{11}, ..., \zeta_{1T}, \zeta_{21}, ..., \zeta_{nT})$, $\zeta_{it} = p_{it}\left(1 - \frac{\theta_i(1-\alpha_{it}\beta_{it}) + (1-\theta_i)\alpha_{it}}{\theta_i(1-\alpha_{it}\beta_{it})\eta_{it} + \alpha_{it}(1-\theta_i)\sigma_{it}}\right) - \boldsymbol{\omega}_{it}'\boldsymbol{\gamma}_i$, Z is a set of instruments and W is a weight matrix obtained by the same procedure used for the demand-side estimations.

2.4.4 Identification

2.4.4.1 Demand-side identification

A major concern in demand estimation is that prices may be endogenous due to the presence of unobserved factors affecting both demand and manufacturers' pricing decisions.[8] This is the standard simultaneity bias problem as discussed in Berry, Levinsohn, and Pakes (1995). To deal with this problem, I evaluate two different types of instruments. The first instrument is the so-called Hausman instrument. Hausman, Leonard, and Zona (1994) propose that the average product price in other DMAs can serve as an instrument for the price in one DMA. These instruments can be constructed as long as the data has a panel structure, which is the

[8]Endogeneity of expenditure is not addressed in this analysis due to data limitations. Hausman, Leonard, and Zona (1994) do not deal with this endogeneity in a similar setting.

case for the data used in this study. Many papers use the Hausman instruments because of their ready availability in panel data (Pinkse and Slade 2004; Rojas 2008; Nakamura and Zerom 2010; Weinberg and Hosken 2013, etc.). The average prices in the other DMAs are correlated with the price to be instrumented through a common cost factor affecting prices across all DMAs. In the case of ground coffee, the import coffee bean price and much of the transport and processing costs are common cost factors for products sold in all DMAs. The assumption justifying the validity of Hausman-type instruments is that city-specific demand shocks must be independent across cities after controlling for product-city-fixed effects. This assumption is violated in the presence of regional or national demand shocks. For instance, in the presence of a national brand ad campaign, demand shocks across DMAs can be correlated.

Because of concerns regarding a potential violation of the identification assumption of the Hausman instruments, I construct another instrument by using the import price of coffee, since it constitutes a major cost factor. I dub this approach the cost instrument. For cost instruments to be valid, unobserved demand shocks must be independent of the import coffee prices. This assumption is violated if common trends in US coffee consumption are major determinants of the import coffee price. However, this is unlikely to be the case because the import coffee price is mainly driven by weather conditions in major coffee producing countries. Since changes in the import coffee price are transmitted to the retail coffee price with some lag (Nakamura and Zerom 2010), it is necessary to determine the number of lagged values to be used as instruments. Thus, I estimate the model using different lags of coffee import prices as instruments and select the lag structure that produces significant first-stage F-statistics.

2.4.4.2 Supply-side identification

The main difficulty in identifying the conduct parameters is that the endogeneity of markups arises due to the presence of unobserved factors affecting firms' decisions on both markups and prices. To correct this endogeneity bias, I follow a suggestion presented by Berry and Haile (2014). They point out that variations in market environments, such as the number of competing firms and the set of characteristics of competing goods, can be used as instruments for conduct parameters because these variables shift markups independently of costs. My identification strategy is in line with this idea as I use the number of products in the fringe segment as an instrument for conduct parameters. This instrument is expected to shift markups exogeneously because it affects the inter-sectoral elasticity of substitution independently of marginal costs. In other words, if the number of products in the fringe segment increases, the substitutability between the dominant segment and the fringe segment increases due to the increased variety of coffee brands available in the industry. The identification assumption is that unobserved cost shifters for products in the dominant segment are independent of the number of products in the fringe segment. This is expected to hold because the marginal costs of Folgers and Maxwell House are unlikely to be correlated with the number of other products in the coffee industry.

Quarterly dummies are also included in the instrument set to exploit possible seasonal demand variations. The production cost of coffee is unlikely to have seasonal variations after controlling for imported coffee price variation.

2.4.5 Tests on weakly separable preferences

As a pretest, I determine which products best belong to the dominant segment. Based on Moschini, Moro, and Green (1994), a null hypothesis for testing a weakly separable preference is as follows:

$$H_0 : \eta_{ik} E_j E_m - \eta_{jm} E_i E_k = 0 \quad \text{for all (i, j)} \in I_g \text{ and (m, k)} \in I_s, \text{for all } g \neq s \tag{2.16}$$

where η_{ik} is the Allen-Uzawa elasticity of substitution between product i and k, E_i is the expenditure elasticity of product i. All products $(q_1, ..., q_J)$ are assigned to one of the mutually exclusive groups $(I_1, ..., I_N)$ under weakly separable preferences. I conduct Wald tests on four preference structures: (1) Folgers and Maxwell House are weakly separable from the others, (2) Folgers, Maxwell House, and Private Label are weakly separable from the others, (3) Folgers, Maxwell House, and Starbucks are weakly separable from the others, (4) Folgers, Maxwell House, Private Label and Starbucks are weakly separable from the others.

To conduct Wald tests on these weakly separable preferences, I estimate the LA/AIDS with five products: 1)Folgers, 2)Maxwell House, 3)Private Label, 4)Starbucks, and 5)All others by SUR and GMM. All regressions include product, DMA, and time fixed effects. In order to evaluate my instruments, I estimate the first-stage F-statistics for each of four endogenous variables ($\ln p_1/p_5$, $\ln p_2/p_5$, $\ln p_3/p_5$, $\ln p_4/p_5$). Staiger and Stock (1997) propose a rule of thumb that an F-statistic greater than 10 suggests that instruments are not weak. The F-statistics from the first-stage model estimations using the Hausman instruments are greater than 10 for all of the four endogenous variables. Therefore, I conclude that the Hausman instruments are not weak. However, some of the F-statistics from the cost instruments are smaller than 10 for these four endogenous variables regardless of choices of lagged values of import coffee prices.[9] Thus, I conduct GMM estimation using the Hausman instruments[10], and then calculate test statistics corresponding to null hypotheses implied by the four separable preferences according to equation (2.16).

The results of the separability tests are shown in table 2.3. These findings show that the preference structures except for (1) are all rejected at the 10% level. This shows that Folgers and Maxwell House are likely to be separable from the other products. As a result, I include Folgers and Maxwell House in the dominant segment while all other products are included in the fringe segment. Under this preference structure, the representative consumer first decides their expenditure on coffee (top level), then chooses between the dominant and fringe (middle level), and then decides on their expenditure between Folgers and Maxwell House (bottom

[9]I use different combinations of lagged values of import coffee prices for instruments, but I can not find the instrument whose first-stage F-statistics are greater than 10 for all of the four endogenous variables.

[10]The results of the LA/AIDS estimation by SUR and GMM show that the own-price elasticities are all negative and statistically significant at the 1 % level. Also, most of the cross-price elasticities are positive and statistically significant at the 5 % level. It is noteworthy that Folgers and Maxwell House are closer substitutes than the other products.

level). The prices and market shares at these three levels are reported in table 2.4.

Table 2.3: Wald tests on weakly separable preference

	Preference structure	SUR	GMM	Critical Value at the 10% level
(1)	(F, M), PL, SB, OH	2.11	5.41	6.25
		(0.55)	(0.14)	
(2)	(F, M, PL), SB, OH	21.96***	8.48*	7.78
		(0.00)	(0.08)	
(3)	(F, M, SB), PL, OH	26.92***	13.92***	7.78
		(0.00)	(0.01)	
(4)	(F, M, PL, SB), OH	13.41***	8.81**	6.25
		(0.00)	(0.03)	

Notes: The column named preference structure shows a testing weakly separable preference. Products in the parentheses are weakly separable from the other products: F=Folgers, M=Maxwell House, PL=Private Label, SB=Starbucks, OH=All others. We use the Hausman instruments for GMM estimation. Wald statistics are distributed chi-square with k degrees of freedom where k is the number of restrictions. The degrees of freedom are 3 for (1) and (4), and 4 for (2) and (3). Figures in parenthesis are P-values for corresponding Wald test. Statistical significance at the 10%, 5% and 1% is denoted by * , ** and *** respectively.

Table 2.4: Prices and market shares of three stage demands

		Prices ($ per 16 ounce)				Shares (% in value)			
	brand	Mean	Std	Min	Max	Mean	Std	Min	Max
	Bottom level								
1	Folgers	2.55	0.33	1.46	4.32	59.17	19.22	10.80	97.82
2	Maxwell House	2.63	0.46	1.47	4.82	40.83	19.22	2.18	89.20
	Middle level								
1	Dominant segment	2.56	0.33	1.67	4.31	55.80	13.62	19.94	83.70
2	Fringe segment	3.70	0.72	2.09	6.22	44.20	13.62	16.30	80.06
	Top level								
	All coffee	3.00	0.44	2.01	4.93	-	-	-	-

2.5 Estimation Results

2.5.1 Demand estimates

The results of LA/AIDS estimation of the bottom-level demand for Folgers and Maxwell House are presented in table 2.5. Since there are only two products, this is a single equation estimation: a share equation of Folgers is estimated by OLS and GMM. All regressions include product, DMA, and time fixed effects. As the first-stage F-Statistics of cost instruments for GMM estimations are all greater than 10, weak instrument problems are not at issue here. Therefore, I proceed with the cost instruments. The results show that the estimate of γ_{11}^{B} is negative and statistically significant at the 1 % level. Because absolute values of γ_{11}^{B} obtained using GMM are greater than that of OLS, my instruments are likely to remove an upward bias caused by the simultaneity problem. In the following, I use the estimates from GMM (3). Next, I estimate the LA/AIDS of the middle level: the dominant segment and fringe segment. A share equation of the dominant segment is estimated by OLS and GMM. I follow the same procedure as the bottom-level estimation. The results are reported in table 2.6. Since the results of the middle-level demand are basically the same as the bottom level, I do not repeat them here. I use the estimates from GMM (1) for the following estimations. Finally, the log-log model for the top-level demand is estimated by OLS and GMM. I allow for the price coefficients to vary by quarter in order to add flexibility on price elasticities. Due to the seasonality of coffee demand, consumers' price responses to total coffee demand may be different by quarter. Since the cost instruments are weak, the instruments used in the GMM estimation are products of the Hausman instrument and quarter dummy variables.

Table 2.7 shows the estimated elasticities obtained from the estimates of the three-stage demand system. First, all of the own-price elasticities are negative and statistically significant at the 1 % level. Also, the GMM estimation generates more elastic price responses than the OLS estimation. Next, the results of the cross-price elasticities show that Folgers and Maxwell House are close substitutes with each other, and the dominant segment and the fringe segment are also substitutes. The top-level demand estimates show the own price elasticity of total coffee demand varying from -1.493 to -1.311 for OLS and from -1.900 to -1.527 for GMM.

Finally, I calculate two elasticities of substitution using these demand estimates. The results are shown in the bottom part of table 2.7. The estimates of intra-sectoral elasticity of substitution which measures substitutability within the dominant segment (Folgers and Maxwell House) are $2.168, 2.274$ for OLS and $2.942, 3.145$ for GMM. The estimates of inter-sectoral elasticity of substitution which measures substitutability against the products outside the dominant segment are 1.675 for OLS and 2.163 for GMM. These estimates show that the intra-sectoral elasticity of substitution is greater than the inter-sectoral one, which is an expected result.

Table 2.5: Estimated parameters of LA/AIDS for the bottom level demand

	Parameter	OLS	GMM		
			(1)	(2)	(3)
Own price	γ_{11}^B	-0.303	-0.564	-0.439	-0.507
		(0.009)	(0.076)	(0.074)	(0.062)
Expenditure	β_1^B	-0.012	-0.017	-0.015	-0.017
		(0.004)	(0.006)	(0.005)	(0.005)
Instruments		-	C_{t-1}, C_{t-4}	C_{t-1}, C_{t-6}	C_{t-1}, C_{t-4}, C_{t-6}
1st stage F-statistic		-	14.79	12.37	12.56

Notes: The table shows the results of LA/AIDS estimation for the bottom level demand: 1=Folgers, 2=Maxwell House. A share equation of Folgers is estimated under the theoretical constraints: $\gamma_{11}^B = \gamma_{22}^B = -\gamma_{12}^B = -\gamma_{21}^B$ and $\beta_1^B + \beta_2^B = 0$. All estimations include product, DMA, and time fixed effects. Figures in parenthesis are robust standard errors.

Table 2.6: Estimated parameters of LA/AIDS for the middle level demand

	Parameter	OLS	GMM	
			(1)	(2)
Own price	γ_{DD}^M	-0.182	-0.372	-0.238
		(0.008)	(0.067)	(0.043)
Expenditure	β_D^M	0.043	0.023	0.037
		(0.004)	(0.008)	(0.006)
Instruments		-	C_{t-2}, C_{t-3}	C_t,C_{t-2}, C_{t-3}
1st stage F-statistic		-	18.58	22.92

Notes: The table shows the results of LA/AIDS estimation for the middle level demand: Dominant segment and Fringe segment. A share equation of the dominant segment is estimated under the theoretical constraints: $\gamma_{DD}^M = \gamma_{FF}^M = -\gamma_{DF}^M = -\gamma_{FD}^M$ and $\beta_D^M + \beta_F^M = 0$. All estimations include product, DMA and time fixed effects. Figures in parenthesis are robust standard errors.

2.5.2 Supply estimates

Using the demand-side estimates, the conduct parameters can now be estimated. I estimate the supply-side model using GMM under different lagged cost structures and inclusion/exclusion of the distance variable. Since the supply model is estimated conditional on the demand estimates, standard errors are calculated with the moment conditions from the supply estimation stacked with the moment conditions from the demand estimation. This emulates the calculation of standard errors as if supply and demand were estimated jointly. The results from each of the three estimations are presented in table 2.8. The sum of the lagged cost coefficients can be interpreted as the cost-pass through rate (Nakamura and Zerom 2010). The coefficient on wage is positive for all regressions, as expected.

The estimates of the conduct parameters for Folgers and Maxwell House are reported at the top of table 2.8. Folgers' conduct parameter is estimated in a tight range between 0.12 and 0.14. Maxwell House's conduct parameters are in an equally tight range of 0.02 to 0.04. These results indicate that the estimated conduct parameters are not sensitive to the cost structure chosen. Given the theoretical restriction that the conduct parameters must vary between zero and one, I test for Bertrand ($\theta_i = 0.5$), using a two-tailed t-test, and for

Table 2.7: Estimated elasticities from the three stage demand estimates

	OLS		GMM	
Bottom (1:Folgers and 2:Maxwell House)				
E_1	0.979	(0.008)	0.969	(0.009)
E_2	1.026	(0.010)	1.037	(0.012)
e_{11}	-1.540	(0.016)	-1.908	(0.111)
e_{12}	0.562	(0.016)	0.939	(0.113)
e_{21}	0.659	(0.020)	1.107	(0.136)
e_{22}	-1.685	(0.019)	-2.142	(0.138)
Middle (Dominant and Fringe)				
E_D	1.074	(0.008)	1.040	(0.014)
E_F	0.895	(0.011)	0.943	(0.020)
e_{DD}	-1.366	(0.013)	-1.661	(0.105)
e_{DF}	0.293	(0.013)	0.621	(0.117)
e_{FD}	0.522	(0.019)	0.941	(0.150)
e_{FF}	-1.361	(0.023)	-1.863	(0.176)
Top (All coffee)				
γ^T (quarter 1)	-1.311	(0.091)	-1.527	(0.184)
γ^T (quarter 2)	-1.328	(0.089)	-1.574	(0.184)
γ^T (quarter 3)	-1.488	(0.084)	-1.844	(0.176)
γ^T (quarter 4)	-1.493	(0.079)	-1.900	(0.164)
Elasticity of substitutions (1:Folgers and 2:Maxwell House)				
Intra-sectoral				
s_1	2.168	(0.039)	2.942	(0.236)
s_2	2.274	(0.039)	3.145	(0.264)
Inter-sectoral				
σ	1.675	(0.056)	2.163	(0.148)

Notes: The GMM estimate for the bottom is GMM (3) in table 2.5 and the GMM estimate for the middle is GMM (1) in table 2.6. E_i is the expenditure elasticity of product i. e_{ij} is the Marshallian price elasticities ($e_{ij} = \partial \ln d_i / \partial \ln p_j$). All elasticities are evaluated at the median of the sample.

collusion ($\theta_i = 0$) and monopolistic competition ($\theta_i = 1$) using one-tailed t-tests. Other than Folgers in the GMM (3) estimates case, all conduct parameters are not statistically different than 0 (collusion) at the 95% level. All conduct parameters are statistically different from Bertrand price competition ($\theta_i = 0.5$) using a 2-tailed test, and monopolistic competition

($\theta_i = 1$) using a one-tailed test. These results suggest that Folgers and Maxwell House operated in a collusive pricing structure.

Finally, I compare the markups from the estimated conduct parameters to three benchmark outcomes obtained by setting $\theta_i = 0$ for collusion, $\theta_i = 0.5$ for Bertrand, and $\theta_i = 1$ for monopolistic competition (see table 2.9). The markup under the Bertrand price competition is around 37%, which is close to the estimates by Nakamura and Zerom (2010). Their median markups are 36.8% over the period 2000-2004. The markups calculated from the conduct parameters are close to the markups under collusion. This is expected since the conduct parameters take values that are close to zero. These results imply that assuming Bertrand price competition would lead to an underestimation of markups in cases, like this analysis, where the true conduct is closer to collusion than Bertrand.

2.6 Conclusion

In this chapter, I develop the empirical procedures to implement a new approach for measuring firm conduct. I construct an empirical structural model using the oligopolistic model proposed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) and d'Aspremont and Dos Santos Ferreira (2016) and apply the model to the U.S. food market for caffeinated ground coffee. One particular finding from this study is that the degrees of collusion for the two largest brands are understated in a model that imposes the restriction of Bertrand pricing. The results suggest that firms may be able to deviate from such a base strategy to improve overall margins, depending on the competitive environment in the industry.

Early scientific developments in the empirical assessment of market power began with crude reduced-form approaches in the structure-conduct-performance paradigm. Since the 1970s, methodological advancements and refinements constructed on game theoretic foundations have met considerable and growing resistance in at least the past few decades, due primarily to theoretical inconsistencies, dimensionality problems, and endogeneity concerns. The propsed model overcomes some of the hurdles in the existing models to analyze non-competitive conduct. By viewing the firm as operating through pairs of price-quantity outcomes, the method sidesteps the problems of theoretical inconsistency associated with the conjectural variations approach. Also, the proposed model is empirically tractable since it is parsimonious in the parameter space, which provides a great advantage for identifying firm conduct in applications. This application demonstrates the applicability of my proposed framework in assessing competition in retail pricing using the standard scanner datasets.

Table 2.8: Estimates of firm conduct and marginal cost parameters

	GMM					
	(1)		(2)		(3)	
	Folgers	Maxwell House	Folgers	Maxwell House	Folgers	Maxwell House
θ_i	0.115	0.030	0.123	0.037	0.139	0.018
	(0.074)	(0.037)	(0.081)	(0.047)	(0.074)	(0.020)
$\sum_k C_{t-k}$	0.321	0.771	0.467	0.522	0.420	0.680
C_{t-1}	-0.249	0.321	-0.179	0.216	-0.311	0.525
	(0.097)	(0.178)	(0.098)	(0.180)	(0.130)	(0.227)
C_{t-2}	-	-	-	-	0.053	-0.531
					(0.156)	(0.232)
C_{t-3}	-	-	-	-	0.331	0.316
					(0.158)	(0.234)
C_{t-4}	0.585	0.978	0.659	0.867	0.154	0.694
	(0.113)	(0.181)	(0.113)	(0.191)	(0.166)	(0.237)
C_{t-5}	-	-	-	-	0.474	0.336
					(0.155)	(0.240)
C_{t-6}	-0.015	-0.528	-0.013	-0.560	-0.281	-0.660
	(0.084)	(0.141)	(0.084)	(0.142)	(0.114)	(0.188)
wage	0.071	0.016	0.086	0.023	0.071	0.020
	(0.009)	(0.018)	(0.009)	(0.020)	(0.009)	(0.015)
distance	-	-	-0.061	0.200	-	-
			(0.011)	(0.025)		

Notes: The table shows the results of the supply-side estimates. All estimations include region-year fixed effects. Figures in parenthesis are robust standard errors.

Table 2.9: Median markups estimated from the competitive toughness parameters

	Folgers	Maxwell House
GMM(1)	44.22	44.82
GMM(2)	44.11	44.76
GMM(3)	43.93	45.05
Collusion	46.05	46.05
Bertrand price competition	37.27	37.14
Monopolistic competition	32.23	30.05

Notes: Markup is defined as $(p - mc)/p \times 100$.

Chapter 3

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

3.1 Introduction

Whether firms compete or collude 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 highly concentrated industries and rising markups (De Loecker, Eeckhout, and Unger 2020; Döpper et al. 2022). These trends raise concerns about the impacts of growing market power on total welfare and its distribution between consumers and firms. However, such high markups are not necessarily caused by anti-competitive conduct such as implicit collusion because they can be attributed to several other factors, including changes in demand and cost. Therefore, empirically identifying firm conduct has been the central issue in the field of industrial organization for obtaining policy-relevant implications in many industries.

Seminal work by Bresnahan (1982) shows that exogenous rotation of demand 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 (Bresnahan 1989). 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 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 chapter, I 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 is empirically tractable even when we employ a high-dimensional oligopoly model in which many firms strategically interact. Importantly, my model retains the flexibility that allows each firm to operate at any level of competition from collusion to monopolistic competition.

On the supply side of the model, I use an oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) to construct an empirical framework to estimate conduct parameters. In their oligopolistic model, each firm maximizes its own profit given prices and quantities of other firms under two demand constraints: market share constraint and market size constraint. The conduct of each firm is measured by a relative attitude toward these two constraints and different conduct leads to different degrees of collusion. Intuitively, when firms compete aggressively with each other, they put more weight on the market share constraint and tend to obtain higher market shares by lowering prices. By contrast, when firms collude with each other, they put more weight on the market size constraint and tend to sustain higher prices by coordinating and controlling the total supply of the market. D'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) show that this dichotomous characterization of competition accommodates varying degrees of competition, which nest the benchmark models such as collusion, monopolistic competition, Nash-Bertrand price, and Cournot quantity competition. While their analysis is purely theoretical with an assumption of single-product firms, I incorporate it into an empirical structural model with an extension to multiproduct firms.[1] This formulation significantly reduces the dimension of conduct parameters because the degree of collusion is measured by a firm-specific single parameter. The estimation equations constructed from firms' first-order conditions are empirically tractable owing to a reduced number of parameters and simpler functional forms.[2]

On the demand side of the model, I use a discrete/continuous logit demand model in which consumers choose one of the products and then choose a purchase amount under their budget constraint (Hanemann 1984). Following Björnerstedt and Verboven (2016), I incorporate random coefficients related to consumer heterogeneity into the discrete/continuous framework. This model generates flexible substitution patterns such as the standard random coefficients logit model originally proposed by Berry, Levinsohn, and Pakes (1995). I choose the discrete/continuous demand system because it allows for recovering utility and expenditure functions of a representative consumer generated from the population of heterogeneous consumers (Anderson, De Palma, and Thisse 1987; Dubé, Joo, and Kim 2023). This integrability property ensures a theoretical consistency between the demand and supply model and enables us to conduct welfare analysis based on the structural model.

In the empirical part of this study, I apply the proposed model to the US corn seed industry.

[1]Sakamoto and Stiegert (2018) incorporate the oligopolistic model by d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) into a structural model with the almost ideal demand system by Deaton and Muellbauer (1980), and estimate conduct parameters of two single-product firms in the US retail coffee industry. The results show that the conduct of these firms is close to collusion and Nash-Bertrand pricing conduct is rejected.

[2]Corts (1999) points out 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 to the model here because I assume that the observed equilibrium is generated from firms' static profit-maximization behavior with true values of conduct parameters. My conduct parameters have structural interpretations conditional on this assumption. This argument is borrowed from Ciliberto and Williams (2014) and Magnolfi and Sullivan (2022).

This 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) accounted for over 85% of the market in 2014. This highly concentrated structure has been shaped by a number of vertical and horizontal mergers. Furthermore, biotech firms such as Monsanto permit other firms to use patented GM traits through cross-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 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).

My aim in the empirical application is to estimate conduct parameters for the five largest firms in the US corn seed market from 2008 to 2014. I use a proprietary data set about farm-level seed choices. The data include expenditure, purchased quantity, brands, parent companies, and types of genetically modified traits for each transaction. I also utilize farmer demographic variables such as farm size and location of production to incorporate preference heterogeneity. I focus on the core region of the Corn Belt spanning 10 major corn-producing states in the midwestern US, which account for a significant portion of US corn production and share relatively similar agro-economic conditions.

The results of the demand estimation show that the product-level demand for GM seeds is quite elastic and that different companies' seeds are imperfect substitutes for one another. The interaction parameter of the price coefficient with farm size indicates that larger farmers are more sensitive to price increases. In contrast, the aggregate demand for GM seeds is inelastic, which might allow firms to sustain higher prices by coordination. The estimates of willingness to pay for GM traits indicate that farmers highly value GM seeds with stacked traits of two types of insect resistance (corn borer and rootworm) and herbicide tolerance.

In the supply side of the empirical analysis, I estimate conduct parameters for each of the five firms along with marginal cost parameters. Identification of the conduct parameters requires addressing the endogeneity arising from the fact that firms consider unobserved marginal costs when setting their markups. The structure of the proposed model significantly reduces the requirement for the number of excluded instruments. Following Berry and Haile (2014), I use the number of rival firms interacting with firm dummies as excluded instruments for conduct parameters; the number of rival firms is expected to shift markups by changing the market environment but to be uncorrelated with marginal costs of seed production.

The results of the supply-side estimation indicate that the conduct parameters for the five firms are all precisely estimated. The values of all estimated conduct parameters lie between collusion and quantity competition, which means that the conduct of these firms is imperfect collusion. The low degree of competition might reflect coordination between firms, internalization by the licensing firms (which can earn licensing fees from sales of the licensed firms), or both. The results of hypothesis testing reject all benchmark conduct, including Nash-Bertrand price competition and Cournot quantity competition. The low degree of competition leads to higher markups, indicating that the markup of the largest firm is about 51%, while the markups of the other four firms range from 38% to 41%.

To quantify the impacts of the collusive conduct on market outcomes, I conduct counterfactual simulations. My results show that, if these firms engaged in price competition, the average price of GM seeds would have been 29% lower. These lower prices would increase farmer surplus while decreasing seed firm profits. As a result, total welfare would have been 3.65 billion US dollars higher over the period from 2008 to 2014. My results indicate that the low degree of competition significantly affects both total welfare and its distribution between farmers and firms in the seed industry.

This study contributes to the literature both methodologically and empirically. Methodologically, my research provides a good 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, Conlon, and Sinkinson 2021; Duarte et al. 2023). 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. In addition, it becomes cumbersome very quickly when the number of firms increases. Furthermore, as shown in my estimation results of the corn seed industry, the true conduct may be in between the benchmark conduct models. My estimation-based approach for conduct parameters can be applicable in many situations, even when the testing-based approach has been considered the only option for analyzing the degree of collusion due to a large number of firms.

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, which is essentially the same approach as in this study. Miller and Weinberg (2017) measure the effects of a joint venture between ABI and MillerCoors on the degree of price coordination in the US beer industry. The focus on the coordination between two firms allows them to estimate only a single conduct parameter. Ciliberto and Williams (2014) also focus on pair-wise relationships between airlines; they reduce the number of parameters by assuming a certain relationship between conduct and a level of multimarket contact. 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 my 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.

This study also contributes to accumulating empirical evidence of the degree of competition in the US seed industry. The previous research focuses on the demand side of this industry (Ciliberto, Moschini, and Perry 2019; Luo, Moschini, and Perry 2023). Compared to the demand analyses, the related empirical evidence about firm conduct is limited, even though many researchers and stakeholders have raised concerns about the growing concentration in the seed industry. To my knowledge, Shi, Meloyan, and Kubo (2023) is the only paper that explicitly analyzes the degree of collusion in the US corn seed industry. They find that firms are implicitly colluding in both product lines and pricing, with a focus on three major players. This study estimates the conduct of the five largest firms in their pricing and analyzes its welfare implications, which provides new policy-relevant empirical evidence, especially on the overall competitiveness in the seed industry.

The rest of the chapter is organized as follows. The next section presents the background of the US corn seed industry. Section 3.3 presents a structural model of demand and supply. The data and identification strategy are discussed in section 3.4. Section 3.5 presents the estimation results. Section 3.6 concludes.

3.2 Background: The US Corn Seed Industry

Rapid advancement of modern biotechnology has contributed to the strong growth of agricultural productivity, especially through the development of genetically modified (GM) seeds. Recombinant DNA techniques make it possible to insert useful foreign genes into the corn 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 such as glyphosate. The insect resistance trait makes corn resistant 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 (Fernandez-Cornejo 2004; Moschini 2008). Figures 3.1 and

3.2 show the adoption rate and the average price of GM corn seeds from 1996 to 2014 in the United States. 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 and farmers have paid the highest prices for the triple-stacked GM seeds.

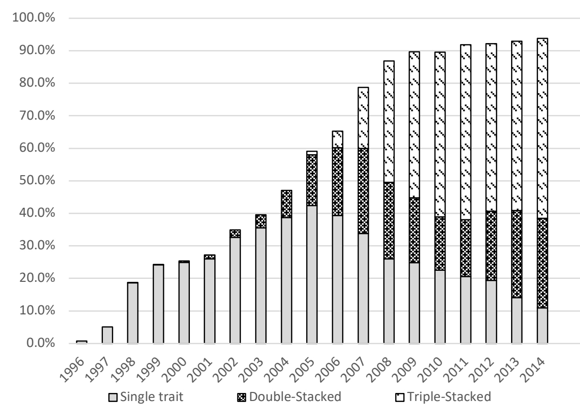

Figure 3.1: Adoption rate of GM corn seeds (in % of total corn acreage) in the US

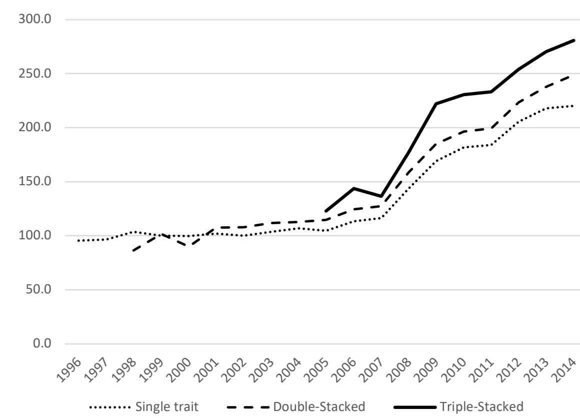

Figure 3.2: The average price of GM corn seeds (in $ per bag) in the US

Note: In Figure 3.1, the adoption rate is the corn acreage of each GM trait divided by the total corn acreage. In Figure 3.2, the average price is measured in dollars per bag. “Single trait” refers to products with only one GM trait (corn borer resistance, rootworm resistance, or herbicide tolerance). “Double-Stacked” refers to products with two GM traits and “Triple-Stacked” refers to products with three GM traits. Source: GfK Kynetec data.

The US seed industry has become more consolidated since the large-scale commercial introduction of GM seeds. One important aspect of GM technologies is that GM traits need to be inserted into elite germplasm through breeding processes. GM traits are developed and owned by a few large 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, Rausser, and Small 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 firms made similar strategic moves. In 1999, Dupont acquired Pioneer, which was the dominant seed company 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. Even after the establishment of the five large firms, these firms continued to acquire regional seed companies in the subsequent years.

Figure 3.3 shows the market shares of GM seed companies from 2004 to 2014. The figure shows that the total market share of the five firms (Monsanto, Dupont, Syngenta, Dow AgroSciences, and AgReliant) increased from 65% in 2004 to 87% in 2014. By contrast, the market share of other local and regional seed companies accounted for about 35% in 2004, but decreased to less than 14% in 2014. Monsanto and Dupont are the two dominant firms that control around 70% of the market. 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 means that the market is highly concentrated based on the horizontal merger guidelines issued by the US Department of Justice and Federal Trade Commission. The market shares of these five firms are relatively stable after 2008.

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 3.4 shows, these firms sign cross-licensing agreements among themselves, allowing them to produce GM seeds with genes 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

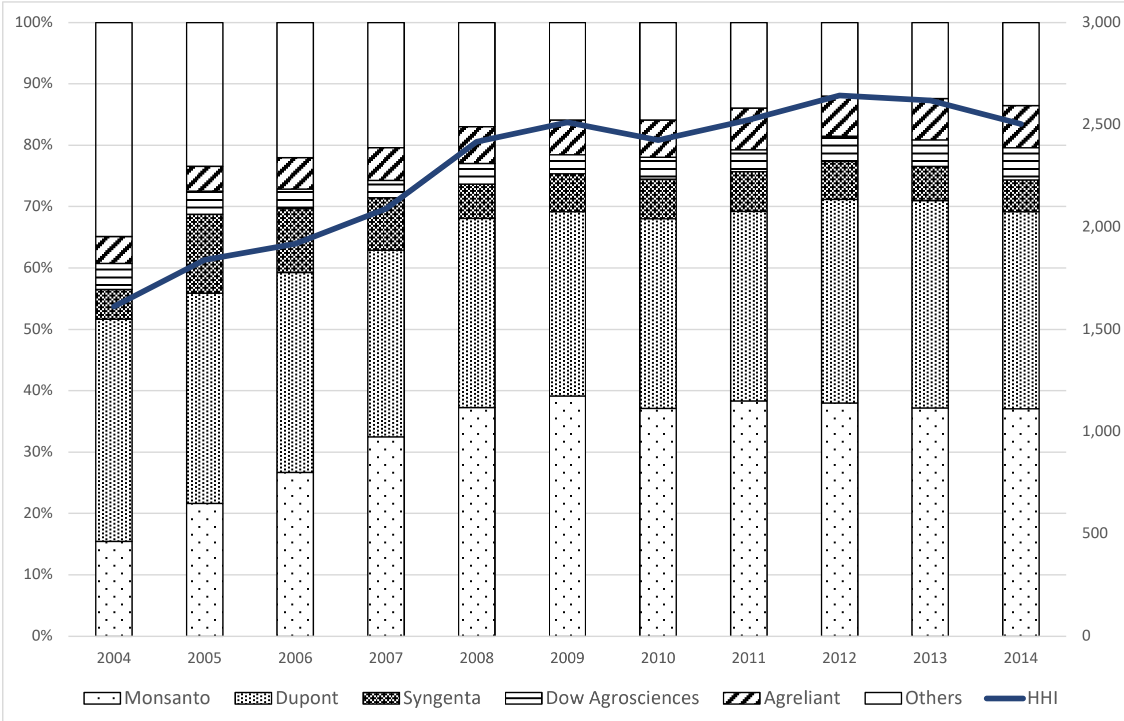

Figure 3.3: Market shares and HHI
Note: Market shares are measured by value for Monsanto, Dupont, Syngenta, Dow AgroSciences, and AgReliant. "Others" refers to the total market shares of the other firms. The Herfindahl-Hirshman Indexes (HHIs) are scaled from 0 to 10,000 on right axis. Source: GfK Kynetec data.

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 seed companies. As a result, the market share of products that incorporate Monsanto's patented traits was approximately 85% in 2014, based on a calculation from GfK Kynetec data. 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 give the licensors additional incentives to increase their prices through internalization of other firms' profits because they can earn additional profits from the sales of other firms.

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

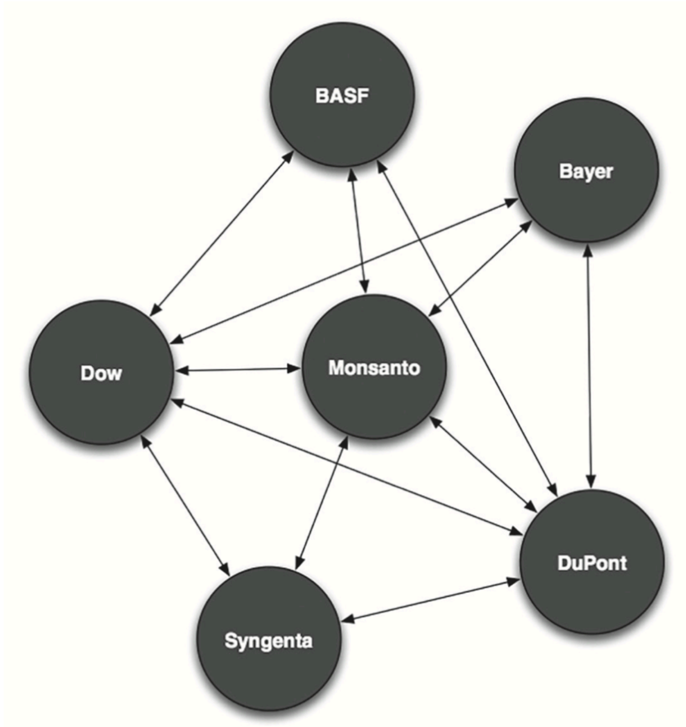

Figure 3.4: Cross-licensing agreements between big six biotech firms for GM traits
Source: Howard (2015)

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).

3.3 Structural model of demand and supply

Several potential factors 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). I develop a novel structural model that allows for flexible estimation of the degree of collusion for a large number of multiproduct firms in an empirically tractable way.

3.3.1 Demand model

On the demand side, I use a variant of a random coefficient logit model. The demand model is theoretically the same as a discrete/continuous demand model proposed by Hanemann (1984). In this model, a consumer first chooses one of the products and then decides how much to purchase under his/her budget constraint. 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 period t. In each market, there are J_{rt} products. I consider farmers to be utility-maximizing individuals who choose the alternative with the highest utility.[3] Farmer i chooses one of the GM seed products ($j = 1, ..., J_{rt}$) or the conventional seed as an outside option. This specification means that it is a conditional demand model in which only corn seed choices are considered.[4]

[3]The 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, Marra, and Carlson (2000) and Breustedt, Müller-Scheeßel, and Latacz-Lohmann (2008).

[4]Although it is common to specify an outside option as a non-purchase choice in discrete demand models, some papers such as Train and Winston (2007) and Sheu (2014) estimate conditional demand models without a non-purchase option. One advantage of conditional demand is that it is not necessary to speculate a total market size, which often requires strong assumptions. Train and Winston (2007) discuss this issue in detail. In the case of seed demand estimation, Luo, Moschini, and Perry (2023) estimate a conditional demand model that considers choices only between soybean seeds.

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

$$u_{ijrt} = \boldsymbol{x}_j'\boldsymbol{\beta}_i + \alpha_i(\ln y_{irt} - \ln p_{jrt}) + \phi_b + \phi_r + \phi_t + \xi_{jrt} + \epsilon_{ijrt} \tag{3.1}$$

where $\boldsymbol{x}_j$ is a vector of observed product characteristics, y_{irt} is the corn seed expenditure of farmer i, 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 (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 time, respectively. I control for ϕ_b, ϕ_r, and ϕ_t using brand, region, and time dummy variables, respectively. The term ξ_{jrt} represents an unobserved quality variation specific to region r and period t, and ϵ_{ijrt} is a structural error term. I normalize the mean utility of the conventional seed ($j = 0$) to zero.

The observable product characteristics include indicator variables for GM traits (GT, CB_RW, CB_GT, RW_GT, CB_RW_GT), where GT, CB, and RW stand for glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. Each of the indicator variables takes the value 1 if the product contains the corresponding trait. For instance, in the case of a product with a single trait of GT, only the indicator variable for *GT* takes the value 1. For products with a double-stacked trait of glyphosate tolerance and corn borer, both indicator variables for *GT* and *CB_GT* take the value 1. If products have a triple-stacked trait of CB, RW, and GT, indicator variables for *GT* and *CB_RW_GT* take the value 1. I do not include an indicator variable for a single trait of CB because there is a linearly dependent relationship between the indicator variables of GM traits (see the discussion in Shi, Chavas, and Stiegert 2010).[5] With this specification, the values of the parameters for each GM trait are measured as a difference from the valuation of CB.

I include random coefficients associated with farmer demographic variables to allow

[5]Also, I do not include an indicator variable for RW because I omit the products with the single trait of RW due to very few observations in my sample.

for flexible substitution patterns following the standard procedure used in the previous research since Berry, Levinsohn, and Pakes (1995). I 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. I allow the price-sensitive coefficient α to vary by farm size, which is measured by planted corn acreage. I also allow the valuation of GM traits $\boldsymbol{\beta}$ to vary by geographic location, which is measured by longitude and latitude of the center of the county where farmers produce corn. These location variables are expected to capture regional differences in soil and climate that affect farmers' willingness to pay for GM traits.

Assuming farmer i chooses a product that maximizes the utility u_{ijrt}, and assuming the error term ϵ_{ijrt} follows the extreme value distribution, the probability that farmer i chooses product j is derived:

$$\mathrm{s}_{ijrt}(\boldsymbol{\delta}_{rt}, \Pi) = \frac{\exp(\delta_{jrt} + \nu_{ijrt}(\Pi))}{1 + \sum_{k=1}^{J_{rt}} \exp(\delta_{krt} + \nu_{ikrt}(\Pi))}$$

where δ_{jrt} is the mean utility of product j and $\nu_{ijrt}(\Pi)$ is the random part of farmer-specific valuations defined by:

$$\begin{aligned} \delta_{jrt} &= \boldsymbol{x}_j'\boldsymbol{\beta} - \alpha \ln p_{jrt} + \phi_b + \phi_r + \phi_t + \xi_{jrt} \\ \nu_{ijrt}(\Pi) &= (\boldsymbol{x}_j', \ln p_{jrt}) * \Pi D_{irt} \end{aligned}$$

To derive the demand for product j, I apply Roy's identity to the indirect utility function (3.1), 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:

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

This expected demand indicates that farmer i chooses one of the products and purchases multiple units of the chosen product.[6]

[6]Dubé (2019) points out that the observed consumer behavior is consistent with multiple purchases in

Aggregating the expected demand for product j over all farmers ($i = 1, ..., I_{rt}$), the market demand for product j in region r and period t is derived:

$$q_{jrt}(\boldsymbol{p}_{rt}, Y_{rt}) = \mathrm{s}_{jrt}(\boldsymbol{\delta}_{rt}, \Pi)\frac{Y_{rt}}{p_{jrt}} \tag{3.2}$$

$$\mathrm{s}_{jrt}(\boldsymbol{\delta}_{rt}, \Pi) = \sum_{i=1}^{I_{rt}} w_{irt} \frac{\exp(\delta_{jrt} + \nu_{ijrt}(\Pi))}{1 + \sum_{k=1}^{J_{rt}} \exp(\delta_{krt} + \nu_{ikrt}(\Pi))} \tag{3.3}$$

f 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 period t.

The market share equation in (3.3) takes the familiar form of the standard random coefficient logit proposed by Berry, Levinsohn, and Pakes (1995). One notable difference is that here the price term enters logarithmically ($-\alpha \ln p_{jt}$), while it enters linearly ($-\alpha p_{jt}$) in the standard logit. Due to this specification, the market share is measured by value, not by quantity as it is determined from equation (3.2). Björnerstedt and Verboven (2016) discuss that this type of discrete choice model is a straightforward variant of BLP's demand specification and the same estimation technique including contraction mapping can be applied.

To estimate demand-side parameters $[\alpha, \boldsymbol{\beta}, \Pi]$, I use a GMM estimator and define its objective function by:

$$J^D(\alpha, \boldsymbol{\beta}, \Pi) = \left[\frac{1}{N}\sum_{j,r,t} \xi_{jrt} Z_{jrt}^D\right]' W^D \left[\frac{1}{N}\sum_{j,r,t} \xi_{jrt} Z_{jrt}^D\right]$$

where N is the number of observations, Z_{jrt}^D is a set of instruments that satisfy moment conditions $E[\xi_{jrt} Z_{jrt}^D] = 0$, and W^D is a GMM weighting matrix.

3.3.2 Supply model

In the supply side of my structural model, I formulate firms' profit maximization problems based on the oligopolistic model developed by d'Aspremont, Dos Santos Ferreira, and Gérard-

many industries.

Varet (2007). In this model, competition between firms is modeled by 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. On the other hand, they have a common interest in coordinating a total market supply to sustain higher prices, which can be viewed as competition against firms or products that are outside the market. The relative attitude on these two kinds of competition determines the degree of competition of each firm. d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) show that different degrees of competition, from monopolistic competition to collusion, can be realized as an oligopolistic equilibrium in their theoretical analyses.

I show how to incorporate this model into an empirical structural model with a discrete/-continuous logit demand. This formulation significantly reduces the number of dimensions of interactions between firms while maintaining flexibility for the degree of competition because a single conduct parameter per firm characterizes optimal markups. To construct the model, I extend theoretical model of d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) to allow for multiproduct firms because their assumption of single-product firms is restrictive in many applications. In the meantime, I suppress the subscript of region r and period t for notational simplicity.

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

$$\begin{aligned} \max_{\boldsymbol{p}_f, \boldsymbol{q}_f} \quad & \sum_{j \in \Omega_f} (p_j - c_j) q_j - FC_f \\ & \text{subject to} \quad Q_f(\boldsymbol{q}_f) \leq H_f(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f})) \\ & \text{and} \quad Q(\boldsymbol{q}_f, \boldsymbol{q}_{-f}) \leq D(\boldsymbol{p}_f, \boldsymbol{p}_{-f}, Y) \end{aligned} \tag{3.4}$$

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 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 on seeds (GM and conventional seeds). The integrability property of the discrete/continuous demand ensures the existence of these quantity aggregators (see Appendix 3.A.1 for further details.).

The first constraint is called the market share constraint, which governs firm f's choices of prices and quantities in terms of the firm-level demand (market share) within the inside products (GM seeds). The Hicksian demand function H_f considers substitution between the inside products conditional on Q. To make the framework compatible with multiproduct firms, I construct the market share constraint using a firm-level demand function rather than a product-level demand to allow for internalization of profits for their own products.[7]

The second constraint is called the market size constraint, which governs firm f's choices of prices and quantities in terms of the aggregate demand for all inside products (GM seeds). The Marshallian demand function D considers substitution between the inside products and the outside product. When the prices of the inside products increase, consumers increase the amount purchased of the outside product. While the constraint on market share captures the conflictual side of competition between the firms, the constraint on market size captures their common interest as a sector.

In models of oligopolistic competition with differentiated products, profit-maximizing firms charge positive markups depending on perceived demand elasticities. For instance, a single-product firm sets a higher markup as the demand becomes more inelastic.[8] In this sense, the demand elasticities summarize necessary information for profit maximization. The same argument applies to the profit maximization problem given in (3.4), but perceived elasticities need to be formulated to be consistent with the market share and size constraints.

[7]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 is the same as one used in d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007).

[8]In the case of a single-product firm and price competition, an optimal markup is determined by a so-called inverse elasticity rule, that is $\mu = 1/(\frac{\partial \ln q_j}{\partial \ln p_j})$. See, for instance, Tirole (1988).

By totally differentiating the two constraints respectively, I derive the following elasticities.

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

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

With the discrete/continuous demand specification, these elasticities of substitutions are given by:

$$\eta_j = \frac{1}{S_{f|in}(s_{j|f} - s_{j|in})} \sum_{i=1}^{I} \alpha_i s_{ij|in}(1 - S_{if|in}) + 1 \quad \text{for j} \in \Omega_f \tag{3.5}$$

$$\sigma_j = \frac{1}{(1-s_0)s_{j|in}} \sum_{i=1}^{I} \alpha_i s_{ij} s_{i0} + 1 \quad \text{for j} \in \Omega_f \tag{3.6}$$

(see Appendix 3.A.2 for details on derivations.)

The elasticity η_j is called the intra-sectoral elasticity of substitution. As it is calculated as a curvature of the market share constraint, this measures substitutability of product j within the inside products (GM seeds). On the other hand, the elasticity σ_j is called the intra-sectoral elasticity of substitution. It is calculated as a curvature of the market size constraint, so this measures substitutability of product j against the outside product (non-GM seed). In many applications, the intra-sectoral elasticity is expected to be greater than the inter-sectoral elasticity, because inside products are more substitutable for each other compared to an outside product; that is, we expect $\eta_j > \sigma_j$.[9]

[9]These elasticities correspond to elasticities of substitution defined in d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007) when a firm produces a single product.

To solve the maximization problem for firm f, I 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 3.A.3 for details on derivations.)

$$\mu_j^* = \frac{p_j - c_j}{p_j} = \frac{\theta_f(1 - S_{f|in}) + (1-\theta_f)S_{f|in}}{\theta_f(1 - S_{f|in})\eta_j + (1-\theta_f)S_{f|in}\sigma_j} \quad \text{for j} \in \Omega_f \tag{3.7}$$

where $S_{f|in}$ is the conditional market share of firm f's products within the inside products (subscript in denotes the inside products hereafter). That is, $S_{f|in} = \sum_{j\in\Omega_f} s_{j|in}$, where $s_{j|in}$ is the conditional market share of product j produced by firm f. θ_f is the conduct parameter that measures the degree of collusion of firm f. This parameter is defined as the ratio of two Lagrange multipliers, $\theta_f = \lambda_f/(\lambda_f + v_f)$, so it is interpreted as the relative attitude toward market share constraint and market size constraint.

Equation (3.7) indicates that the optimal markup is determined by the firm market share, two elasticities of substitution, and the conduct parameter. To further understand the relationship between these factors, I rewrite the equilibrium markup equation as a weighted harmonic mean of the two elasticities of substitution.

$$\mu_j^* = \frac{1}{(1-w_f)\eta_j + w_f\sigma_j} \tag{3.8}$$

where the weight w_f is given by:

$$w_f = \frac{(1-\theta_f)S_{f|in}}{\theta_f(1-S_{f|in}) + (1-\theta_f)S_{f|in}} \tag{3.9}$$

From equation (3.8), the markup μ_j increases as the weight w_f increases when $\eta_j > \sigma_j$. From equation (3.9), 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. Thus, the markup is higher for higher market shares and lower values of the conduct parameter, ceteris paribus. For instance, if $S_{f|in} = 1$, which is a monopoly case, the weight is equal to zero and the markup is $1/\sigma_j$. Also, if $\theta_f = 0$, the markup attains the same level as the monopoly case even though $S_{f|in} < 1$. It turns out that 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 3.B for details on derivations.)

To illustrate the model, I present a simple example in which two firms each produce two products. I 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, I calculate markups by using equation (3.7) for values of θ_f from 0 to 1.

Figure 3.5 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 3.C for further details.).

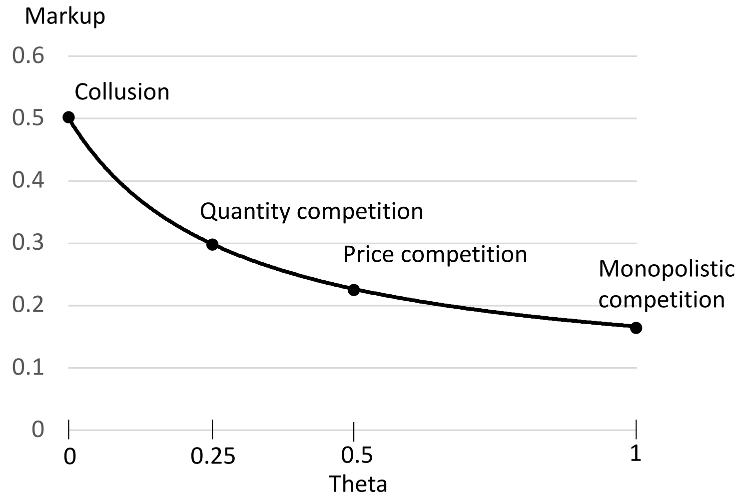

Figure 3.5: Relationship between markup ($\mu_j = (p_j - c_j)/p_j$) and conduct parameter (θ_f)
Note: Author's computations. I set $\eta_j = 6, \sigma_j = 2, S_{f|1} = 0.5$ and calculate the equilibrium markups for values of conduct parameters from 0 to 1. See Appendix 3.C for further details.

As a final step for deriving estimation equations, I assume that the marginal cost of product j in region r and period 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 about licensing on GM traits. ϕ_r is the region fixed effects that are expected to absorb region-specific costs such as distributional and marketing costs. ζ_{jrt} is an unobserved cost shifter left as a structural error.

Substituting this marginal cost equation into the equilibrium markup equation (3.7), we have the following estimation equations.

$$\zeta_{jrt} = p_{jrt}\left(1 - \frac{\theta_f(1-S_{frt|in}) + (1-\theta_f)S_{frt|in}}{\theta_f(1-S_{frt|in})\eta_{jrt} + (1-\theta_f)S_{frt|in}\sigma_{jrt}}\right) - \boldsymbol{\omega}'_{jrt}\boldsymbol{\gamma} \quad \text{for j} \in \Omega_f \quad f = 1, ..., F \tag{3.10}$$

To estimate supply-side parameters $[\boldsymbol{\gamma}, \boldsymbol{\theta}]$, I construct an objective function for a GMM estimator as:

$$J^S(\boldsymbol{\gamma}, \boldsymbol{\theta}) = \left[\frac{1}{N}\sum_{j,r,t} \zeta_{jrt} Z^S_{jrt}\right]' W^S \left[\frac{1}{N}\sum_{j,r,t} \zeta_{jrt} Z^S_{jrt}\right]$$

where N is the number of observations, Z^S_{jrt} is a set of instruments that satisfy moment conditions $E[\zeta_{jrt} Z^S_{jrt}] = 0$, and W^S is a GMM weighting matrix.

In equation (3.10), the estimated parameters are marginal cost parameters ($\boldsymbol{\gamma}$) and firm conduct parameters $\boldsymbol{\Theta} = (\theta_1, ..., \theta_F)$. The markup term is endogenous in the sense that it is necessarily correlated with the unobserved costs. This correlation arises from the fact that firms consider unobserved marginal costs when setting their prices and the markups are functions of the prices of all products in the market. This endogeneity requires excluded instruments for $\boldsymbol{\Theta} = (\theta_1, ..., \theta_F)$.

3.4 Data and Identification

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

3.4.1 Data Sources

My primary data source is the corn TraitTrak data set, collected by GfK Kynetec, a major market research organization that specializes in agriculture-related industries. This data set is constructed from a stratified sample of US corn growers surveyed annually from 1995 to 2014. In the data set, expenditure, quantity, brands, parent companies, and types of genetically modified traits are recorded for individual transactions between seed firms and farmers. The data is supposed to represent each crop reporting district (CRD) of the US Department of Agriculture. There are 407,801 observations in 254 CRDs from 47 states over 1995-2014. Every year there are about 5,000 farmers on average in the sample and 25% of them are kept in the subsequent year.

I focus on the core region of the Corn Belt in the midwestern US. The market share of the Corn Belt accounts for approximately 85% of the total corn seed market and the share of the core region accounts for roughly half of the Corn Belt. My definition of the core region includes 25 CRDs in six states: Illinois, Indiana, Iowa, Minnesota, North Dakota, and South Dakota.[10] The selected regions share relatively similar agro-economic conditions, such as soil fertility and rainfall. Stiegert, Shi, and Chavas (2011) discuss that the core of the Corn Belt is where farmers are less likely to substitute between corn and different crops, compared with the fringe region. These features are suited to my demand estimation, which specifies a conditional demand for corn seeds given that allocation between crops is predetermined.

I also focus on the years 2008-2014, which seem to undergo fewer structural changes in both demand and supply. On the demand side, as Figure 3.1 shows, the introduction of triple-stacked traits in 2006 drastically changed the market situation. I expect that farmer preference is relatively stable after the diffusion of the triple-stacked traits. On the supply side, major biotech firms engaged in many acquisitions and mergers in the 2000s. In particular, the leading company, Monsanto, completed a series of acquisitions by 2007. Thus, the structure of the industry has not experienced a considerable change within the selected years, which is important for obtaining reliable estimates of firm conduct parameters. As a result, there are 68,129 observations from 2008 to 2014.

I define products as combinations of brand and GM traits following the previous papers that estimate discrete choice demand using the same dataset (Ciliberto, Moschini, and

[10] I follow Stiegert, Shi, and Chavas (2011) for a definition of the core region, but I make a slight change to reflect the trend of corn acreage in my estimation period.

Perry 2019; Luo, Moschini, and Perry 2023). Corn farmers perceive the product qualities of corn seeds through brands and types of GM traits. There are a large number of brands, which are sold by large seed firms or other local/regional seed companies. I choose brands whose market shares are greater than 1% in the estimation period. Smaller brands are aggregated into one brand for each parent company: Monsanto, Dupont, Syngenta, Dow AgroSciences, AgReliant, and regional companies. I aggregate GM traits to CB (corn borer), RW (rootworm), GT (glyphosate tolerance), double-stacked (CB_RW, CB_GT, RW_GT), and triple-stacked (CB_RW_GT). I do not treat Liberty Link as a separate trait because it is usually considered a marker gene (Ciliberto, Moschini, and Perry 2019). I also drop products with a single trait of RW or other herbicide tolerance because there are very few observations and their market shares are less than 0.1% in the estimation years.

Table 3.1 shows the market shares of GM seeds calculated by brand and GM trait, respectively. The market shares of products are measured in value, not in quantity, to maintain consistency with discrete/continuous demand models. The table shows that Dekalb, owned by Monsanto, and Pioneer, owned by Dupont, are two dominant brands that together have more than a 50% market share. These brands keep a significant presence in the seed market, possibly due to brand loyalty and long-term relationships with customers. The market share of triple-stacked seeds (CB_RW_GT) is larger than 70%. The triple-stacked seeds were introduced in 2006 and their shares expanded rapidly. On the other hand, the market shares of seeds with other traits have decreased. In particular, the shares of CB-single, CB_RW, and RW_GT are very small –about a 1% share.

Table 3.1: Brand and GM trait market shares

Parent company	Brand	Market share	GM trait	Market share
Monsanto	Dekalb	35.7%	CB-single	1.2%
	Channel	4.2%	GT-single	11.4%
	Others	6.5%	CB_RW	1.0%
Dupont	Pioneer	23.8%	CB_GT	11.5%
	Others	1.0%	RW_GT	0.8%
Syngenta	Golden Harvest	3.6%	CB_RW_GT	74.1%
	NK Seeds	1.2%	Total	100%
	Others	0.4%		
Dow AgroSciences	Mycogen	1.6%		
	Others	1.0%		
AgReliant	Agrigold	4.2%		
	LG Seeds	2.0%		
	Producer Hybrids	1.0%		
	Others	1.3%		
Regional	Myfeels Hybrids	2.2%		
	Croplan Genetics	1.7%		
	Beck's Hybrids	1.4%		
	Others	7.2%		
Total		100%		

Note: Market shares of GM seeds are calculated by brands and GM traits over 2008-2014 in the core region of the Corn Belt. GT, CB, and RW stand for glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. Source: GfK Kynetec data.

The price of each product is calculated by dividing expenditure by purchase quantity (number of bags). Table 3.2 reports the average prices for each GM trait. This shows stylized facts about seed prices. First, all prices tend to increase over time. Second, the prices of GM seeds are consistently higher than conventional (non-GM) seeds. The price of the triple-stacked seeds is the highest among GM seeds. Third, the prices of GM seeds increase by more than the prices of conventional seeds.

The outside option is choosing conventional seeds. The average share of the outside option is 5% in the sample. In the estimation, the price of each GM product is divided by the price of the outside product.

I also construct farmer demographics from the same TraitTrak data to incorporate heterogeneity of preferences. First, I calculate the corn-planted acreage of farmers as the farm

Table 3.2: Average seed prices

Year	Conventional	Single trait		Double-Stacked			Triple-Stacked
		CB	GT	CB_RW	CB_GT	RW_GT	CB_RW_GT
2008	114.0	137.5	149.2	163.6	158.6	166.5	181.1
2009	140.3	159.1	180.8	185.1	191.2	200.4	232.5
2010	142.5	172.6	186.2	200.4	198.6	221.6	235.3
2011	147.2	184.0	188.5	199.1	208.6	219.9	236.3
2012	168.3	205.1	210.9	203.7	228.0	260.6	260.6
2013	177.7	243.3	225.3	235.7	247.6	260.1	276.5
2014	178.5	243.4	227.1	234.5	254.4	254.9	285.6

Note: The table reports the average seed prices paid by farmers ($/bag). GT, CB, and RW stand for glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. Source: Kynetec data

size. This variable is used to allow different price sensitivity parameters for different-sized farms. Second, following Shi, Chavas, and Stiegert (2010), I construct location variables using longitude and latitude of the center of the county where farmers cultivate their corn. These location variables are expected to reflect different geographical conditions and to capture the heterogeneity of farmer preference for GM traits. Summary statistics of variables used for demand estimation are presented in Table 3.3.

On the supply side, the expected price of corn is a major component of the marginal costs of seed production. Seed firms sign a contract with farmers to produce commercial seeds in year $t-1$ for the firm to sell in year t (Fernandez-Cornejo 2004). Under the contract, seed companies must pay at least what farmers could have obtained if they had sold their own corn. Following Kim and Moschini (2018) and Luo, Moschini, and Perry (2023), I use the previous year's future corn price as a proxy of the expected price of corn, which is used as the observed marginal cost shifter. To construct this variable, I collect the data for corn futures prices from the database of Barchart.com. Using futures prices with a delivery month of December, I average daily closing prices from January to March, which are the periods before the planting season.

I utilize technological information about how firms incorporate GM traits licensed from

Table 3.3: Summary statistics of variables for demand estimation

Variable	obs	Mean	Std. Dev.	Min	Max
Product share	5,749	0.275	0.057	0.00003	0.628
Relative price	5,749	1.446	0.291	0.442	2.859
GT	5,749	0.868	0.057	0	1
CB_RW	5,749	0.056	0.231	0	1
CB_GT	5,749	0.181	0.385	0	1
RW_GT	5,749	0.022	0.146	0	1
CB_RW_GT	5,749	0.359	0.480	0	1
Farm size (100 acre)	34,489	6.241	6.517	0.08	108
Longitude	34,489	-92.46	3.286	-100.13	-86.65
Latitude	34,489	42.23	1.789	38.01	46.47

Note: Author's computations from Kynetec data. Relative price is calculated by dividing the price of the product by the average price of conventional seed in each market. GT, CB, and RW stand for glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. Farm size is the corn-planted acreage of a farm. Longitude and latitude are the center of the county where farmers cultivate corn.

others. For instance, Pioneer's product AcreMax Xtreme contains Monsanto's YieldGard, Syngenta's Agrisure, and Dow-Dupont's Herculex HX1 for insect resistance traits, as well as Monsanto's Roundup Ready and Bayer's LibertyLink for herbicide tolerance. In this case, Dupont is supposed to pay certain royalty fees to Monsanto, Syngenta, and Bayer for its utilization of their patented traits. Thus, I use dummy variables that take the value 1 if the product contains the corresponding licensed trait. For instance, if the product contains Monsanto's traits and its seller is not Monsanto, the corresponding dummy variable takes the value 1. Because the corn TraitTrak data set contains the names of specific seed products such as SmartStack and AcreMax, I supplement it with technical documentation that is available on company websites, to infer which GM traits are incorporated in the products.

The licensing dummy variables explain differences in how seed firms utilize licensed GM traits from other firms. Monsanto mostly utilizes its own patented technologies: Roundup Ready and YieldGard. Dupont and Dow rely heavily on Monsanto's traits; more than 80% of their products incorporate Roundup Ready. In addition, they incorporate Bayer's Liberty Link for 70% and 50% of their products. On the other hand, Syngenta does not use Monsanto's traits as much as the other firms. Syngenta utilizes its own patented trait, Agrisure, and also uses Bayer's trait. Lastly, AgReliant, which does not own any patented GM traits, extensively utilizes Monsanto's traits. More than 90% of the products use Monsanto's Roundup Ready and YieldGard, while the utilization rate of other firms' traits is fairly low. To summarize, how firms rely on licensed traits affects marginal costs through payments of licensing fees. In this sense, Monsanto and Syngenta are expected to be cost-efficient firms, while Dupont, Dow, and AgReliant's marginal costs may be higher due to licensing fees.

Table 3.4 shows the summary statistics of variables for supply estimation. I calculate them for the entire sample (all firms) and each firm, respectively. In the supply estimation, I focus on the largest five firms: Monsanto, Dupont, Syngenta, Dow AgroSciences, and AgReliant.

Table 3.4: Summary statistics of variables for supply estimation

	Variable	obs	Mean	Std. Dev.	Min	Max
All firms	Product price	4,448	215.6	45.7	74.0	350.4
	Firm-level share	4,448	0.215	0.193	0.0005	0.757
	License_Roundup Ready	4,448	0.757	0.480	0	1
	License_YieldGard	4,448	0.393	0.473	0	1
	License_DowDupont	4,448	0.045	0.162	0	1
	License_Syngenta	4,448	0.111	0.085	0	1
	License_Bayer	4,448	0.359	0.458	0	1
	Corn future price	4,448	495.0	80.30	398.3	589.4
By Firms						
Monsanto	Product price	1,237	222.9	47.13	77.54	350.4
	Firm-level share	1,237	0.467	0.118	0.141	0.757
	License_Roundup Ready	1,237	0	0	0	0
	License_YieldGard	1,237	0	0	0	0
	License_DowDupont	1,237	0.105	0.236	0	1
	License_Syngenta	1,237	0	0	0	0
	License_Bayer	1,237	0.105	0.236	0	1
Dupont	Product price	893	220.0	39.29	100.0	319.0
	Firm-level share	893	0.254	0.101	0.054	0.543
	License_Roundup Ready	893	0.838	0.363	0	1
	License_YieldGard	893	0.423	0.454	0	1
	License_DowDupont	893	0	0	0	0
	License_Syngenta	893	0.037	0.151	0	1
	License_Bayer	893	0.708	0.446	0	1
Syngenta	Product price	820	195.9	41.85	74.0	327.6
	Firm-level share	893	0.056	0.027	0.001	0.161
	License_Roundup Ready	820	0.052	0.197	0	1
	License_YieldGard	820	0.057	0207	0	1
	License_DowDupont	820	0.033	0.134	0	1
	License_Syngenta	820	0	0	0	0
	License_Bayer	820	0.676	0.460	0	1
Dow AgroSciences	Product price	557	215.2	47.42	91.0	342.0
	Firm-level share	500	0.030	0.021	0.0005	0.156
	License_Roundup Ready	500	0.832	0.365	0	1
	License_YieldGard	500	0.682	0.426	0	1
	License_DowDupont	500	0	0	0	0
	License_Syngenta	500	0.026	0.137	0	1
	License_Bayer	500	0.498	0.474	0	1
AgReliant	Product price	999	219.2	46.84	88.89	345.75
	Firm-level share	999	0.090	0.065	0.012	0.545
	License_Roundup Ready	998	0.928	0.253	0	1
	License_YieldGard	998	0.972	0.156	0	1
	License_DowDupont	998	0.044	0.160	0	1
	License_Syngenta	998	0.004	0.043	0	1
	License_Bayer	998	0.046	0.161	0	1

Note: Roundup Ready and YieldGard are owned by Monsanto. 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.

3.4.2 Identification

I discuss my identification strategy to estimate the parameters of the demand and supply models. On the demand side, the key identification issue is the endogeneity of seed prices that are attributed to the fact that oligopolistic firms set their 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 valid instruments to obtain consistent estimates, because the OLS estimate of the price coefficient is positive even after controlling brand, region and year fixed effects, as discussed in the next section. I rely on the commonly used identification assumption that the product characteristics are uncorrelated with the error term (Berry, Levinsohn, and Pakes 1995).

This assumption seems fairly reasonable in the seed industry as is discussed in Ciliberto, Moschini, and Perry (2019), which estimates the nested logit demand models for the US corn and soybean seeds market. They argue that the introduction of new products is predetermined and is largely exogenous to pricing decisions because the introduction of 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.

To construct instruments using product characteristics of GM seeds, I count the number of products that embed each GM trait (CB, GT, CB_RW, CB_GT, RW_GT, CB_RW_GT), following the same idea used in Ciliberto, Moschini, and Perry (2019). Then, I calculate the interaction of the counting numbers in each market with the dummy variables that take the value 1 if the product has the corresponding trait. There are six instrumental variables for the price coefficient.

It is also necessary to construct instruments for random coefficients on demographic variables. Following Romeo (2013) and Miller and Weinberg (2017), I exploit cross-market variation of demographic variables. Specifically, I compute the mean and variance of longitude and latitude at each market. Then, they interact with exogenous product characteristics (CB, GT, CB_RW, CB_GT, RW_GT, CB_RW_GT). There are 20 instrumental variables for

10 non-linear parameters of longitude and latitude. I follow the same idea for a random coefficient related to farm size, but the farm size variable interacts with the logarithm of endogenous price. Therefore, to compute the predicted value of the logarithm of price, I first regress the logarithm of price on the six instruments used for the price coefficient. Then, the predicted log price interacts with the mean and variance of farm size in each market. This generates two instruments. In total, my demand estimation uses 28 instruments (6 IVs for the price coefficient, and 22 IVs for the non-linear parameters).

On the supply side, it is necessary to deal with the endogeneity of the markups that are correlated with unobserved marginal costs. This is because the markups are functions of the firm-level market share and two demand elasticities, all of which are functions of unobserved marginal costs through endogenous prices. To obtain consistent estimates of conduct parameters, it is necessary to find excluded instruments that are correlated with the markups but uncorrelated with the unobserved marginal costs. Berry and Haile (2014) argue that candidates for instruments require variation in market conditions that rotate the marginal revenue curve, which includes the number of competing firms, the set of competing goods, characteristics of competing products, or costs of competing firms. Following their argument, I use the number of rival firms' products interacting with firm dummy variables as excluded instruments. It is expected that the number of rivals' products affects the market share and substitutability between products and thus shifts the optimal markups. The assumption of identification is that they are uncorrelated with the unobservable marginal costs. This seems fairly reasonable in the seed industry because the marginal cost of seed production is not likely to be correlated with the number of rival products.

3.5 Empirical results

3.5.1 Demand estimates

Table 3.5 presents the results of the seed demand estimation. Columns (i) and (ii) correspond to the discrete/continuous logit with OLS and efficient GMM estimators. Column (iii) corresponds to the discrete/continuous logit with random coefficients interacting with farmer demographics. All specifications include brand, CRD, and year-fixed effects. I use the pyBLP python package developed by Conlon and Gortmaker (2020) for estimations.

Table 3.5: Demand estimates

	(i)	(ii)		(iii)	
Demand model	DC-Logit	DC-Logit		DC-RCL	
Estimator	OLS	GMM		GMM	
Mean (β)					
log(Price)	1.259***	-2.018***		-5.836***	
	(0.122)	(0.580)		(0.933)	
GT	0.538***	0.790***		1.265***	
	(0.073)	(0.089)		(0.143)	
CB_RW	0.070	0.467***		1.104***	
	(0.097)	(0.127)		(0.205)	
CB_GT	-0.066	0.107		0.412***	
	(0.054)	(0.072)		(0.101)	
RW_GT	-1.265***	-0.927***		-0.316	
	(0.124)	(0.155)		(0.232)	
CB_RW_GT	1.281***	2.021***		2.905***	
	(0.048)	(0.135)		(0.220)	
Demographics interaction(Π)			Farmsize	Longitude	Latitude
log(Price)			-0.320***		
			(0.092)		
GT				0.657***	0.805***
				(0.187)	(0.190)
CB_RW				-0.036	0.173
				(0.245)	(0.247)
CB_GT				-0.349***	-0.165
				(0.129)	(0.122)
RW_GT				-0.714**	-0.429
				(0.342)	(0.312)
CB_RW_GT				0.290***	0.202**
				(0.093)	(0.096)
Mean of price elasticities					
Own-price	0.224	-3.002		-6.871	
Cross-price	-0.033	0.053		0.158	
Mean of elasticities of substitution					
Intra-sectoral elasticity				7.059	
Inter-sectoral elasticity				1.290	

Notes: DC-logit and DC-RCL refer to the discrete/continuous logit model and the discrete/continuous random coefficient logit. In the parameters, GT, CB, and RW stand for GM traits of glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. All of the estimates include brand, CRD, and year-fixed effects. Standard errors are robust standard errors. The number of observations is 5,794. $*$, $**$, $***$ denote significance of the test statistic at the 10%, 5%, and 1% level, respectively.

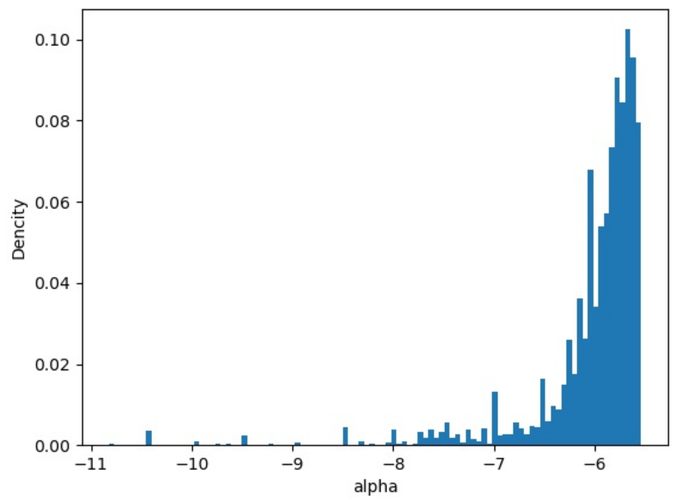

Figure 3.6: Estimaetd distribution of price coefficients among farmers in all markets

The price coefficient is positive in the OLS estimation, suggesting that prices are indeed endogenous. In two GMM estimations, it is negative as expected and statistically significant at the 1% level. The results indicate that the excluded instruments are valid in the sense that the upward bias on the price coefficient decreases in the right direction. In specification (iii), the estimate of the log(p)-farm size interaction parameter is negative and statistically significant at the 1% level. The negative value indicates that larger farmers are more sensitive to price. Figure 3.6 shows the distribution of estimated $\alpha_i (= \alpha + \Pi_\alpha \ farmsize_i)$ in all markets. The shape of the distribution reflects the empirical distribution of the farm size variable, which is relatively left-tailed due to the existence of very large farms. The value of α ranges from -5.53 to -10.83 between farmers. All farmers have a negative preference for higher prices, as expected.

The mean of the estimated own-price elasticities is -6.87 for the DC-RCL specification, indicating that the product-level demand for GM seeds is quite elastic. This value is very close to the own-price elasticity -6.99 in Ciliberto, Moschini, and Perry (2019), which estimates the nested logit demand model for corn and soybean seed in the US over 1996-2011. The mean of the cross-price elasticities is 0.158, which indicates that different types of GM corn

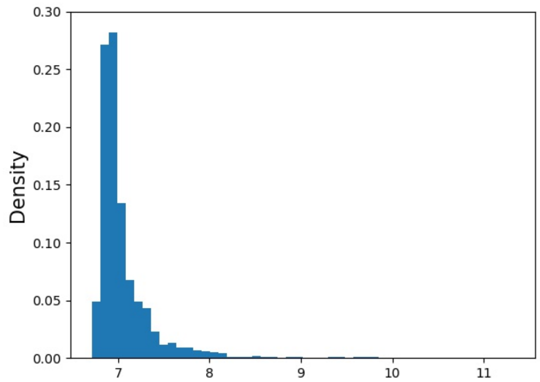

Figure 3.7: Estimated distribution of intra-sectoral elasticities of substitution in all markets

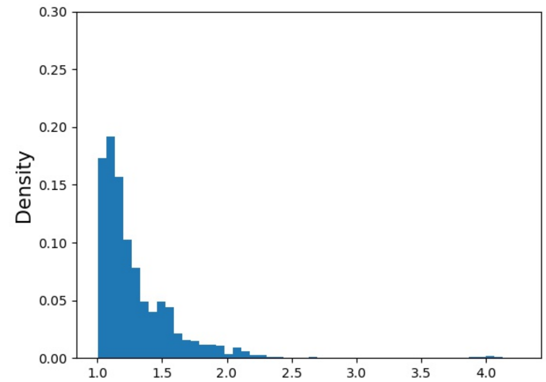

Figure 3.8: Estimated distribution of inter-sectoral elasticities of substitution in all markets

seeds are imperfect substitutes for each other.

The average values of estimated intra- and inter-sectoral elasticities of substitution are 7.059 and 1.290, respectively. The value of intra-sectoral elasticity is much larger than the value of inter-sectoral elasticity, as expected. This is consistent with the definitions of these elasticities, in which the intra-sectoral elasticity measures substitutability between GM seeds, while the inter-sectoral elasticity measures substitutability against the outside product (non-GM seeds). The larger value of the intra-sectoral elasticity indicates that GM products are more substitutable with other GM products compared to non-GM products. The low value of the inter-sectoral elasticity indicates that the market demand for GM seeds is fairly inelastic. Because the estimates of these elasticities are used for a supply-side estimation, I show the distribution of the estimates in all markets in Figures 3.7 and 3.8. The figures indicate that they range from 6.710 to 11.331 and 1.001 to 4.264, respectively. There are distinct variations across markets, reflecting farmer preference and market conditions such as product availability.

The coefficients ($\boldsymbol{\beta}$) associated with the GM trait dummy variables are positive and precisely estimated, other than β_{RW_GT}. The values of these parameters are measured as a difference from the value of CB. The result, $\beta_{GT} = 1.265$, indicates that farmers value the glyphosate tolerance trait more than the corn borer resistance trait. This is consistent with the results of Ciliberto, Moschini, and Perry (2019), which finds that farmers' willingness to pay for the GT trait is higher than the CB trait after 2007. The coefficients of the stacked traits are also positive, indicating that farmers value the stacked traits more than the CB trait. The only exception is β_{RW_GT}, which is negative. The negative value suggests that farmers see little additional value in stacking RW with GT, although this coefficient is insignificant.[11]

The demographics interaction parameters of each trait (Π_β) are statistically significant at the 5% level for 6 out of 10 parameters. The positive value of longitude and latitude means that farmers put more value on the corresponding trait from south to north and from west to east, respectively. The results show that farmers tend to value GT and CB_RW_GT more to the north and east of the core region of the Corn Belt, while farmers tend to value CB_GT and RW_GT more in the south. These statistically significant coefficients reflect preference heterogeneity between farmers in different locations.

To obtain the economic interpretation of these coefficients, I compute farmers' willingness to pay (WTP). In the standard logit, it is well known that the ratio of a coefficient of the product characteristics of interest to a price coefficient indicates willingness to pay (see Train 2009). In my demand specification, the price term enters logarithmically in the conditional indirect utility function. Thus, I calculate WTP using the following formula.

$$
\begin{aligned}
WTP_i^{GT} &= \beta_i^{GT}/(\alpha_i/p_i) \\
WTP_i^{CB\_RW} &= \beta_i^{CB\_RW}/(\alpha_i/p_i) \\
WTP_i^{CB\_GT} &= (\beta_i^{GT} + \beta_i^{CB\_GT})/(\alpha_i/p_i) \\
WTP_i^{RW\_GT} &= (\beta_i^{GT} + \beta_i^{RW\_GT})/(\alpha_i/p_i) \\
WTP_i^{CB\_RW\_GT} &= (\beta_i^{GT} + \beta_i^{CB\_RW\_RW})/(\alpha_i/p_i)
\end{aligned}
$$

[11]This imprecise estimate may be due to a very small market share of products with RW_GT. Its market share is less than 1% in the entire sample. Also, since there are no observations with the single-RW trait, it may be difficult to identify the value of RW separately from GT.

Table 3.6 reports the results of the estimated distribution of farmers' WTP for each GM trait. These estimates of WTP are measured as a difference from the CB trait, which is used as a reference in the estimation. Farmers have different WTP depending on their demographic variables. I present the median, 10th percentile, and 90th percentile of the estimated distribution.

The estimated values of WTP take the highest value for the triple-stacked traits (CB_RW_GT), indicating that the median value is $154.35 per bag. The result is consistent with its large market share, which is over 70% in the entire sample. Also, the WTP estimates of CB_GT and GT tend to be higher than the remaining traits, reflecting their relatively larger market shares. The results also indicate that the estimates of WTP tend to be higher than the observed price difference. In particular, the WTP for the triple-stacked traits is larger than the observed price difference for most of the farmers, as the WTP at the 10th percentile is still larger than the price difference. This suggests that the introduction of the stacked GM traits significantly increases farmers' welfare, which is consistent with the empirical findings by Ciliberto, Moschini, and Perry (2019).

Overall, I judge that the results of the DC-RCL specification are reasonable and economically meaningful. I use this result for the subsequent supply-side estimation, which is of main interest.

3.5.2 Supply estimates

On the supply side, I 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 used in past research (Miller and Weinberg 2017; Michel, Manuel Paz y Mino, and Weiergraeber 2023). In the two-step procedure, the estimation errors of the demand parameters need to be considered. Therefore, I calculate robust standard errors that account for the inclusion of the demand parameters, following Wooldridge (2010). In the estimation, I use OLS to concentrate the linear marginal cost parameters and CRD fixed effects out of

Table 3.6: Estimates of willingness-to-pay

	Distribution of willingness to pay			Observed
	10th percentile	Median	90th percentile	price difference
$GT - CB$	20.86	46.11	77.76	26.87
	(5.14)	(6.07)	(10.96)	
$CB\_RW - CB$	25.55	41.24	58.55	18.91
	(5.15)	(6.18)	(10.54)	
$CB\_GT - CB$	34.63	62.12	93.51	46.09
	(5.10)	(6.07)	(10.33)	
$RW\_GT - CB$	11.60	35.48	60.25	29.55
	(11.26)	(8.68)	(14.19)	
$CB\_RW\_GT - CB$	100.94	154.35	219.76	79.26
	(10.07)	(15.58)	(23.17)	

Notes: GT, CB, and RW stand for glyphosate tolerance, corn borer resistance, and rootworm resistance, respectively. The estimates of willingness to pay are measured as a difference from CB, which is used as a reference trait in the estimation. Values in parentheses are standard errors that are calculated by parametric bootstrap using the asymptotic distribution of the estimated parameters. The number of simulation draws is 1,000. Observed price differences are calculated as the average of differences between the prices of CB alone and each trait of each market.

the optimization problem, which reduces the dimensionality of the nonlinear search to only five conduct parameters.

Table 3.7 presents the results of the supply-side parameters using an efficient GMM estimator. The conduct parameters for the five firms are all precisely estimated and take values from 0 to 1, as the theoretical model requires. The results show that the conduct of these firms is imperfect collusion, in the sense that the estimated conduct parameters are values between collusion ($\theta_f = 0$) and quantity competition ($\theta_f = 0.16$).[12] The low values of the conduct parameters might 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, which gives the licensing firms additional incentives to sustain higher prices.

Table 3.8 indicates the results of hypothesis testing on the benchmark conduct. The

[12] In the case of quantity competition, $\theta_f = 1/(1 + \eta_j/\sigma_j)$, where (η_j, σ_j) are the intra- and inter-sectoral elasticities of substitution of product j. I calculate this value using the average of the elasticities in the sample.

Table 3.7: Supply estimates

		Coefficient	Standard Error
θ_f (firm conduct)	Monsanto	0.106***	0.027
	Dupont	0.092***	0.025
	Syngenta	0.015***	0.004
	Dow AgroSciencies	0.008***	0.002
	AgReliant	0.020***	0.006
γ (marginal cost)	Corn future price	0.136***	0.005
	License_RoundupReady	15.387***	1.346
	License_YieldGard	8.273***	1.499
	License_DowDupont	17.535***	3.470
	License_Syngenta	4.665	4.278
	License_Bayer	19.495***	1.082

Notes: The estimation includes CRD fixed effects. Roundup Ready and YieldGard are owned by Monsanto. Standard errors are robust standard errors that account for two-step estimation. The number of observations is 4,448. $***$ denotes significance of the test statistic at the 1%-level.

testing results strongly reject price competition and monopolistic competition, both of which are more competitive conduct than quantity competition.[13] Collusive conduct is also rejected for all firms at the 1% significance level. The results also reject quantity competition for all firms, with significance levels at 10% for Monsanto, 5% for Dupont, and 1% for the other three firms.

[13]Pricing competition is more competitive than quantity competition when the intra-sectoral elasticity of substitution is larger than the inter-sectoral elasticity of substitution. My results of demand estimation satisfy this inequality.

Table 3.8: Hypothesis testing on benchmark conduct

Null Hypothesis	Collusion $\theta_f = 0$	Quantity competition $\theta_f = 0.16$	Price competition $\theta_f = 0.5$	Monopolistic competition $\theta_f = 1$
t-statistics				
Monsanto	3.956***	1.833*	14.705***	33.366***
Dupont	3.567***	2.512**	16.173***	36.016***
Syngenta	3.401***	33.153***	116.432***	236.422***
Dow AgroSciencies	3.401***	62.377***	215.099***	433.599***
AgReliant	3.444***	22.855***	81.003***	165.45***

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 intra- and inter-sectoral elasticities of substitution of product j. I calculate this value using the average of the elasticities, which is 0.16. Standard errors account for two-step estimation. $*$, $**$, $***$ denote significance of the test statistic at the 10%, 5%, and 1% level, respectively.

Back to Table 3.7, the marginal cost parameters are all positive, as expected. The positive coefficient on corn future price implies that seed firms must pay more to corn farmers when corn price is expected to increase in the future. The positive parameters on the dummy variables for licensed traits indicate that the utilization of licensed traits increases marginal costs. This result reflects the fact that, through licensing agreements, firms are supposed to pay a licensing fee to licensors when they incorporate patented traits. The parameters for Monsanto's two traits (Roundup Ready and YieldGard) are precisely estimated. The value for YieldGard is relatively smaller, possibly reflecting the smaller WTP for CB compared to GT. The other parameters also take positive values. Bayer's trait (Liberty Link) and DowDupont's trait (Herculex) take larger values, while the value is smaller for Syngenta's trait (Agrisure).[14]

To understand the economic meaning of these estimates, I calculate marginal costs and markups for these firms. The results are shown in Table 3.9. The average values of the marginal costs are lower for Monsanto ($108) and Syngenta ($118), while the other three firms have higher marginal costs ($128-136). The structure of patented traits explains these marginal cost differences. Monsanto and Syngenta mainly use their own patented GM traits,

[14] The estimates of License_Syngenta are imprecise. As Table 3.4 shows, the market shares of the products with this licensed trait are fairly small. This limited variation of the data may cause imprecise estimates.

but Syngenta additionally uses Bayer's trait for about 70% of their products, while Monsanto uses it for only 10% of their products. This makes Monsanto more cost-efficient than Syngenta. On the other hand, Dupont, Dow, and AgReliant heavily rely on Monsanto's GM traits, which results in additional licensing costs. To better see this tendency, I show a kernel density of estimated marginal costs in all markets for Monsanto, Syngenta, and Dupont in Figure 3.9. It shows the clear ranking of the marginal cost efficiency of these three firms.

The estimates of markups are also shown in Table 3.9. Monsanto charges the highest markup, while the other firms charge their markups in relatively similar ranges. The average values of the relative markup ($= (p-mc)/p$) are 51.45% for Monsanto and $37.89-41.12\%$ for the other four firms. Figure 3.10 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.

To summarize, the results indicate that the conduct of the seed firms is between collusive conduct and quantity competition, with a strong rejection of pricing competition, and the low degree of competition translating into high markups.

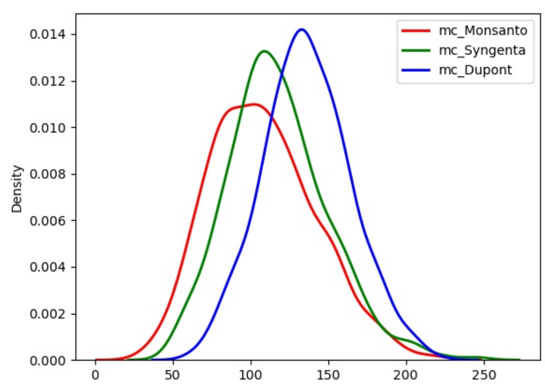

Figure 3.9: Estimated distribution of marginal costs (in \$ per bag)

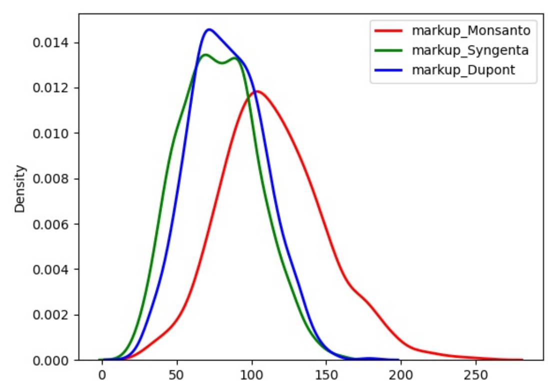

Figure 3.10: Estimated distribution of markups ($p - mc$) (in \$ per bag)

Table 3.9: Estimates of marginal costs and markups of GM seeds

	Price (in \$) p (observed)	Marginal cost (in \$) mc (estimated)	Markup (in \$) $p - mc$ (estimated)	Relative markup $(p - mc)/p$ (estimated)
Monsanto	222.88	108.15	114.73	51.45%
[95% CI]		[88.07, 128.22]	[94.65, 134.81]	[42.49, 60.43]
Dupont	219.97	136.13	83.85	37.89%
[95% CI]		[114.88, 157.37]	[62.60, 105.09]	[28.28, 47.50]
Syngenta	195.86	117.78	78.08	39.8%
[95% CI]		[98.62, 136,94]	[58.92, 97.25]	[30.06, 49.57]
Dow AgroSciencies	215.17	130.66	84.51	39.08%
[95% CI]		[108.75, 152.56]	[62.61, 106.42]	[28.93, 49.21]
AgReliant	219.18	128.31	90.87	41.12%
[95% CI]		[106.63, 150.00]	[69.19, 112.55]	[31.32, 51.00]

Notes: The table reposts the average of observed prices, estimated marginal costs, and markups of GM seeds. 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 1,000.

3.5.3 Counterfactual simulations

Welfare analysis can be conducted based on the structural model. To quantify the importance of the estimated firm conduct, I conduct counterfactual simulations about how changes in firm conduct would affect market outcomes. I analyze three counterfactual scenarios. First, I consider the situation in which the conduct of all firms is price competition (CF1 $\theta_f = 0.5$ for all firms), which is referred to as competitive conduct in the following discussion. Next, I consider the situations in which the conduct of a subset of the firms is competitive. Based on the observed market shares, I categorize the five seed firms into two groups: large firms (Monsanto and Dupont) and small firms (Syngenta, Dow AgroSciencies, and AgReliant). I analyze two scenarios in which the conduct is competitive for only large firms (CF2: $\theta_f = 0.5$ for large firms, $\theta_f = \theta^*$(the estimated values) for small firms) and for only small firms (CF3: $\theta_f = \theta^*$ for large firms, $\theta_f = 0.5$ for small firms).

In each simulation, I set the values of conduct parameters depending on the considered scenario. Then, I generate new equilibria by solving firms' first-order conditions with fixed-point iterations. The calculations are conducted separately for each market. I find that the fixed-point iterations attain convergence within 500 iterations. I assume that the price of regional seed firms and the price of outside products are unchanged, as my supply model focuses on the five seed firms. Also, I assume that the marginal costs are fixed in the simulations.

I denote the new equilibrium price as $\boldsymbol{p}_1$ for each scenario and the observed (baseline) price as $\boldsymbol{p}_0$. As a measure of consumer welfare, I use a compensating valuation. Following Dubé, Joo, and Kim (2023), the consumer's compensating variation for a change in price from $\boldsymbol{p}_0$ to $\boldsymbol{p}_1$ in the discrete/continuous logit demand model is:

$$CV = Y^0 \frac{I(\boldsymbol{\delta}(\boldsymbol{p}^1)) - I(\boldsymbol{\delta}(\boldsymbol{p}^0))}{I(\boldsymbol{\delta}(\boldsymbol{p}^1))} \tag{3.11}$$

where

$$I(\boldsymbol{\delta}(\boldsymbol{p})) = \exp\left(-\sum_{i=1}^{I} w_i \ln\left(1 + \sum_{k=1}^{J} \exp(\delta_k(p_k) + \nu_i(\Pi))\right)^{1/\alpha_i}\right) \tag{3.12}$$

In addition, as a measure of producer surplus, I calculate the difference in the sum of firms' variable profits from $\boldsymbol{p}_0$ to $\boldsymbol{p}_1$.

$$\Delta PS = \sum_{f=1}^{F} (\pi_f(\boldsymbol{p}_1) - \pi_f(\boldsymbol{p}_0)) \tag{3.13}$$

Table 3.10 presents the results of counterfactual simulations. I report the change in price, quantity, firm profit, farmer surplus, and total welfare. In CF1, in which the conduct is competitive for all firms, the average price decreases by 29%. Firm profits decrease by 3,032 million dollars. On the other hand, farmer surplus increases by 6,682 million dollars. As a result, total welfare increases by 3,650 million dollars. The simulation results of CF2 and CF3 highlight how the effects of increased competition on market outcomes differ when the conduct of large firms and small firms changes in different ways. The values of the total welfare change are 3,155 million dollars in CF2 and 1,736 million dollars in CF3. The former result is similar to CF1, indicating that the conduct of large firms is more important in terms of total welfare.

Table 3.10: Welfare analysis from counterfactual simulations

	CF1	CF2	CF3
Hypothetical conduct			
Large firms	Competitive	Competitive	Non-Competitive
Small firms	Competitive	Non-Competitive	Competitive
Simulation results			
Δ Price (in %)	-28.718	-18.936	-19.959
Δ Quantity (in mio-bag)	57.729	41.710	39.432
Δ Firm profit (in mio-USD)	-3031.770	-2042.901	-2178.464
Δ Farmer surplus (in mio-USD)	6681.594	5197.968	3914.924
Δ Total welfare (in mio-USD)	3649.825	3155.067	1736.460

Note: 'Competitive' indicates the conduct parameter (θ_f) takes 0.5 and 'Non-competitive' indicates the conduct parameter (θ_f) takes the estimated values given in Table 3.7. The simulation results are changes of each variable from the base scenario in which the conduct of all firms is non-competitive. CF1: The conduct of all firms is competitive. CF2: The conduct of the large firms (Monsanto and Dupont) is competitive, while the small firms (Syngenta, Dow, and AgReliant) remain non-competitive. CF3: The conduct of small firms is competitive, while the large firms remain non-competitive. Price changes are averages over all markets. For quantity, firm profit, farmer surplus, and total welfare, I report the total changes aggregated over all years and all CRDs.

Next, to see how different conduct affects the price and profits of each firm, I report the firm-level values of each counterfactual simulation in Table 3.11. In CF1, all firms lower their prices due to competitive conduct. In this case, the quantity increases for all firms by stealing demand from the regional seed firms and the outside option, but the negative effects of the price decrease exceed the positive effects of the quantity increase, and the firm profits decrease for all firms. In CF2, the large firms with competitive conduct lower their prices by more than 20%. The smaller firms, whose conduct remains non-competitive, also lower their prices due to the strategic complements of pricing. Firm profits decrease for all firms. On the other hand, the result of CF3 shows a different tendency from CF1 and CF2. In CF3, the prices decrease by more than 25% for smaller firms whose conduct is competitive. The decreases in the relative prices increase their quantity. As a result, small firms obtain higher profits.

The counterfactual results show that the seed firms extract substantial surplus from farmers by setting prices higher than the competitive level. If the seed firms were to behave more competitively, total welfare would significantly increase. Also, the results of the firm-level decomposition indicate that the effects of more competitive conduct are disproportionate among firms. When the conduct becomes more competitive, the profits of the large firms decrease more than the profits of the small firms, because the price decrease significantly reduces the current sales of large firms. This negative impact might induce the large firms to behave less competitively and sustain higher prices. On the other hand, the profits for the smaller firms would increase if they lower their prices. This result suggests that the smaller firms might have an incentive to deviate from the imperfect collusive equilibrium by lowering their prices and stealing market demand, at least in the short run. However, there are several possible explanations for why the smaller firms do not deviate. For instance, they may consider long-run profits. The results of the counterfactual show that small firms can increase their profits in CF3, but their profits decrease in CF1 and CF2. This indicates that, if large firms also lower their prices when small firms lower their prices, all firms lose some profits. These results also imply that the large firms may be price leaders, while the small firms are followers. To analyze this point, a dynamic model needs to be considered as proposed in Miller, Sheu, and Weinberg (2021). Another possibility is that the small firms might have different strategic incentives related to complicated licensing agreements. I do not formally analyze these issues further, and this remains a future task.

3.6 Conclusion

This study 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 is also empirically tractable even when conduct parameters of many multiproduct firms are estimated. 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 competition can be formulated by two dimensions: one is competition within differentiated products and the other is competition against an outside product. This requirement is compatible with the standard settings using the discrete choice demand models without additional assumptions.

A limitation of the model is that it cannot identify pair-wise relationships of coordination. The existing methods are suitable for analyzing such pair-wise relationships, but they are applicable only when the number of parameters is reduced sufficiently. Instead, the proposed model is suitable for analyzing the degrees of collusion of many firms toward the whole market.

I 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, while the related empirical evidence is limited. I estimate firm-specific conduct parameters for the five largest firms. The results indicate that all firms are engaged in imperfect collusion. The results of counterfactual simulations indicate that seed firms extract substantial rent from farmers through collusive pricing. 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.

Table 3.11: Firm-level decomposition of counterfactual results

	CF1	CF2	CF3
Hypothetical conduct			
Large firms	Competitive	Competitive	Non-Competitive
Small firms	Competitive	Non-Competitive	Competitive
Simulation results			
Δ Price (in %)			
Monsanto	-31.151	-26.975	-12.434
Dupont	-24.428	-23.034	-10.113
Syngenta	-29.061	-13.427	-27.858
Dow AgroSciencies	-28.376	-13.138	-27.676
AgReliant	-29.428	-12.735	-27.738
Δ Quantity (in mio-bag)			
Monsanto	31.797	36.799	-5.577
Dupont	3.614	10.962	-6.547
Syngenta	5.820	-2.086	16.728
Dow AgroSciencies	4.462	-0.996	11.144
AgReliant	12.037	-2.970	23.694
Δ Firm profits (in mio-USD)			
Monsanto	-1309.216	-327.812	-1731.756
Dupont	-1212.264	-842.320	-961.949
Syngenta	-221.295	-281.783	103.533
Dow AgroSciencies	-82.630	-146.005	123.185
AgReliant	-206.363	-444.982	288.523

Note: 'Competitive' indicates that the conduct parameter (θ_f) takes 0.5 and 'Non-competitive' indicates that the conduct parameter (θ_f) takes the estimated values given in Table 3.7. The simulation results are changes of each variable from the base scenario in which the conduct of all firms is non-competitive. CF1: The conduct of all firms is competitive for all firms. CF2: The conduct of the large firms (Monsanto and Dupont) is competitive, while the small firms (Syngenta, Dow, and AgReliant) remain non-competitive. CF3: The conduct of small firms is competitive, while the large firms remain non-competitive. Price changes are averages over all markets. For quantity and firm profit, I report the total changes aggregated over all years and all CRDs.

Appendix

3.A Further details on derivations

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

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

$$q_{j|in}(\boldsymbol{p}, Y_{In}) = \frac{1}{I} \sum_{i=1}^{I} \frac{\exp(\delta_j + \nu_{ij}(\Pi))}{\sum_{k=1}^{J} \exp(\delta_k + \nu_i(\Pi))} \frac{Y_{in}}{p_j} = s_{j|in}(\boldsymbol{p}) \frac{Y_{in}}{p_j} \tag{3.14}$$

where $s_{j|in}$ is the choice probability of product j conditional on choosing the inside products, $\delta_j = \boldsymbol{x}_{\boldsymbol{j}}'\boldsymbol{\beta} - \alpha \ln p_j + \xi_j$ 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, Joo, and Kim (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 (3.14).

Following Dubé, Joo, and Kim (2023), I derive the expenditure function as:

$$e(\boldsymbol{p}, Q) = \exp\left(-\frac{1}{I}\sum_{i=1}^{I}\ln\left(\sum_{k=1}^{J}\exp(\delta_k + \nu_i(\Pi))\right)^{1/\alpha_i}\right)Q = P(\boldsymbol{p})Q \tag{3.15}$$

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

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

$$D = \sum_{j=1}^{J} s_j \frac{Y}{P(\boldsymbol{p})} = S_{in}\frac{Y}{P(\boldsymbol{p})} \tag{3.16}$$

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

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

$$q_{j|f}(\boldsymbol{p}_f, Y_f) = \frac{1}{I}\sum_{i=1}^{I}\frac{\exp(\delta_j + \nu_{ij}(\Pi))}{\sum_{k\in\Omega_f}\exp(\delta_k + \nu_i(\Pi))}\frac{Y_f}{p_j} = s_{j|f}(\boldsymbol{p}_f)\frac{Y_f}{p_j} \tag{3.17}$$

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 (3.17) is

$$Y_f = e_f(\boldsymbol{p}_f, Q_f) = \exp\left(-\frac{1}{I}\sum_{i=1}^{I}\ln\left(\sum_{k\in\Omega_f}\exp(\delta_k + \nu_i(\Pi))\right)^{1/\alpha_i}\right)Q_f = P_f(\boldsymbol{p}_f)Q_f \tag{3.18}$$

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

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

$$H_f = \sum_{j \in \Omega_f} s_{j|in} \frac{Y_{in}}{P_f(\boldsymbol{p}_f)} = S_{f|in} \frac{P(\boldsymbol{p})Q}{P_f(\boldsymbol{p}_f)} \tag{3.19}$$

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 equation (3.15) and (3.18)). The homotheticity generates the following useful properties.

$$\frac{\partial \ln Q}{\partial \ln q_j} = \frac{\partial \ln P}{\partial \ln p_j} = s_{j|in}, \quad \frac{\partial \ln Q_f}{\partial \ln q_j} = \frac{\partial \ln P_f}{\partial \ln p_j} = s_{j|f} \quad \frac{\partial \ln H_f}{\partial \ln Q} = 1 \tag{3.20}$$

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, Joo, and Kim 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.

3.A.2 Derivations of intra- and inter-sectoral elasticity of substitution

I show how to derive Intra- and Inter-sectoral elasticities of substitution.

3.A.2.1 Intra-sectoral 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 intra-sectoral elasticity of substitution of product j.

$$\left.\frac{d \ln q_j}{d \ln p_j}\right|_{Q_f(\boldsymbol{q}_f) = H_f(\boldsymbol{p}_f, Q(\boldsymbol{q}))} = -\frac{\dfrac{\partial \ln H_f}{\partial \ln p_j}}{\dfrac{\partial \ln Q_f}{\partial \ln q_j} - \dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f \tag{3.21}$$

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, I 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 proposed in d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007). The difference is that I 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.

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

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 (3.20).

Next, I show how to derive equation (3.5). By differentiating the Hicksian demand given in equation (3.19) 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 (3.21) and using equation (3.20), 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:

$$\eta_j = \alpha + 1 \tag{3.22}$$

3.A.2.2 Inter-sectoral 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 inter-sectoral elasticity of substitution of product j.

$$\sigma_j \equiv -\frac{d\ln q_j}{d\ln p_j}\bigg|_{Q(\boldsymbol{q})=D(\boldsymbol{p},Y)} = -\frac{\dfrac{\partial \ln D}{\partial \ln p_j}}{\dfrac{\partial \ln Q}{\partial \ln q_j}} \quad \text{for j} \in \Omega_f \tag{3.23}$$

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 inter-sectoral elasticity of substitution defined in d'Aspremont, Dos Santos Ferreira, and Gérard-Varet (2007).

Next, I show how to derive equation (3.6). By differentiating the Marshallian demand function given in equation (3.16) with respect to p_j and expressing the terms in elasticity forms, we have:

$$\begin{aligned}\frac{\partial \ln D}{\partial \ln p_j} &= \frac{\partial \ln S_{in}}{\partial \ln p_j} - \frac{\partial \ln P}{\partial \ln p_j}\\ &= -\frac{1}{1-s_0}\sum_i^I \alpha_i s_{ij} s_{i0} - s_{j|in}\end{aligned}$$

By substituting this into equation (3.23) and using equation (3.20), we have:

$$\sigma_j = \frac{1}{(1-s_0)s_{j|in}}\sum_{i=1}^N \alpha_i s_{ij} s_{i0} + 1 \tag{3.24}$$

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

$$\sigma_j = \alpha s_0 + 1 \tag{3.25}$$

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

I show how to solve the profit maximization problem of firm f given in (3.4). 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:

$$(p_j) \quad q_j = \frac{\lambda_f}{p_j} \left(-\frac{\partial \ln H_f}{\partial \ln p_j}\right) + \frac{v_f}{p_j} \left(-\frac{\partial \ln D}{\partial \ln p_j}\right) \quad \text{for j} \in \Omega_f \tag{3.26}$$

$$(q_j) \quad p_j - c_j = \frac{\lambda_f}{q_j} \left(\frac{\partial \ln Q_f}{\partial \ln q_j} - \frac{\partial \ln H_f}{\partial \ln Q} \frac{\partial \ln Q}{\partial \ln q_j}\right) + \frac{v_f}{q_j} \frac{\partial \ln Q}{\partial \ln q_j} \quad \text{for j} \in \Omega_f \tag{3.27}$$

Dividing equation (3.27) by equation (3.26) and arranging the terms, we have:

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

where I 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:

$$\mu_j^* = \frac{p_j - c_j}{p_j} = \frac{\theta_f(1 - S_{f|in}) + (1 - \theta_f)S_{f|in}}{\theta_f(1 - S_{f|in})\eta_j + (1 - \theta_f)S_{f|in}\sigma_j} \quad \text{for j} \in \Omega_f \tag{3.28}$$

where η_j and σ_j are the intra- and inter- sectoral elasticities of substitution of product j.

3.B Relationship with benchmark competition models

I show how the specific values of θ_f generate the equilibrium markups that correspond to ones generated from benchmark models. I 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.

3.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)), I set $\mu = (p_j - c_j)/p_j$ for all j. Rearranging the terms, we have:

$$\mu = \frac{p_j - c_j}{p_j} = \frac{1}{(1 - S_f)\alpha + 1} \tag{3.29}$$

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, I 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 (3.22) and (3.25), 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 (3.29). 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.

3.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:

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

$$\frac{p_j - c_j}{p_j} = -\frac{\partial \ln D^{-1}}{\partial \ln Q}\sum_{k\in\Omega_f}\frac{\partial \ln Q}{\partial \ln q_k} - \frac{1}{\dfrac{\partial Q}{\partial q_j}}\sum_{k\in\Omega_f}\frac{\partial^2 Q}{\partial q_j q_k}q_k \tag{3.30}$$

The first term in equation (3.30) is written by:

$$-\frac{\partial \ln D^{-1}}{\partial \ln Q} \sum_{k \in \Omega_f} \frac{\partial \ln Q}{\partial \ln q_k} = \frac{1}{\frac{\partial \ln D}{\partial \ln P}} \sum_{k \in \Omega_f} s_{k|1} = \frac{S_{f|1}}{\alpha s_0 + 1} \tag{3.31}$$

For the second term in equation (3.30), I recover the direct utility function corresponding to the expenditure function in equation (3.15) 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.

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

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

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

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

Substituting these derivatices into the second term in equation (3.30), we have:

$$
\begin{aligned}
-\frac{1}{\frac{\partial Q}{\partial q_j}}\sum_{k\in\Omega_f}\frac{\partial^2 Q}{\partial q_j q_k}q_k &= \frac{\frac{C_j}{\alpha+1}q_j^{\frac{-1}{\alpha+1}}\left(\sum_{j=1}^J C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1}{\alpha}} - \sum_{k\in\Omega_f}\left(\frac{C_jC_k}{\alpha+1}q_j^{\frac{-1}{\alpha+1}}q_k^{\frac{-1}{\alpha+1}}\left(\sum_{j=1}^J C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1-\alpha}{\alpha}}q_k\right)}{C_j q_j^{\frac{-1}{\alpha+1}}\left(\sum_{j=1}^J C_j q_j^{\frac{\alpha}{\alpha+1}}\right)^{\frac{1}{\alpha}}} \\
&= \frac{1}{\alpha+1} - \frac{1}{\alpha+1}\sum_{k\in\Omega_f}\frac{C_k q_k^{\frac{-1}{\alpha+1}}}{\sum_{j=1}^J C_j q_j^{\frac{\alpha}{\alpha+1}}}q_k \\
&= \frac{1}{\alpha+1} - \frac{1}{\alpha+1}\sum_{k\in\Omega_f}s_{k|in} = \frac{1-S_{f|in}}{\alpha+1}
\end{aligned}
\tag{3.32}
$$

Substituting equations (3.31) and (3.32) into equation (3.30), we have the equilibrium markup under multiproduct quantity competition.

$$
\frac{p_j - c_j}{p_j} = \frac{S_{f|in}}{\alpha s_0 + 1} + \frac{1-S_{f|in}}{\alpha+1} \tag{3.33}
$$

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 (3.22) and (3.25) generates the same markup equation given in (3.33). 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.

3.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:[15]

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

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:

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

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

$$\frac{p_j - c_j}{p_j} = \frac{1}{\alpha + 1 - \alpha S_{in}} = \frac{1}{\alpha s_0 + 1} \tag{3.34}$$

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.

[15] 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.

3.B.4 Monopolistic competition

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

$$\frac{p_j - c_j}{p_j} = \frac{1}{\eta_j} = \frac{1}{\alpha + 1} \tag{3.35}$$

I 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:

$$\frac{p_j - c_j}{p_j} = \frac{1}{\alpha + 1} \tag{3.36}$$

Combining these facts indicates the equivalency between the proposed model with $\theta_f = 1$

and the monopolistic competition model.

3.C Illustration of the supply model in a simple case

I 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 ($j = 0$).

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

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

I suppose that we observe $Y = 1$, $\boldsymbol{s} = (0.2, 0.2, 0.2, 0.2)'$, $\boldsymbol{p} = (1, 1, 1, 1)'$, $\boldsymbol{q} = (0.2, 0.2, 0.2, 0.2)'$. I 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 :

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

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

Solving the first-order conditions, we have the following equilibrium markups (see equation (3.7)).

$$\frac{p_j - c_j}{p_j} = \frac{\theta_1(1 - S_{1|in}) + (1 - \theta_1)S_{1|in}}{\theta_1(1 - S_{1|in})\eta_j + (1 - \theta_1)S_{1|in}\sigma_j} \quad \text{for j} = 1, 2$$

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

From equations (3.22) and (3.25), the intra- and inter-sectoral 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.

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

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