Essays on new product introduction, bargaining power, and school choice

by

Elif Burcu Dilden

B.S., Gazi University, 2011
M.S., TOBB University of Economics and Technology, 2014
M.A., Kansas State University, 2017

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Abstract

This dissertation combines three essays on the industrial organization and the industrial organization of education markets. These three essays study how the strategic behavior of firms influences market outcomes and consumer decisions. The first chapter examines the manufacturer's product variety and its relation to the manufacturer's bargaining power with retailers. The second chapter focuses on the empirical analysis of the economic impact of new product introduction. The third chapter considers the role of state laws in student's school choice.

The first essay, co-authored with Dr. Philip G. Gayle, analyzes how a manufacturer's preexisting number of distinct product lines, and the number of horizontally differentiated products within each line affects its bargaining power with retailers, where a manufacturer's bargaining power is measured by the share of variable profits retained by the manufacturer when contracting with retailers to sell its products. We find that a manufacturer's expanded provision of horizontally differentiated products under a given line and the number of distinct product lines do not have a statistically significant impact on its bargaining power with retailers, i.e., do not change the manufacturer's *share* of the profit pie with retailers. However, consistent with existing theory, we find evidence that product menu expansions increase the manufacturer's variable profit, no doubt owing to an expansion in the *size* of the full variable profit pie shared with retailers. As such, the evidence suggests that it is profit-maximizing for manufacturers to product proliferate, even though this strategy has no effect on its bargaining power with retailers.

In the second essay, co-authored with Dr. Philip G. Gayle, we investigate the market impacts associated with the introduction of Greek yogurt in the U.S. yogurt industry. With the entrance of Chobani to the U.S. yogurt market in 2007, the popularity of Greek yogurt has risen widely in the U.S. To assess the market impacts of the introduction of Greek yogurt, first, we

estimate a structural econometric model of demand and supply, then use the estimated model to perform counterfactual experiments where we remove Greek-type yogurt from the consumer's choice set. Our analyses reveal that the presence of Greek-type products causes the price of Non-Greek yogurt products to be lower by a mean 39.85% and increases the quantity demand of Non-Greek products by a mean 45.22%. In addition, we find the fraction of consumers choosing not to purchase yogurt products decreases, which shows that the introduction of Greek-type yogurt has a market expansionary effect on the U.S. yogurt market.

Student loan default is an important policy concern; for example, the *Coronavirus Aid, Relief, and Economic Security Act* (CARES Act) allows the U.S. Department of Education to suspend payments on student loans, stop collections on defaulted loans and use a 0% interest rate due to economic challenges surrounding the COVID-19 pandemic. One policy aimed at reducing student loan default that has received little attention by researchers is the 1990 recommendation by the U.S. Department of Education that states should *"deny professional licenses to defaulters until they take steps to repayment"*. In the third essay, co-authored with Dr. Philip G. Gayle and Dr. Amanda Gaulke, we study the impacts of state laws that deny, revoke, or suspend state licenses due to student loan default (LSD laws). We estimate a structural econometric model of students' college choice and find that students become more sensitive to cohort default rates (CDRs) after LSD laws are implemented. Despite the student response putting downward pressure on CDRs, schools' response may counteract that effect due to facing higher marginal cost to reduce default. Thus, we find mixed results of LSD laws' impact on CDRs: an overall increase in CDRs for some states, but an overall decrease for some states.

Essays on new product introduction, bargaining power, and school choice

by

Elif Burcu Dilden

B.S., Gazi University, 2011
M.S., TOBB University of Economics and Technology, 2014
M.A., Kansas State University, 2017

A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Approved by:

Major Professor
Dr. Philip G. Gayle

Copyright

Abstract

This dissertation combines three essays on the industrial organization and the industrial organization of education markets. These three essays study how the strategic behavior of firms influences market outcomes and consumer decisions. The first chapter examines the manufacturer's product variety and its relation to the manufacturer's bargaining power with retailers. The second chapter focuses on the empirical analysis of the economic impact of new product introduction. The third chapter considers the role of state laws in student's school choice.

The first essay, co-authored with Dr. Philip G. Gayle, analyzes how a manufacturer's preexisting number of distinct product lines, and the number of horizontally differentiated products within each line affects its bargaining power with retailers, where a manufacturer's bargaining power is measured by the share of variable profits retained by the manufacturer when contracting with retailers to sell its products. We find that a manufacturer's expanded provision of horizontally differentiated products under a given line and the number of distinct product lines do not have a statistically significant impact on its bargaining power with retailers, i.e., do not change the manufacturer's *share* of the profit pie with retailers. However, consistent with existing theory, we find evidence that product menu expansions increase the manufacturer's variable profit, no doubt owing to an expansion in the *size* of the full variable profit pie shared with retailers. As such, the evidence suggests that it is profit-maximizing for manufacturers to product proliferate, even though this strategy has no effect on its bargaining power with retailers.

In the second essay, co-authored with Dr. Philip G. Gayle, we investigate the market impacts associated with the introduction of Greek yogurt in the U.S. yogurt industry. With the entrance of Chobani to the U.S. yogurt market in 2007, the popularity of Greek yogurt has risen widely in the U.S. To assess the market impacts of the introduction of Greek yogurt, first, we

estimate a structural econometric model of demand and supply, then use the estimated model to perform counterfactual experiments where we remove Greek-type yogurt from the consumer's choice set. Our analyses reveal that the presence of Greek-type products causes the price of Non-Greek yogurt products to be lower by a mean 39.85% and increases the quantity demand of Non-Greek products by a mean 45.22%. In addition, we find the fraction of consumers choosing not to purchase yogurt products decreases, which shows that the introduction of Greek-type yogurt has a market expansionary effect on the U.S. yogurt market.

Student loan default is an important policy concern; for example, the *Coronavirus Aid, Relief, and Economic Security Act* (CARES Act) allows the U.S. Department of Education to suspend payments on student loans, stop collections on defaulted loans and use a 0% interest rate due to economic challenges surrounding the COVID-19 pandemic. One policy aimed at reducing student loan default that has received little attention by researchers is the 1990 recommendation by the U.S. Department of Education that states should *"deny professional licenses to defaulters until they take steps to repayment"*. In the third essay, co-authored with Dr. Philip G. Gayle and Dr. Amanda Gaulke, we study the impacts of state laws that deny, revoke, or suspend state licenses due to student loan default (LSD laws). We estimate a structural econometric model of students' college choice and find that students become more sensitive to cohort default rates (CDRs) after LSD laws are implemented. Despite the student response putting downward pressure on CDRs, schools' response may counteract that effect due to facing higher marginal cost to reduce default. Thus, we find mixed results of LSD laws' impact on CDRs: an overall increase in CDRs for some states, but an overall decrease for some states.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I am incredibly grateful for the abundance of support, guidance, and mentorship from my advisor, Philip G. Gayle. He always brought up questions that would push me to think harder, challenge myself, and grow. His door was always open to me, and I feel very lucky to work under his supervision. I am also deeply indebted to Amanda Gaulke. She opened my eyes to the fascinating research opportunities on education and public policy, and helped shape me as an economist. She provided tremendous support and advice on numerous aspects of the graduate school experience. I could not have made this far as I did without having two amazing scholars, Philip G. Gayle and Amanda Gaulke, as my role models.

I would like to thank my committee members, Peri Da Silva, Jin Wang, and Tian Xia, for their feedback on my research. I also thank Fadi Aramouni for taking the time to serve as my outside committee chair.

I would like to extend my sincere thanks to Yang Ming Chang, Hugh Cassidy, Steve Cassou, Lance Bachmeier, Yoon-Jin Lee, William Blankenau, Daniel Kuester, and the rest of the Department of Economics faculty for inspiring me to become a better teacher and researcher. Many thanks to the administrative staff for all the help behind the scenes.

I would like to thank my friends and classmates for their helpful comments and discussions and for making my time in graduate school a positive and memorable experience.

I would like to thank my wonderful parents, Betül and Ertan Dilden, for the opportunities that they have given to me and for always believing in and cheering for me. I also would like to thank my sister, Zeynep Cansu Dilden, for always being there and keeping me sane.

Special thanks go to Maxime Salin, who tirelessly listened to me. This dissertation is better thanks to his never-ending support.

Dedication

To my family, Betül, Ertan, and Zeynep Cansu: this would not have been possible without your love, support and belief in me.

Chapter 1 - Strawberry or Plain Yogurt? Product Line Expansions and Manufacturer's Bargaining Power with Retailers

1.1 Introduction

New product introductions that extend the firm's product line have become a popular competition strategy of product managers (Kekre and Srinivasan (1990); Kadiyali et al. (1998), Draganska and Jain (2005)).[1] With new product introductions, firms can choose to introduce new product lines or expand the existing product lines to extract more consumer surplus. For example, Apple Inc. introduced a series of iPhone models into the smartphone market. At any given point in time, the series of Apple smartphones available to consumers, currently iPhone 6 to iPhone11, differ in price and quality given the fact that consumers differ in their intensity of preference for quality (Moorthy (1984)). Adopting a "vertical" line extension strategy, which corresponds to establishing product lines of differing quality, can better enable firms to target different market segments distinguished by consumers' differing willingness to pay for a change in quality (Mussa and Rosen (1978); Lancaster (1990)).

On the other hand, firms can offer new products that differ in some attributes, but do not differ in overall quality and price; yet these new introductions may serve as effective competitive tools for the firms. For example, Unilever & Pepsi Co introduced Lipton Iced Tea and Diet Lipton Iced Tea products. These two products have similar price and quality, but vary in other attributes, primarily sugar content, that do not have unanimous preference rankings across consumers, making this an example of a "horizontal" product line extension. With the help of horizontal

---

[1] Villas-Boas (1998) shows the theoretical foundation for understanding how a manufacturer designs a product line within the distribution channel.

product line extensions, firms can use a product proliferation strategy as a substitute for price competition (Connor (1981)). Increased variety and longer product lines allow for a firm to capture consumers with heterogeneous tastes. Hence, firms have the advantage to use product proliferation as a defensive mechanism to protect themselves against competitors (Connor (1981); Lancaster (1979); Bayus and Putsis (1999)).

The yogurt industry provides ideal examples of product proliferation strategies since there are constant brand and flavor introductions. Several yogurt manufacturers each carries multiple product lines and offers different flavors under each line. For instance, General Mills carries yogurt product lines such as Yoplait, Liberte, and Annie's, Mountain High. These product lines are sold under different brand names and price, seeking to distinguish themselves from each other for the purpose of better segmenting consumers. On the other hand, the actual yogurt products within each product line, are horizontally differentiated, that is, products within a given line sell for a similar price and are typically distinguished by attributes, such as flavor, that are not unanimously preferred by consumers.

Profitability of the distribution channel depends on the size of the total margins, and how these margins are split between manufacturers and retailers. The size of the profit pie is determined by the ability of manufacturers and retailers to extract surplus from consumers by charging higher prices. However, the *slices* of the profit pie going to manufacturers and retailers respectively are a reflection of their relative bargaining power in interacting with each other (Draganska et al. (2010)). By offering a greater number of product lines with promotions, manufacturers can increase market share and profitability of their products (Lancaster (1979); Kekre and Srinivasan (1990)), and perhaps their bargaining power with retailers. In other words, while the size of the profit pie likely increases with a greater number of product lines and perhaps with a greater number of horizontally differentiated products within each line, which in turn likely increases manufacturer's profit, it is not clear whether manufacturers' *share* of the profit pie also increases. When Chobani entered the U.S. yogurt market in 2007, it had a single product line (brand) with a large number of flavors. A recent website search shows that Chobani now offers eleven different product lines with a large number of flavors within each line.[2] While Chobani's expanded product lines, and expanded flavors within each line, are likely to have positive impacts on its profit, did these product expansions increased its share of the profit pie, i.e., its bargaining power with retailers?

The primary objective of this study is to investigate the extent to which the preexisting number of distinct product lines, as well as the preexisting number of horizontally differentiated products within each product line influence manufacturers' bargaining power with retailers. To achieve our objective, we follow the general framework of Draganska et al. (2010). Our study focuses on the yogurt industry since this industry provides ideal examples of varying degrees of horizontal product differentiation and product line introduction across several manufacturers.

Our research methodology involves three distinct steps. In the first step, we estimate a differentiated products consumer demand model using scanner data on yogurt sales at supermarket and drug store retail outlets. Given demand parameter estimates, in the second step we use a supply-side model of Nash bargaining in which each manufacturer-retailer pair negotiates over the retailer carrying in its store the manufacturer's *group* of products. A supply-side model of Nash bargaining over relevant product groups is more appropriate for the objectives of our study, and contrasts with the assumed product-by-product negotiations in Draganska et al. (2010) and other studies. The empirical model of Nash bargaining over relevant product groups is used for

[2] https://www.chobani.com/products/, accessed (December 19, 2019).

estimating parameters that capture the relative bargaining power between manufacturer-retailer pairs. With parameter estimates of relative bargaining power between manufacturer-retailer pairs in hand, in the third step we use a sequence of linear regression models to estimate the influence of the preexisting number of distinct product lines (brands), and the preexisting number of horizontally differentiated products within product lines, on manufacturers' bargaining power with retailers.

Our analysis adds to the literature that studies manufacturer-retailer relative bargaining powers within the vertical channel (Draganska et al. (2010); Crawford and Yurukoglu (2012); Doudchenko and Yurukoglu (2016); Bonnet and Bouamra-Mechemache (2015); Bonnet et al. (2015); Grennan (2013); Grennan (2014); Haucap et al. (2013); Ellickson et al. (2018)). Earlier studies in this literature focused on the determinants of the retailer's bargaining power. In this study, we empirically investigate the basic assumption of Lancaster (1979) and Kekre and Srinivasan (1990) that offering many product lines and assortment increases the market share, profitability and indirectly the bargaining power of the manufacturer with retailers.

For the yogurt industry, our results indicate that bargaining power is mostly on the manufacturer side. We find that relative bargaining power varies depending on the manufacturer-retailer pair. Surprisingly, we find that: *(i)* expanding existing product lines horizontally; and *(ii)* expanding the number of unique brands, have no statistically discernable impact on the manufacturer's bargaining power with retailers. However, consistent with theoretical predictions in Lancaster (1979) and Kekre and Srinivasan (1990), we find evidence suggesting that it is still optimal for manufacturers to choose to product proliferate horizontally and introduce a greater number of unique brands, even though these product proliferation strategies have no impact on the manufacturer's bargaining power with retailers.

The rest of the paper is organized as follows: Section 2 provides a description of the data; Section 3 outlines an econometric model of the market for yogurt; Section 4 explains the estimation and identification strategies; Section 5 discusses the results; and Section 6 provides the main conclusions of the paper.

1.2 Data

This study primarily uses data made available by the U.S. marketing firm, Information Resources Inc. (IRI). IRI collected data by using scanning devices from a sample of stores belonging to different retail chains located in various areas of the U.S. The data consist of weekly prices and the total sales of almost all brands of yogurt sold in the U.S. We use data in year 2012.[3]

We chose to delineate the geographic market areas by county, which is often a smaller geographic area compared to IRI designated geographic market areas. In our study, each market is defined as the unique combination of county, month and year. Each product in the dataset is defined as a unique combination of non-price characteristics, such as, yogurt style (Greek vs. non-Greek), brands, flavor/scent, organic information, and packaging type. Thus, packaged yogurt under the same brand with a different yogurt style, and organic information are designated as different products (e.g. Organic Greek yogurt with a strawberry flavor is a different product than Organic Greek yogurt with a blueberry flavor in a given retailer store). For each product in each market, we aggregate weekly data up to monthly sales and dollar value revenue from sales. The average retail product prices are computed by dividing monthly sales revenue by monthly unit sales.

[3] Data are available from 2001 to 2012.

We use a discrete choice demand model similar to Villas-Boas (2007), which requires computing product shares, as well as the share of an outside option in each market. First, we describe how potential market size is measured in this study, which is used in computing product shares and the share of the outside option in each market. Following Villas-Boas (2007), we assumed per capita yogurt consumption for each individual in the U.S. is half of the per capita yogurt consumption per month. After obtaining the population of each county from the Bureau of Labor Statistics (BLS), we multiplied the number of adult population with half of the per capita yogurt consumption, which yields the measure we use for potential market size for each defined market, respectively. The observed share associated with each product in a given market is computed by dividing the product's unit sales by the market's potential size measure. The observed share of the outside option is computed as one minus the sum of observed shares across products within a given market. Table 1.1 lists and defines the variables used in the analysis.

Table 1.1 Description of available variables

Name	**Description**
Price	Average monthly prices in dollar per ounce.
Market Share (S_j)	Monthly market shares for each product (S_j) are computed as the total quantity sold divided by the potential market size.
Feature count	Counts feature(s) (i.e., frequent shopper program, large size advertisement) occurred for product during that month.
Display count	Counts the special display(s) (e.g. end aisle, lobby) occurred for each product during that month.
Sugar	Sugar price per ounce
Protein	Protein information per ounce of yogurt
Organic Information	Dummy=1 if the product is organic, zero otherwise

Yogurt style	Dummy=1 if the product is Greek yogurt, zero otherwise
Total Sugar	Amount of sugar per ounce of yogurt
Sodium	Amount of sodium per ounce of yogurt
Total Fat	Amount of total fat per ounce of yogurt

For the empirical analysis, we need to supplement the IRI-dataset with data on non-price product characteristics and consumer demographics. Data on non-price product characteristics are collected based on nutritional facts from label reads of each brand, such as calorie, sugar, fat, and protein contents, under the assumption that those characteristics did not change over the observed period. Assuming an individual's income is presumably relevant to his/her demand for yogurt, we have drawn income information of consumers from the U.S. Census Integrated Public Microdataset Sample (IPUMS). Our model considers the interactions of consumer demographics with the price and select non-price product characteristics, such as yogurt style, i.e. Greek versus non-Greek style.

Table 1.2 provides descriptive statistics for single-pack, 6-ounces yogurt products. The average price of yogurt per ounce is \$0.149. Data on the price for sugar, a cost-shifting variable, are obtained from the United States Department of Agriculture (USDA) database.[4]

Table 1.2 Descriptive Statistics of single-pack, 6-ounces yogurt products

Description	**Mean**	**S.E.**	**Min**	**Max**
Average price (\$/ounce)	0.149	0.0005	0.05	0.55
Aggregate sales (ounces)	1191.26	17.93	6	35154
Sugar prices (cents/ounce)	68.935	0.004	67.9	69.6
Feature	0.507	0.006	0	4

[4] https://www.ers.usda.gov/data-products/sugar-and-sweeteners-yearbook-tables.aspx , accessed (December 19,2019).

Display	0.045	0.002	0	4
Total Sugar (per ounce)	2.85	0.094	0	6.22
Protein (per ounce)	1.236	0.0509	0.5	2.64
Sodium (per ounce)	14.66	0.037	0.66	45.28
Total Fat (per ounce)	0.227	0.003	0	2.5

1.2.1 Relevant Measures of Manufacturer's Product Line(s)

To assess the influence of number of distinct product lines (product line width), and number of horizontally differentiated products within product lines (product line depth) on the bargaining power of manufacturers, we constructed measures of product line width and product line depth, respectively.

Supposedly, the number of flavors offered under each brand of a given manufacturer can increase consumers' brand loyalty and willingness to pay for that manufacturer's products. The idea is that if the manufacturer differentiates itself from the other competitors horizontally, then it can increase consumer loyalty and demand, and perhaps in turn charge higher price-cost margins. We construct measures of manufacturers' product line depth using the number of flavors under each product line of a given manufacturer. Some manufacturers carry more than one product line; however, our empirical framework requires assigning to each manufacturer a single value measuring their product line depth. Thus, we define two alternative measures of a manufacturer's product line depth: (*i*) *Product Line Depth - Maximum,* which is the number of flavors offered within the given manufacturer's largest product line; and (*ii*) *Product Line Depth - Average,* which is the average number of flavors offered across the given manufacturer's product lines.

Due to product attribute (tangible and intangible) differences across unique brands, a greater number of brands, synonymous here with product lines, can better enable firms to capture distinct segments of the market. Thus, we hypothesize that manufacturers with relatively more brands have greater bargaining power with a given retailer. We define *Product Line Width* as the number of brands carried by each manufacturer.

To ensure that we use measures of product line depth and product line width that are exogenous, or at least pre-determined, within the context of our empirical bargaining model, we constructed these variables by using manufacturers' product menu information from January through April in year 2012, which is a period preceding the period used for actual econometric estimation of the demand and supply-side bargaining models. Table A1 in Appendix A lists manufacturers and their available brands. The demand and supply-side bargaining models are estimated using sales of products from May through December of 2012. Table 1.3 provides descriptive statistics on product line width, product line depth and industry sales share, respectively, across manufacturers in our data sample.

Column (1) of Table 1.3 shows the number of product lines for each manufacturer. Among the 30 manufacturers in our data sample, nineteen of them (i.e., 63 percent of them) offer a single product line; nine of them (i.e., 30 percent of them) offer two product lines; one (i.e., 3.33 percent of them) offers seven product lines; and one manufacturer (i.e., 3.33 percent of them) offers nine product lines.

Columns (2) and (3) of Table 1.3 show manufacturers *Product Line Depth - Maximum* and *Product Line Depth – Average*, respectively. Private labels (PL) products - under the assumption of each PL is produced by a common, outside manufacturer - offers 89 different flavors; while Chobani offers a single product line with 16 flavors; General Mill's largest product line has 27 flavors, with an average 11 flavors per line; and Group Dannon's largest product line offers 17 flavors, with an average 9 flavors per line.

The last column of Table 1.3 shows the industry sales share of each manufacturer in the data. Based on the share of industry sales data, Chobani has the highest share of industry sales, followed by Private Label, General Mills and Group Dannon, respectively.

Table 1.3 Each manufacturer's product line width, product line depth and industry sales share

Producer Name	**(1) Product Line Width**	**(2) Product Line Depth-Maximum**	**(3) Product Line Depth-Average**	**(4) Industry sales share(%)**
Chobani Inc.	1	16	16	34.0214
Private Label	1	89	89	26.2043
General Mills Inc.	7	27	10.71	21.3147
Group Dannon	9	17	8.56	16.4584
Liberty Products Inc.	2	6	5	0.3047
Johanna Foods Inc	2	18	10	0.2977
WhiteWave	1	5	5	0.2839
Fage	1	1	1	0.2180
Turtle Mountain Inc	1	7	7	0.1400
Wallaby Yogurt Company Inc.	2	14	9.5	0.1139
Tula Food Inc	1	6	6	0.1097
The Hain Celestial Group Inc.	2	4	4	0.0747
Tillamook	1	9	9	0.0728
WholeSoy & Co	1	7	7	0.0614
Cascade Fresh	2	11	6.5	0.0567
Redwood Hill Farm	1	5	5	0.0550
Dean Foods	1	4	4	0.0518
Alpina	2	1	1	0.0383
Prairie Farms	1	11	1.22	0.0293
H P Food Inc	2	7	7	0.0202
Greece By Tyras	1	6	6	0.0177
Emmi Roth Inc.	1	7	7	0.0156
Green Mountain Creamery	1	5	5	0.0149
Kalona Organics	1	2	2	0.0072
Maple Hill Creamery	1	2	2	0.0058
Schreiber Foods Inc.	1	4	4	0.0047
Mehadrin Dairy	2	4	3	0.0033
National Dairy Holdings	2	15	9.5	0.0014
Green Valley Organics	1	2	2	0.0011
Springfield Creamery	1	5	5	0.0003

Notes: Product line width and Product line depth measurements are computed based on manufacturers' product menu information from January through April of year 2012.

1.3 Econometric Model of the Yogurt Market

We model the market for yogurt using a structural model of demand and strategic behavior of retailers and manufacturers. The empirical strategy is as follows. First, we estimate consumers' preferences in the yogurt market. Consumers in a market face a choice set that includes the offers of different yogurt products, and each product is defined as a combination of non-price characteristics. Using demand estimates, along with an assumed static Nash equilibrium price-setting behavior among downstream retailers, we recover retail price-cost margins. By using exogenous cost-shifting variables of yogurt production within a supply-side manufacturer-retailer Nash bargaining framework, we estimate parameters that measure the relative bargaining power of manufacturers with respect to retailers for each manufacturer-retailer pair. In the final step of the empirical strategy, we use a sequence of linear regression models to estimate the influence of number of distinct product lines, and number of horizontally differentiated products within product lines on manufacturers' bargaining power with retailers.

1.3.1 Demand Model

We use a random coefficients logit model to estimate the demand and related price elasticities (Berry and Pakes (2001)). Suppose there are M markets, $m=1,...,M$ and in each market, there are L_m potential consumers. A typical consumer i can choose to either buy one of the J differentiated products, $j=1,...,J$ or otherwise choose the outside good (j=0), allowing for the possibility of consumer i not buying one of the J marketed goods. Therefore, consumer i chooses between $J+1$ alternatives in market m during time t. Consumer i's conditional indirect utility for the outside good is $u_{i0t} = \varepsilon_{i0mt}$, while for products $j=1,...,J$ it is:

$$U_{ijmt} = x_{jmt}\beta_i + \alpha_i p_{jmt} + county_m + v_t + product_j + \xi_{jmt} + \varepsilon_{ijmt} \quad (1)$$

where in equation (1), x_{jmt} is a vector of observed non-price product characteristics. The parameter vector β_i contains consumer-specific valuations for the product characteristics. Parameter α_i captures consumer-specific disutility of price. p_{jmt} is the price of yogurt per ounce; $county_m$ captures county-specific fixed effects; v_t captures time (month) fixed effects; $product_j$ captures product-specific fixed effects; and ξ_{jmt} is the unobserved (by the econometrician) brand characteristics (i.e., quality, reputation, etc.) that have an impact on consumer utility, whereas ε_{ijmt} is a mean-zero stochastic error term.

The distribution of consumer-specific taste parameters, β_i and α_i , is specified as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \phi D_i + \Sigma\vartheta_i \quad (2)$$

In Equation (2), α and β parameters are the mean marginal utilities of respective observable product characteristics. D_i is an *m*-dimensional column vector of demographic variables, while ϑ_i is a *k*-dimensional column vector that captures unobserved consumer characteristics. ϕ is a $k \times m$ matrix of parameters that measure how taste characteristics vary with demographics, and Σ is a $k \times k$ diagonal matrix with a set of parameters, σ_k, on the diagonal that measures the variation in consumer tastes for respective product attributes due to random shocks. In our estimation, we consider income as a demographic variable, and we expressed the demographic variable in deviation from its respective mean. Thus, the mean of D_i is zero. Following Nevo (2000b), we assume that ϑ_i has a standard multivariate normal distribution, $\vartheta_i \sim N(0,1)$. The assumptions regarding D_i and ϑ_i along with equation (2) imply that, the mean of α_i is α, and the mean of β_i is β, while variances of these consumer-specific marginal utilities are equal to the square of the elements on the main diagonal of Σ.

We can break down the indirect utility into a mean utility, $\delta_{jmt} = x_{jmt}\beta + \alpha p_{jmt} + county_m + v_t + product_j + \xi_{jmt}$, and a deviation from this mean utility $\mu_{ijmt}(x_{jmt}, p_{jmt}, D_i, \vartheta_i; \phi, \Sigma) = [p_{jmt}, x_{jmt}](\phi D_i + \Sigma\vartheta_i)$. As such, the indirect utility can be re-written as:

$$U_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt} \tag{3}$$

For computational tractability, the idiosyncratic error term ε_{ijmt} is assumed to be governed by an independent and identically distributed extreme value density. Individual *i*'s probability of buying product *j* in market *m* at time *t* is as follows:

$$s_{ijmt} = \frac{exp\ (\delta_{jmt} + \mu_{ijmt})}{\sum_{k=0}^{J_{mt}} exp\ (\ \delta_{kmt} + \mu_{ikmt})} \tag{4}$$

The market share of product *j* in market *m* at time *t* is given by:

$$s_{jmt} = \int \frac{exp\left(\delta_{jmt} + \mu_{ijmt}\right)}{\sum_{k=0}^{J_{mt}} exp\ (\ \delta_{kmt} + \mu_{ikmt})} d\widehat{F(D)} dF(v) \tag{5}$$

where $d\widehat{F(D)}$ and $dF(v)$ are population distribution functions for consumer demographics and random taste shocks assumed to be independently distributed. For the integral in Equation (5), there is no closed-form solution. Thus, it must be approximated numerically by using random draws from $\widehat{F(D)}$ and $F(v)$.

Finally, the demand for product j is given by:

$$d_{jmt} = L_m \times s_{jmt}(x, p, \xi; \theta_d) \tag{6}$$

where in equation (6), L_m is a measure of market size in a given county; $s_{jmt}(x, p, \xi; \theta_d)$ is the model predicted share of product j; x, p, and ξ are vectors of observed non-price characteristics, price and the unobserved vector of product characteristics, respectively; and θ_d=(α, β, $county_m$, v_t, $product_j$, ϕ, Σ) is a vector of demand parameters to be estimated.

1.3.2 Supply Side of the Model

We consider the vertical structure of the yogurt industry as consisting of n_f upstream manufacturers and n_r downstream retailers. Each upstream manufacturer produces a set of products, G^f, and each downstream retailer sells a set of products, R^r. A given market consists of J differentiated products. The marginal cost a manufacturer incurs in producing product j is denoted by mc_j^f, while the marginal cost a retailer incurs in offering the product to consumers is denoted as mc_j^r. The retail price of product j is denoted as p_j, and the wholesale price the retailer pays the manufacturer for the product is denoted as p_j^w. To simplify notation, we drop the time subscripts for the remainder of this section.

Retailer's profit function is given by:

$$\pi^r(p) = \sum_{j \in R^r} \left[p_j - p_j^w - mc_j^r\right] \times q_j(p) \tag{7}$$

$$= \sum_{j \in R^r} (p_j - p_j^w - mc_j^r) \times [L \times s_j(p)]$$

The profit of manufacturer *f* from all products sold to retailers is denoted by:

$$\pi_{G_f}^f\big(p(p^w)\big) = \sum_{j \in G^f} \left[p_j^w - mc_j^f\right] \times q_j(p(p^w)) \tag{8}$$

$$= \sum_{j \in G^f} [\Gamma_j \times L \times s_j\,(p(p^w))]$$

where $\Gamma_j \equiv p_j^w - mc_j^f$ represents the manufacturer's markup on product *j*.

As in Draganska et al. (2010), first, we derive the retail margins under the assumption of retailers in the yogurt market choosing final prices based on Bertrand-Nash competition. We subsequently describe the wholesale price equilibrium under the assumption that upstream manufacturers and downstream retailers negotiate the wholesale prices based on a Nash bargaining game.

Retail Margins

Each retailer r chooses retail prices for the products it sells to maximize its profit, $\pi^r(p)$. The resulting first-order conditions are:

$$s_j(p) + \sum_{k \in R^r} (p_k - p_k^w - mc_k^r) \frac{\partial s_k(p)}{\partial p_j} = 0 \qquad \forall\, j \tag{9}$$

We can conveniently recover the set of retail markups by re-writing the above equation in matrix form. To do so, we define a $J \times J$ matrix that characterizes retailers' ownership structure of the products in the market. Let $J \times J$ matrix T_r have a general element, $T_r(k,j)$, equal to 1 if product k and j are sold by the same retailer, and 0 otherwise. Second, let Δ_r be the $J \times J$ matrix that captures the response of product share to retail prices, i.e., matrix Δ_r contains first-order partial derivatives of product shares with respect to all retail prices:

$$\Delta_r = \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \cdots & \frac{\partial s_J}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial p_J} & \cdots & \frac{\partial s_J}{\partial p_J} \end{pmatrix}$$

In vector notation, the first-order conditions characterized by equation (9) implies that the $J \times 1$ vector of retail markups (γ) is given by the following expression:

$$\gamma \equiv p - p^w - mc^r = -(T_r * \Delta_r)^{-1} \times s(p) \tag{10}$$

where p, p^w, mc^r, and $s(\cdot)$ are $J \times 1$ vectors of retail prices, wholesale prices, retail marginal costs, and product shares respectively; while $T_r * \Delta_r$ represents element-by-element multiplication of the two matrices.

Wholesale Margins

The equilibrium wholesale prices for a set of products are derived from the bilateral bargaining problem between a manufacturer and a retailer. Manufacturer f will negotiate with each retailer to either carry the entire group of products, G_{fr}, or none in the group, where $G_{fr} \subset G_f$. Each manufacturer and retailer pair maximizes the Nash product:

$$\left[\pi^r_{G_{fr}}(p^w) - d^r_{G_{fr}}\right]^{\lambda_{G_{fr}}} \left[\pi^f_{G_{fr}}(p^w) - d^f_{G_{fr}}\right]^{1-\lambda_{G_{fr}}} \tag{11}$$

where $\pi^{f}_{G_{fr}}(p^{w})$ is manufacturer f's profit and $\pi^{r}_{G_{fr}}(p^{w})$ retailer r's profit for the group of products G_{fr}. Note that the product-by- product bargaining framework in Draganska et al. (2010) and other studies is a special case of the product group bargaining framework used in this paper. In particular, the framework in this paper yields a product-by-product bargaining framework in the case where G_{fr} always contains a single unique element, i.e., $G_{fr} = j$ for all *fr* pairs and *j*.

During negotiations, each player earns its disagreement payoff $d^{r}_{G_{fr}}$ and $d^{f}_{G_{fr}}$, plus a share of $\lambda_{G_{fr}} \in [0,1]$ of the incremental gain from trade going to the retailer, and $1 - \lambda_{G_{fr}}$ going to the manufacturer. Here, $\lambda_{G_{fr}}$ is the bargaining power of the retailer and $1 - \lambda_{G_{fr}}$ is the bargaining power of the manufacturer. The manufacturer's profit obtained from the group of products, G_{fr}, is given as:

$$\begin{aligned} \pi^{f}_{G_{fr}}(p^{w}) &= \sum_{j \,\in\, G_{fr}} (p^{w}_{j} - mc^{f}_{j}) \times L \times s_{j}(p(p^{w})) \\ &= \sum_{j \,\in\, G_{fr}} [\Gamma_{j} \times L \times s_{j}(p(p^{w}))] \end{aligned} \tag{12}$$

where $\Gamma_j \equiv (p^{w}_{j} - mc^{f}_{j})$ defines manufacturer's markup on product j. Retailer r's profit obtained from the group of products, G_{fr}, is given as:

$$\pi^{r}_{G_{fr}}(p^{w}) = \sum_{j \,\in\, G_{fr}} (p_j - p^{w}_{j} - mc^{r}_{j}) \times L \times s_j(p) = \sum_{j \,\in\, G_{fr}} [\gamma_j \times L \times s_j(p)] \tag{13}$$

The retailer realizes disagreement payoff, $d^r_{G_{fr}}$, if it does not carry manufacturer *f*'s group of products, G_{fr}, in its store, but contracts with others. Similarly, the manufacturer realizes a disagreement payoff, $d^f_{G_{fr}}$, from the sales to other retailers in the case where the negotiation fails with retailer *r* for product group G_{fr}. Assuming that the retail prices are fixed during negotiation, then the disagreement payoffs are given by:

$$d^r_{G_{fr}} = \sum_{k \epsilon R^r \setminus \{G_{fr}\}} \gamma_k \times L \times \Delta s_k^{-G_{fr}}(p) \tag{14}$$

$$d^f_{G_{fr}} = \sum_{k \epsilon G^f \setminus \{G_{fr}\}} \Gamma_k \times L \times \Delta s_k^{-G_{fr}}(p) \tag{15}$$

where $L \times \Delta s_k^{-G_{fr}}(p)$ is the change in market demand of product *k* that occurs when product group G_{fr} is no longer sold on the market. Those quantities can be derived through the substitution patterns estimated in the demand model as follows:

$$\Delta s_k^{-G_{fr}}(p) = \int \left[\frac{\exp(\delta_{kmt} + \mu_{ikmt})}{\sum_{l=0}^{J_{mt} \setminus \{G_{fr}\}} \exp(\delta_{lmt} + \mu_{ilmt})} - \frac{\exp(\delta_{kmt} + \mu_{ikmt})}{\sum_{l=0}^{J_{mt}} \exp(\delta_{lmt} + \mu_{ilmt})} \right] d\widehat{F(D)} dF(v) \tag{16}$$

Optimizing equation (11) in the bargaining problem with respect to wholesale price, p_j^w, leads to the first-order condition:

$$\lambda_{G_{fr}}\left(\pi^f_{G_{fr}} - d^f_{G_{fr}}\right)\frac{\partial \pi^r_{G_{fr}}}{\partial p^w_j} + \left(1-\lambda_{G_{fr}}\right)\left(\pi^r_{G_{fr}} - d^r_{G_{fr}}\right)\frac{\partial \pi^f_{G_{fr}}}{\partial p^w_j} = 0 \tag{17}$$

Under the assumption that the retail prices for products are treated as fixed when wholesale prices are decided during the bargaining process, we have $\frac{\partial \pi^r_{G_{fr}}}{\partial p^w_j} = -L \times s_j(p)$ and $\frac{\partial \pi^f_{G_{fr}}}{\partial p^w_j} = L \times s_j(p)$ from equations (12) and (13). Equation (17) can thus be re-written as $\pi^f_{G_{fr}} - d^f_{G_{fr}} = \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}(\pi^r_{G_{fr}} - d^r_{G_{fr}})$. Using equations (12), (13), (14) and (15), the following expression can be derived for the bargaining solution:

$$\sum_{j \in G_{fr}} [\Gamma_j \times L \times s_j(p)] - \sum_{k \epsilon G_f \setminus G_{fr}} [\Gamma_k \times L \times \Delta s_k^{-G_{fr}}(p)]$$
$$= \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}\left(\sum_{j \in G_{fr}} [\gamma_j \times L \times s_j(p)] - \sum_{k \epsilon R_r \setminus G_{fr}} [\gamma_k \times L \times \Delta s_k^{-G_{fr}}(p)]\right) \tag{18}$$

Using equation (18) for all products, we obtain the matrix notation equation (18) can be written as:

$$\left(T_f * S_{G_{fr}}\right) \times \Gamma = \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}\left(T_f * S_{G_{fr}}\right) \times \gamma$$

$$\Gamma = \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}\left(T_f * S_{G_{fr}}\right)^{-1}\left(T_r * S_{G_{fr}}\right) \times \gamma \tag{19}$$

where Γ is $J \times 1$ vector of manufacturer's margins; analogous to T_r in the case of retailers, T_f characterizes manufacturers' ownership structure of the products in the market; and $S_{G_{fr}}$ is a $J \times J$ matrix with the element $S_{G_{fr}}(l,k)$ defined as follows:

$$S_{G_{fr}}(l,k) = \begin{cases} s_k & \text{if product } k \text{ is an element of manufacturer} - \text{retailer product group}, G_{fr} \\ -\Delta s_k^{-G_{fr}}(p) & \text{Otherwise} \end{cases}$$

Adding equations (19) and (10) leads to the vector of the total margins for manufacturer-retailer pairs:

$$p - mc^f - mc^r = \Gamma + \gamma = \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}\left(T_f * S_{G_{fr}}\right)^{-1} \times \left(T_r * S_{G_{fr}}\right) \times \gamma - (T_r * \Delta_r)^{-1} \times s(p)$$
$$= \frac{1-\lambda_{G_{fr}}}{\lambda_{G_{fr}}}\left[\left(T_f * S_{G_{fr}}\right)^{-1} \times \left(T_r * S_{G_{fr}}\right) \times \gamma\right] + \gamma \tag{20}$$

where $\gamma = -(T_r * \Delta_r)^{-1} \times s(p)$ is a $J \times 1$ vector of retail markups.

Because we do not directly observe manufacturers' marginal production costs, as well as retailers' marginal distribution costs, we are not able to determine analytically the bargaining power $\lambda_{G_{fr}}$. We estimate the total marginal cost up to parameter vector φ by specifying the aggregate channel *MC* as follows:

$$MC = \varphi\omega + \eta \tag{21}$$

where ω is a vector of cost-shifting variables; φ is the vector of parameters associated with the cost-shifting variables; and η is the error term that accounts for the unobserved shocks to marginal cost.

Using equation (20) and equation (21), the supply-side equation to be estimated is given by:

$$p = MC + \frac{\left(1 - \lambda_{G_{fr}}\right)}{\lambda_{G_{fr}}} B_{G_{fr}} + \gamma \tag{22}$$

where we can see from equation (22) that $B_{G_{fr}} = \left[\left(T_f * S_{G_{fr}}\right)^{-1}\left(T_r * S_{G_{fr}}\right) \times \gamma\right]$, which is a $J \times 1$ vector. Instead of using vector notation, equation (22) can be written at the product observation level as follows:

$$p_j = \varphi\omega_j + \frac{1 - \lambda_{G_{fr}}}{\lambda_{G_{fr}}} B_{G_{fr}} + \gamma_j + \eta_j \tag{23}$$

Since our objective is to use equation (23) to estimate manufacturer-retailer pair-specific $\lambda_{G_{fr}}$, we interact variable $B_{G_{fr}}$ with a full set of manufacturer-retailer pair zero-one dummy variables, i.e., we estimate:

$$p_j = \varphi \omega_j + \sum_{fr \in (n_f \times n_r)} \frac{1 - \lambda_{G_{fr}}}{\lambda_{G_{fr}}} (B_{G_{fr}} \times I_{fr}) + \gamma_j + \eta_j \tag{24}$$

where *fr* indexes manufacturer-retailer pairs; $(n_f \times n_r)$ is the set product of manufacturer-retailer pairs; and I_{fr} is a zero-one dummy variable that is equal to one only for the group of products offered by manufacturer-retailer pair *fr*. We are then able to obtain an estimate of $\lambda_{G_{fr}}$ for each manufacturer-retailer pair.

There are two points about the econometric estimation of equation (24) worth mentioning here. First, note that the theory requires that each $\lambda_{G_{fr}}$ lie between zero and one. As such, our generalized method of moments (GMM) estimation of equation (24) imposes this parameter restriction to be consistent with the theory. Second, as shown in describing equation (22), term $B_{G_{fr}}$ is a function of retail markups, γ, and predicted product shares in $S_{G_{fr}}$. As such, $B_{G_{fr}}$ is likely correlated with unobserved shocks to marginal cost, η_j, making $B_{G_{fr}}$ in equation (24) endogenous. Therefore, consistent estimates of $\lambda_{G_{fr}}$ can only be obtained if appropriate instruments for $B_{G_{fr}}$ are used in estimation.

1.4 Estimation and Identification

1.4.1 Demand

To estimate the set of demand parameters, we use generalized methods of moments (GMM) following the previous literature (Berry (1994); Berry, Levinson and Pakes (1995) (BLP); Nevo (2000a); and Petrin (2002)). The general strategy is to derive parameter estimates such that the observed product shares, S_{jmt}, are equal to predicted product shares, s_{jmt}.

Instruments for Demand Estimation

To obtain consistent estimates of price coefficients, α_i, instrumental variables are required because when firms are setting their prices, they consider not only the product characteristics observed by us the researchers, x_{jmt}, but also the product characteristics, ξ_{jmt}, that are not observed by us the researchers, but observed by all consumers. Firms also take into account any changes in the product characteristics and consumer valuations.[5] To mitigate the endogeneity problem, we include product and market fixed effects. However, instruments for retail product prices are needed to deal with endogeneity problems that may remain even after controlling for product and market fixed effects.

In constructing one set of retail product price instruments, we assume that input prices are uncorrelated with the unobserved econometric error, ξ_{jmt}, but highly correlated with retail price. The justification for this assumption is that consumers' brand loyalty across yogurt products is most likely uncorrelated with the prices of inputs in the production of yogurt, e.g. prices of milk, sugar, strawberry, electricity etc., but these input prices do influence the retail price of yogurt (Villas-Boas (2007)). In addition, the intensity with which each input is used is likely to vary across yogurt brands. For example, some yogurt brands may use relatively more sugar than others; some brands may use more electricity for extra processing; only some brands use strawberry etc. As such, a change in price of a given input is likely to differentially influence production cost and therefore retail prices across yogurt brands. To allow input price to have differential production cost effects across brands of yogurt, we interact input prices with product dummies, and use these

[5] Villas-Boas (2007)

interaction variables as instruments for retail price. In fact, brands focusing on the production of different flavors are likely to use more sugar than plain yogurt brands. Therefore, the sugar usage intensity would be different between the yogurt brands. Thus, sugar prices interacted with the brand dummies are valid instruments for the endogenous retail price of yogurt. Data on the monthly price of sugar are obtained from the U.S. Department of Agriculture.

Further, as shown by Berry and Haile (2014), the heterogeneity in consumer preferences for product characteristics creates an endogeneity problem that arises from the interaction of unknown demand parameters with market shares. The mean utilities that equate observed shares to predicted shares and the income terms will also be correlated with the unobserved error term. To mitigate this source of endogeneity, first, we define "count" variables of advertising characteristics for each product, i.e. number of times within the relevant month each product has been featured and specially displayed. This type of advertising information can be obtained from the data for each product to construct BLP type instruments. Then, we compute mean advertising counts across yogurt-type (Greek versus non-Greek type) products within each market, which facilitates computation of the deviation of each product's advertising characteristic count from the relevant mean across similar yogurt-type products. We use deviation of each product's advertising characteristic count as instruments in demand estimation. Deviation of each product's advertising characteristic count from the relevant mean across similar yogurt-type products are likely to be correlated with products' market shares because consumers' preferences are likely to be influenced by differences in advertising intensities across products.

To identify parameters governing consumer heterogeneity, we use the interaction of mean income with the input costs (price of sugar) and brand dummies as instruments.

1.4.2 Supply Equation

On the supply side, we account for the endogeneity of the bargaining variable ($B_{G_{fr}}$ in equation (24)) in the estimation for the relative bargaining power parameters, $\lambda_{G_{fr}}$. As previously discussed, $B_{G_{fr}}$ is a function of retail markups, γ, and predicted product shares in $S_{G_{fr}}$. As such, an appropriate instrument variable for $B_{G_{fr}}$ should be correlated with either retail markups, predicted product shares, or both, but uncorrelated with unobserved shocks to marginal cost captured in η_j.

Instruments for Supply Estimation

To construct instruments for $B_{G_{fr}}$ we make two key assumptions. First, we assume that a given change in consumer income will have differential effects across manufacturer-retailer pairs due to differential demand effects across the differing menu of products across manufacturer-retailer pairs. Second, we assume that any variable that shifts marginal production cost will not have complete pass-through to retail prices due to the oligopoly structure of the industry. This assumption implies that any variable that shifts marginal production cost will also influence retail markups. As discussed above, a change in price of a given input is likely to differentially influence production cost across brands of products due to the differential intensities with which brands of products use the given input. Combined with incomplete cost-price pass-through, we therefore expect a change in price of a given input will in turn differentially influence retail markups across brands of products. Furthermore, the differential retail markup effects across brands of products will drive differential retail markup effects across manufacturer-retailer pairs due to differing menu of products across manufacturer-retailer pairs.

Since consumers' income and the prices of inputs are unlikely to be correlated with unobserved shocks to the marginal cost of supplying yogurt, η_j, then the assumptions and discussion in the previous paragraph imply that three-way interactions of input price (e.g. price of sugar) with mean consumer income and manufacturer-retailer pair dummy variables are appropriate instruments for $B_{G_{fr}}$. We use these three-way interaction variable instruments when estimating the bargaining power parameters, $\lambda_{G_{fr}}$, in the supply equation.

1.5 Empirical Results

1.5.1 Demand

Standard Logit Model of Demand

The first and second columns in Table 1.4 present the coefficient estimates from the linear regression of mean utility $\delta_j = log(S_{jmt}) - log(S_{0mt})$ on various product and market characteristics, which is the standard logit specification of the demand model. Coefficient estimates of the standard logit specification of the demand model in columns 1 and 2 of Table 1.4 are obtained using ordinary least squares (OLS) and two-stage least squares (2SLS) estimation procedures, respectively. The estimates of price coefficients from OLS and 2SLS are negative and statistically significant. As mentioned before, price is an endogenous variable in demand estimation. Hence, OLS estimation in column 1 of Table 1.4 produces biased and inconsistent estimate of the price coefficient. To eliminate the endogeneity problem of price, we re-estimate the demand equation using 2SLS. The Wu-Hausman exogeneity test rejects the exogeneity of price at conventional levels of statistical significance, and suggests the instruments used are necessary.

Random Coefficients Logit Model of Demand

Results from the random coefficients logit (RCM) specification of the demand model are presented in columns (3), (4) and (5) of Table 1.4. The coefficient estimate of price in the RCM model is negative and statistically significant at conventional levels of statistical significance. Column (4) reports parameters that capture consumer taste variation unobserved by the researchers for various product characteristics. The estimated effects are statistically and economically significant, suggesting that consumers are heterogeneous with respect to their marginal disutility for price changes of yogurt products.

Consumers tend to prefer yogurt products that are Greek style. This result is evident from the positive and statistically significant coefficient estimate on the Greek dummy variable. Furthermore, the negative and statistically significant coefficient estimate on the interaction variable of Greek with consumer income suggests that lower income consumers have relatively stronger preferences for Greek style yogurt.

The positive and statistically significant coefficient estimate on the *Organic* dummy variable suggests that organic yogurt products are associated with higher levels of utility compared to non-organic yogurt products, *ceteris-paribus*.

Table 1.4 Demand estimation results for single-pack, 6-ounces yogurt products

Variable	Standard Logit		Random Coefficients Logit		
	OLS	2SLS	GMM		
	Mean Coef	Mean Coef	Mean Coef	Standard Deviations	Demographic Interactions
	(α, β)	(α, β)	(α, β)	(σ)	(Income)
Price	-15.732***	-30.945***	-53.067***	-4.382***	1.443***
	(0.213)	(1.18)	(2.108)	(1.138)	(0.081)
$Constant^{a}$	0.568***	0.971***	1.170***	1.120***	
	(0.067)	(0.073)	(0.073)	(0.356)	
Greek	0.291***	1.488***	3.135***	-1.293***	-0.126***
	(0.053)	(0.105)	(0.312)	(0.256)	(0.011)

Organic	0.144***	0.629***	1.196***
	(0.046)	(0.064)	(0.071)
Label reads			
$Sugar^a$	-0.281***	-0.242***	-0.189***
	(0.025)	(0.0246)	(0.025)
$Protein^a$	0.072***	0.071***	0.061***
	(0.020)	(0.0204)	(0.020)
$Sodium^a$	-0.064***	-0.0734***	-0.076***
	(0.005)	(0.0048)	(0.005)
Fat^a	0.178***	0.181***	0.231***
	(0.056)	(0.0559)	(0.056)
Advertising			
Feature	0.117*	-1.117***	-0.342*
	(0.082)	(0.129)	(0.176)
Display	0.864***	0.448***	0.764***
	(0.177)	(0.206)	(0.202)
Fixed Effects			
County	yes	yes	yes
Month	yes	yes	yes
Brand	yes	yes	yes
Exogeneity Test for IVs			
Wu-Hausman		264.792***	
		(*p*=0.000)	
Other Statistics			
R^2	0.98		
GMM Objective			336.361
# of Observations	15,224	15,224	15,224

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. [a] Estimates are calculated using the Minimum Distance approach described in Nevo (2000b).

On average, consumers tend to dislike sugar-intensive and sodium-intensive yogurt brands as evidenced by the negative and statistically significant coefficient estimates on these two variables, *Sugar* and *Sodium*, respectively. This finding may in part reflect effective nutrition awareness campaigns of various groups and institutions. For example, Harvard Medical School suggests that sugar obtained from processed foods such as flavored yogurt, cereals, and cookies can lead to obesity, and have a serious impact on heart health.[6] Based on research, there is an

[6] https://www.health.harvard.edu/heart-health/the-sweet-danger-of-sugar, accessed (December 19, 2019).

association between higher sugar diet and a greater risk of dying from heart disease (Yang et al., 2014). According to the US Department of Health and Human Services, consuming low-sodium snacks can help to control daily sodium intake - which can help consumers to reduce the risk for high blood pressure and heart disease (Weinberger (1996)).

The coefficient estimate on the variable *Fat* is positive and statistically significant, suggesting that whole-fat content yogurts are preferred by consumers, *ceteris-paribus*. There is evidence that full-fat dairy is correlated with a decreased risk of obesity: If something has a richer flavor, you may need less of it to feel satisfied. As such, consumers' choice behavior with respect to yogurt consumption seems to be consistent with healthy nutrition recommendations.[7] Recent study shows that whole-fat dairy consumption is associated with lower risk of mortality and major cardiovascular disease events (Dehghan et al., (2018)).

Consumers are more likely to buy protein-intensive yogurt brands as evidenced by the positive and statistically significant coefficient estimate on the *Protein* variable. Eating yogurt each day can help individuals to achieve their daily protein intake.[8] If protein-intensive yogurt is chosen as a snack, research shows that there is a longer delay in requesting food; which helps to mitigate obesity (Khoury et al., (2014)). In line with these findings, our results show that protein-intensive brands incentivize consumption of yogurt.

[7] https://www.health.harvard.edu/blog/is-it-time-to-stop-skimming-over-full-fat-dairy-2019102118028, accessed (December 19, 2019).

[8] http://healthyeating.sfgate.com/much-protein-yogurt-6135.html, accessed (December 19, 2019).

1.5.2 Elasticities

Given the structural demand estimates, we compute price elasticities of demand for each differentiated product.

The average of own-price elasticities is -7.54. The estimated own-price elasticities are within the “ballpark” of estimates in previous studies on the yogurt industry. For example, Draganska and Jain (2006) estimated average own-price elasticities of -4.25, and Villas-Boas (2007) find average own-price elasticity estimates of -5.9. For consumption goods, Pinkse and Slade (2004) estimate average own-price elasticities equal to -2 for beer in the UK, Nevo (2000a) finds that own-price elasticities for ready-to-eat cereals are approximately -4 on average in the US, and Chintangunta et al. (2001) report own-price elasticities that range between -2 and -4.

1.5.3 Supply Estimates

Using demand estimates, we compute retail margins using equation (10), which are subsequently used when estimating parameters of the supply specification in equation (24).

Supply Modeling Choice with Respect to the Production of Private Labels

With the given scanner data for private label products, we do not have any information on the identity of manufacturer(s) of these products sold by retailers. As such, we need to make assumptions about the manufacturers of private label products, and estimate the supply-side model specification in equation (24) under each of the distinct assumptions. In particular, we estimate the supply-side model under each of the following two distinct assumptions:

Assumption 1: A single outside manufacturer produces all private label products carried by retailers in our data sample.

Assumption 2: Each retailer that carries private label products contracts with a unique manufacturer to exclusively produce its private label products.

Similar to the research methodology in Bonnet and Dubois (2010) and Celine and Boumra-Mechmemache (2015), we use Vuong (1989) statistical non-nested test to assess which assumption on private label production best fits our data. The computed test statistic of the Vuong test is 22.47, which is greater than 1.64, implying that at the 5% level of statistical significance for this one-tale statistical test, *Assumption 1* better fits the data compared to *Assumption 2*. Thus, we rely on the assumption that each retailer's private label is produced by a common outside manufacturer in the dataset.

To facilitate checking the robustness of our results, in Appendix A, we also report our estimation results under Assumption 2.

Bargaining Power Parameter Estimates

In Table 1.5, we provide manufacturer's bargaining power parameter estimates produced by the supply-side model specification in equation (24) under *Assumption 1*. In the table, retailers are distinguished across columns, while manufacturers are distinguished across rows. The table reports on all manufacturers in the data sample, but due to space limitation, not all retailers are reported in the table.[9] For a given manufacturer-retailer pair, the table reports the associated

[9] Upon request, we are happy to make available to the interested reader the full matrix of manufacturer-retailer pairs.

estimate of, (1 - $\lambda_{G_{fr}}$), that are strictly greater than zero. Many of the manufacturer's bargaining power parameter estimates are statistically different from zero, and differ across manufacturer-retailer pairs. Our estimates suggest that bargaining power is not an inherent characteristic of a retailer or a manufacturer, but varies depending on the identity of negotiating parties.

On average, the manufacturer's bargaining power, (1 - $\lambda_{G_{fr}}$), is a mean 0.6963, suggesting that, overall the balance of bargaining power between manufacturers and retailers in the United States yogurt industry disproportionately lies with the manufacturers. However, there exists substantial heterogeneity in relative bargaining power across manufacturer-retailer pairs. It is worth noting that bargaining power estimates for the manufacturer of private label products are a mean 0.2947, while manufacturers of national brands (all manufacturers except private label) have a mean bargaining power with retailers of 0.7101. Thus, as expected, national brand manufacturers have greater bargaining power with retailers compared to the manufacturer of private label products. These findings are consistent with the previous research suggesting that the introduction of store brands, i.e., private label products, increases retailers' bargaining power (Chintagunta et al. (2002)).

Among the manufacturers in our data sample, Turtle Mountain has the highest degree of bargaining power across retailers, with a mean level of bargaining power equal to 0.9538, followed by bargaining power levels of Redwood Farm Hill (mean of 0.9398) and Mehadrin Dairy Corp (mean of 0.9278), respectively. At the other extreme, Johanna Foods, Dean Foods, and Prairie Farms Dairy are manufacturers among the lowest-ranked with respect to bargaining power with retailers.

It is natural to expect that manufacturers with larger share of industry sales are also likely to have greater bargaining power with retailers. However, our formal empirical results in Table

1.5 clearly reveal that this is not the case. The last two columns in the table report the manufacturers' rank based on bargaining power and industry sales share, respectively. The data in these two columns reveal that the manufacturers who are ranked first, second, and third based on bargaining power are ranked ninth, sixteenth, and twenty- seventh respectively, based on the share of industry sales. In addition, manufacturers that are ranked as twenty-first, twenty-seventh, and twenty-second based on bargaining power are ranked as first, second, and third, respectively, based on the share of industry sales. A notable case in the table is Chobani, a manufacturer ranked first based on share of industry sales, but ranked twenty-first based on mean bargaining power across retailers.

	Table 1.5 Manufacturer's Bargaining Power Parameter Estimates, (1-λ), with each retailer																
Manufacturer's Name	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**	**Retailer 5**	**Retailer 6**	**Retailer 7**	**Retailer 8**	**Retailer 9**	**Retailer 10**	**Retailer 11**	**Retailer 12**	**Retailer 13**	**Retailer 14**	$1-\lambda$ (average across all retailers in the data that carry the manufacturers' products)	$1-\lambda$ rank	Industry Sales Share rank
Turtle Mountain Inc.				0.9702						0.9749	0.9461	0.8908			0.9530	1	9
				(0.2352)						(0.0243)	(0.5138)	(1.4127)					
Redwood Farm Hill	0.95042									0.9549					0.9398	2	16
	(0.08951)									(0.0248)							
Mehadrin Dairy Corp								0.9277							0.9278	3	27
								(0.5132)									
The Hain Celestial Group Inc.	0.9055			0.9568	0.8990		0.8528		0.9085	0.9085					0.9095	4	12
	(0.5504)			(0.6399)	(0.3231)		(2.8932)		(0.0491)	(0.0603)							
Green Valley Organics					0.8883										0.8883	5	29
					(0.2207)												
Groupe Danone	0.9278	0.8936	0.8464	0.8924	0.8692	0.9214	0.9567	0.9220	0.8457	0.8917	0.8490	0.8450			0.8864	6	4
	(0.69569)	(0.16113)	(0.7370)	(3.1181)	(0.2616)	(0.1087)	(0.6061)	(1.3837)	(0.2114)	(0.2121)	(5.4320)	(5.7560)					
Emmi Roth USA Inc	0.934														0.8854	7	22
	(0.2359)																
Greece By Tyra S A			0.8786												0.8797	8	21
			(0.4376)														
Maple Hill Creamery										0.8824					0.8778	9	25
										(0.2946)							
Kalona Organics									0.8762						0.8762	10	24
									(0.5706)								
Fage		0.8412				0.8408		0.8901							0.8745	11	8
		(0.6991)				(0.7028)		(1.3451)									
Liberty				0.8846	0.8753		0.9094			0.8623					0.8725	12	5
				(1.7552)	(0.0946)		(1.1594)			(0.1551)							
Wholesoy & Co	0.9096			0.8917				0.8551							0.8724	13	14
	(0.5757)			(2.2248)				(2.5903)									
Wallaby .	0.8323			0.8662	0.8570										0.8608	14	10
	(1.8403)			(2.7059)	(0.7361)												

Table 1.5 Continues

Springfield Creamery												0.8318			0.8318	15	30
												(3.5152)					
Cascade Fresh				0.8449	0.0002		0.9322			0.8853					0.8288	16	15
				(3.4913)	(10.8067)		(1.0863)			(0.0995)							
Alpina			0.7812	0.6896			0.8528				0.7857	0.8036			0.7952	17	18
			(0.6373)	(15.2373)			(2.8682)				(5.9352)	(5.4282)					
Green Mountain Creamery	0.7571														0.7557	18	23
	(3.9510)																
Whitewave Foods Company					0.7862	0.8307				0.6911	0.8054	0.8053			0.7526	19	7
					(0.3996)	(0.2763)				(0.7049)	(5.3903)	(5.3959)					
Schreiber Foods Inc											0.7373	0.7449			0.7454	20	26
											(10.8823)	(10.7586)					
Chobani	0.6715	0.7388	0.7894	0.8607	0.7633	0.7620	0.7792	0.7761	0.7886	0.0014	0.7834	0.7856	0.8432	0.8505	0.6662	21	1
	(1.1033)	(2.9676)	(4.2478)	(2.2600)	(4.8235)	(2.9450)	(4.7052)	(3.1402)	(3.0524)	(38.2292)	(12.7896)	(12.4954)	(3.3255)	(3.3638)			
General Mills	0.6616	0.6203	0.7075	0.5143	0.0005	0.6606	0.5504	0.7057	0.7499	0.4807	0.6153	0.6120			0.6336	22	3
	(6.1492)	(0.9490)	(3.4898)	(40.8564)	(9.7893)	(0.7868)	(29.2684)	(9.0571)	(3.620)0	(4.0238)	(26.2846)	(26.5827)					
Tula Foods					0.5966										0.5966	23	11
					(3.2423)												
H P Hood Inc														0.2912	0.46113	24	20
														(34.0372)			
National Dairy Holdings	0.7336		0.4565		0.5200						0.4591	0.2866			0.3964	25	28
	(3.1050)		(7.8133)		(1.1462)						(42.5767)	(74.0695)					
Tillamook Creamery							0.3166								0.3166	26	13
							65.6816										
Private Label	0.2078	0.0018		0.1250	0.0008	0.0006	0.0091	0.502		0.6837					0.2947	27	2
	(40.5333)	(28.0132)		(212.8623)	(19.7367)	(26.4724)	(198.006)	(45.386)		(1.7170)							
Johanna Foods		0.0027			0.7180	0.0003									0.2727	28	6
		(5.7240)			(0.3648)	(6.4750)											
Dean Foods													0.0296		0.0361	29	17
													(58.907)				
Praire Farms Dairy				0.00009											0.0005	30	19
				(143.1130)													

Note: Standard errors in parentheses.

The Influence of Product Line Width and Depth on Manufacturer's Bargaining Power

To gain more insight into the impact of preexisting *product line width* and *product line depth* on the bargaining power of manufacturers with retailers, we first estimate the following regression:

$$\left(1-\lambda_{fr}\right)=\sum_{f=1}^{n_f}\tau_f I_f+\sum_{r=1}^{n_r-1}\tau_r I_r+\epsilon_{fr} \qquad (25)$$

where I_f represents a zero-one dummy variable that equals to 1 only for bargaining power measures $\left(1-\lambda_{fr}\right)$ that belong to manufacturer *f* with other retailers; τ_f is a fixed effect parameter for manufacturer *f* that captures manufacturer-specific attributes that are observed as well as unobserved by us the researchers, which influence the manufacturer's bargaining power with retailers; n_f is the number of manufacturers in our data sample; I_r represents a zero-one dummy variable that equals to 1 only for bargaining power measures $\left(1-\lambda_{fr}\right)$ associated with retailer *r*; τ_r is a fixed effect parameter for retailer *r* that captures retailer-specific attributes that are observed as well as unobserved by us the researchers; n_r is the number of retailers in our data sample; and ϵ_{fr} is a mean-zero stochastic error term. Using fixed effects, note that equation (25) controls for both observed as well as unobserved manufacturer-specific and retailer-specific attributes that may influence the bargaining power of manufacturers with retailers.

Once estimates of τ_f are obtained from equation (25), we then estimate the following regression:

$$\tau_f=\rho_0+\rho_1 Product\ Line\ Depth_f+\rho_2 Product\ Line\ Width_f+\zeta_f \qquad (26)$$

where ζ_f is a mean-zero stochastic error term capturing other manufacturer-specific determinants of the manufacturer's bargaining power with retailers. The advantage of the empirical approach captured by equation (25) and equation (26) above is that we explicitly recognize and account for determinants of manufacturers' bargaining power that are unrelated to *product line depth* and *product line width*. Since we do not have information to enable computing measures of *product line width* and *product line depth* for store brand manufacturers, we exclude private label manufacturer(s) from the linear regressions in equation (25) and equation (26).

Table 1.6 presents the estimation results where there are two specifications of equation (26) distinguished only by the measure of preexisting *product line depth* used. Model 1 uses the measure *Product Line Depth – Maximum*, which as previously described is a variable measuring the number of flavors offered within the given manufacturer's largest product line. However, Model 2 uses the measure *Product Line Depth – Average*, which as previously described is a variable measuring the average number of flavors offered across the given manufacturer's product lines. The coefficient estimates in Table 1.6 suggest that a manufacturer's preexisting range of horizontally differentiated products, product line depth, driven by its strategy to extend the depth of existing product lines, has no statistically discernable impact on its bargaining power with retailers. Similarly, a manufacturer's preexisting number of distinct brands, i.e., *product line width*, has no statistically discernable impact on the manufacturer's bargaining power with retailers. In other words, the empirical evidence suggests that neither greater depth in a manufacturer's existing product lines, nor number of unique product lines have an influence on its bargaining power with retailers. Our results are robust under both assumptions regarding manufacturer(s) of private label products. Table A2 in Appendix A shows the impact of the manufacturer's characteristics on its bargaining power under Assumption 2: A unique outside manufacturer produces each private label.

These results raise the following question: If expanding *product line depth* and *product line width* have no influence on manufacturers' bargaining power with retailers, then why do so many manufacturers actively pursue product proliferation strategies? The subsequent analysis and discussion shed some light on answering this question.

Why do so many manufacturers actively pursue product proliferation strategies?

Why do manufacturers continue to introduce similar products under existing product lines? Is it because expanding product lines horizontally serves to increase the size of the profit pie that is shared with retailers? Is there also evidence that by offering broader product lines, manufacturers have the advantage to meet the needs and wants of heterogeneous consumers; and thus increase consumer demand for the manufacturer's menu of products? Our empirical analysis now provides some evidence with respect to answering these questions.

Previous theoretical research (e.g. Lancaster (1990) and Ratchford (1990)) examined the reasons for firms' decision to product proliferate, and posit the following:

- A broader product line can increase the overall demand faced by the firm.
- Instead of focusing on one product, a broader product line may yield cost advantages for the firm owing to economies of scope.
- Broad product lines can deter entry and allow an incumbent firm to increase its prices.

Table 1.6 Bargaining power as a function of manufacturer's characteristics

	(1) Model 1	(2) Model 2
Product Line Depth (Maximum)	-0.0118	
	(0.0123)	
Product Line Depth (Average)		-0.0142
		(0.0178)
Product Line Width	-0.0163	-0.0333
	(0.0334)	(0.0273)
Constant	1.100***	1.125***
	(0.0993)	(0.129)
Observations	29	29
R-squared	0.090	0.081

Notes: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

As mentioned in Connor (1981); manufacturers are choosing to apply product proliferation because they believe that new products are essential for firm growth and for financial success. In addition, Connor (1981) argues that manufacturers believe that product proliferation can broaden consumers' choice, and through market segmentation, better meets consumer demand. Developing horizontally differentiated products may also work as an effective defense strategy to maintain the market share for the manufacturer's leading products. For example, manufacturers offering unique flavors, or other unique attributes under a given brand might generate an increase in that brand's reputation among consumers (Berger et al. (2007)).

With the arguments from the theoretical research in hand, we use our measurements for manufacturers' product line depth and product line width to assess their impact on the manufacturer's variable profit, quantity sold (demand), and price-cost margins. For this part of the analysis we run the following regressions:

$$Z_{fr} = \sum_{f=1}^{n_f} \psi_f I_f + \sum_{r=1}^{n_r - 1} \psi_r I_r + \omega_{fr} \qquad (27)$$

where for economy of presentation, we define Z_{fr} to represent either variable profit, quantity sold (demand), or mean price-cost margin of each manufacturer; while the variables and parameters on the right-hand-side of equation (27) are defined similar to those in equation (25). In particular, ψ_f is a fixed effect parameter for manufacturer f that captures manufacturer-specific attributes that are observed as well as unobserved by us the researchers, which influence either the manufacturer's variable profit, quantity sold (demand), or mean price-cost margin, depending on which of these three measures Z_{fr} represents in equation (27). Once estimates of ψ_f are obtained from equation (27), we then estimate the following regression:

$$\psi_f = \kappa_0 + \kappa_1 Product\ Line\ Depth_f + \kappa_2 Product\ Line\ Width_f + \varsigma_f \qquad (28)$$

Table 1.7 report results from estimating equation (28) in cases where Z_{fr} represent either variable profit, quantity sold (demand), or mean price-cost margin of each manufacturer in the previously estimated equation (27). Results for the impact of manufacturers' product line depth and product line width on their variable profits are reported in columns (1) and (2) of the table. The results indicate that expanding product line depth increases the variable profit of manufacturers. However, increasing the number of distinct product lines does not have a statistically significant impact on the manufacturer's variable profit. In summary, even though expanding product line depth seems to have no impact on the bargaining power of a manufacturer with retailers, we find evidence that such an expansion increases the manufacturer's variable profit, no doubt owing to an expansion in the *size* of the full variable profit pie shared with retailers. As such, consistent with the theoretical literature (Lancaster (1979); Connor (1981); Quelch and Kenny (1994)), the evidence suggests that it is profit-maximizing for manufacturers to product proliferate.

Results reported in columns (3) and (4) of Table 1.7 show that a manufacturer's product line depth has a positive impact on the unit sales of its products. However, a manufacturer's product line width does not have a statistically significant effect on unit sales of its products. Again consistent with the theoretical literature (Lancaster (1979); Connor (1981); Quelch and Kenny (1994)), our empirical results suggest that offering deeper product lines with similar qualities (horizontal product differentiation) can allow better matching of products with consumers' heterogonous tastes, yielding higher demand for the given manufacturer's products.

Table 1.7 Variable profit, Quantity sold and Price-cost Margins as a function of manufacturer's characteristics

	(1) Variable Profit	(2) Variable Profit	(3) Quantity sold	(4) Quantity sold	(5) Mean Price-cost Margins	(6) Mean Price-cost Margins
Product line depth (maximum)	43.98		1,837		0.0300**	
	(36.07)		(1,318)		(0.0117)	
Product line depth (average)		87.86*		3,487*		0.0468***
		(50.61)		(1,847)		(0.0164)
Product line width	26.96	85.94	1,457	3,945	0.0184	0.0602**
	(97.95)	(77.56)	(3,578)	(2,830)	(0.0317)	(0.0252)
Constant	-2,003***	-2,291***	-79,412***	-90,434***	-0.865***	-0.989***
	(290.9)	(365.9)	(10,629)	(13,352)	(0.0940)	(0.119)
Observations	29	29	29	29	29	29
R-squared	0.103	0.150	0.140	0.187	0.337	0.366

Notes: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Last, results reported in columns (5) and (6) of Table 1.7 show that both manufacturer's product line depth and product line width has a positive and statistically significant impact on the manufacturer's mean price-cost margin charged across its menu of products. The results suggest that our finding of a positive impact of a manufacturer's product line depth on its variable profit is driven by the product line depth's influence on both unit sales and price-cost margins. Our results are robust under both assumptions regarding the manufacturer(s) of private label products. Table A3 in Appendix A shows the impact of the manufacturer's characteristics on its variable profit, quantity sold, and price-cost margins under Assumption 2: A unique outside manufacturer produces each private label.

1.6 Conclusion

In this paper, we empirically investigate how a manufacturer's offering of different branded product lines, and number of flavors under a given line, separately influences the manufacturer's bargaining power with retailers in the U.S. yogurt industry. To answer this question, we first estimated a structural econometric model to recover parameter estimates of relative bargaining power for a sample of manufacturer-retailer pairs. We then use a sequence of linear regression models to study how the estimates of manufacturers' bargaining power with retailers relate to the manufacturers' preexisting number of unique product lines, i.e., their product line width, as well as the number of horizontally differentiated products within these product lines, i.e., their product line depth. Our study contributes to the literature on determinants of bargaining power within the manufacturer-retailer vertical channel (Draganska et al. (2010); Crawford and Yurukoglu (2012); Doudchenko and Yurukoglu (2016); Bonnet and Bouamra-Mechemache (2015); Bonnet et al.

(2015); Grennan (2013); Grennan (2014); Haucap et al. (2013); Ellickson et al. (2018)), and provides new, and surprising, empirical evidence on a couple determinants.

We find that a manufacturer's range of preexisting horizontally differentiated products, *product line depth*, driven by its strategy to extend the depth of existing product lines, and a manufacturer's preexisting number of distinct brands, i.e. *product line width*, surprisingly, have no statistically discernable impact on the bargaining power of the manufacturers with retailers. These findings raise the following question: If expanding *product line depth* and *product line width* have no influence on manufacturers' bargaining power with retailers, then why do so many manufacturers actively pursue product proliferation strategies?

Even though expanding product line depth and product line width seems to have no impact on the bargaining power of a manufacturer with retailers, i.e., does not influence the manufacturer's *share* of the profit pie with retailers, consistent with the theoretical literature (Lancaster (1979); Connor (1981); Quelch and Kenny (1994)), we find evidence that such an expansion increases the manufacturer's variable profit, no doubt owing to an expansion in the *size* of the full variable profit pie shared with retailers. As such, the evidence suggests that it is profit-maximizing for manufacturers to product proliferate. Also consistent with the theoretical literature, we find evidence suggesting that a manufacturer's product line depth has a positive impact on its unit sales across its menu of products. Furthermore, our findings suggest that the positive impact of a manufacturer's product line depth on its variable profit is driven by the product line depth's influence on both unit sales and price-cost margins charged.

Our analysis provides other interesting results. First, we find that the balance of bargaining power between manufacturers and retailers in the United States yogurt industry disproportionately lies with the manufacturers. However, there exists substantial heterogeneity in relative bargaining power across manufacturer-retailer pairs. Second, while it is natural to expect that manufacturers with larger share of industry sales are also likely to have greater bargaining power with retailers, our empirical results clearly reveal that this is not the case. From a policy perspective, an implication of this finding is that competition authorities will need to sharpen their focus case-by-case when assessing bargaining power, and not be unduly influenced by the relative size of the manufacturer in the industry. Last, as expected, the evidence suggests that national brand manufacturers have greater bargaining power with retailers compared to manufacturer of private label products.

1.7 References

Bayus, B. L., & Putsis, W. P. (1999), “Product Proliferation: An Empirical Analysis of Product Line Determinants and Market Outcomes”, *Marketing Science*, 18(2): 137-153.

Berger, J., Draganska, M., & Simonson, I. (2007), “The Influence of Product Variety on Brand Perception and Choice”, *Marketing Science,* 26(4): 460–472.

Berry, S. T. (1994), “Estimating discrete choice models of product differentiation”, *The RAND Journal of Economics*, 25(2): 242-262.

Berry, S., & Pakes, A. (2001), “Additional information for: comments on alternative models of demand for automobiles by Charlotte Wojcik”, *Economics Letters*, 74(1): 43-51.

Berry, S., Levinsohn, J., & Pakes, A. (1995), “Automobile prices in market equilibrium”, *Econometrica,* 63(4): 841- 890.

Berry, S. T., & Haile, P., A. (2014), “Identification in Differentiated Products Markets Using Market Level Data”, *Econometrica,* 82(5): 1749-1797.

Bonnet, C. & Dubois, P. (2010), “Inference on vertical contracts between manufacturers and retailer allowing for nonlinear pricing and resale price maintenance”, *The RAND Journal of Economics,* 41(1):139-164.

Bonnet, C. & Bouamra-Mechemache, Z. (2015), “Organic Labeling and Bargaining Power in the French Fluid Milk Sector”, *American Journal of Agricultural Economics,* 98(1): 113-133.

Bonnet, C. and Boumra-Mechemache, Z. & Molina, H. (2015), “Brand Portfolio as a Source of Bargaining Leverage: An Empirical Analysis”, *Working Paper*. Toulouse School of Economics, Toulouse, France.

Crawford, G. S., & Yurukoglu, A. (2012), “The Welfare Effects of Bundling in Multichannel Television Markets”, *American Economic Review,* 102(2): 643-685.

Chintagunta, P. K., Bonfrer, A., & Song, I. (2002), “Investigating the Effects of Store-Brand Introduction on Retailer Demand and Pricing Behavior”, *Management Science,* 48(10): 1242-1267.

Connor, J. M. (1981), “Food Product Proliferation: A Market Structure Analysis”, *American Journal of Agricultural Economics,* 607-617.

Doudchenko, N., & Yurukoglu, A. (2016), “Size Effects and the Bargaining Power in the Multichannel TV Industry”, *Working Paper*.

Draganska, M. & Jain, D. C. (2005), “Product Line as a Competitive Tool”, *Journal of Economics & Management Strategy,* 14(1): 1-28.

Draganska, M. & Jain, D. C. (2006), "Consumer Preferences and Product-Line Pricing Strategies: An Empirical Analysis", *Marketing Science*, 25(2): 164-174.

Draganska, M., Klapper, D. & Villas-Boas, S. (2010), "A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel", *Marketing Science*, 29(1), 57-74.

Dehghan, M., Mente, A., Rangarajan, S., Sheridan, P., Mohan, V., Iqbal, R., Gupta, R., Lear, S., Wentzel-Viljoen, E., Avezum, A., Lopez-Jaramillo, P., Mony, P., Varma, R. P., Kumar, R., Chifamba, J., Alhabib, K. F., Mohammadifard, N., Oguz, A., Lanas, F., Rozanska, D., Bostrom, K. B., Yusoff, K., Tsolkile, L. P., Dans, A., Yusufali, A., Orlandini, A., Poirier, P., Khatib, R., Hu, B., Wei, L., Yin, L., Deeraili, A., Yeates, K., Yusuf, R., Ismail, N., Mozaffarian, D., Teo, K., Ananda, S. S., Yusuf, S. (2018), "Assocication of Dailty Intake with Cardiovascular Disease and Mortality in 21 Counties from Five Continents (PURE)", *Lancet* , 392: 2288-97.

Ellickson, P.B., Kong, P., & Lovett, M.J. (2018), "Private Labels and Retailer Profitability: Bilateral Bargaining in the Grocery Channel", *Working Paper*.

Grennan, M. (2013), "Price Discrimination and Bargaining: Empirical Evidence from Medical Devices", *American Economic Review*, 103(1): 145-177.

Grennan, M. (2014), "Bargaining Ability and Competitive Advantage", *Management Science*, 60(12): 3011-3025.

Haucap, J., Heimeshoff, U., Klein, G., J., Rickert, D., & Wey, C., (2013), "Bargaining power in manufacturer-retailer relationships", Düsseldorf Institute for Competition Economics (DICE) Discussion Paper, No. 107.

Kadiyali, V., Vilcassim, N. & Chintagunta, P. (1998), "Product Line Extensions and Competitive Market Interactions: An Empirical Analysis", *Journal of Econometrics*, 89(2): 339-363.

Kekre, S. & Srinivasan, K. (1990), "Broader Product Line: A Necessity to Achieve Success?", *Management Science*, 36(10): 1216-1231.

Khoury, D. E., Brown, P., Smith, G., Berengut, S., Panahi, S., Kubant, R., & Anderson, H. (2014), "Increasing the protein to carbohydrate ratio in Yogurt Consumed as a Snack Reduces Post-Consumption Glycaemia Independent of Insulin", *Clinical Nutrition*, 33(1): 29-38.

Lancaster, K. (1979), "Variety, Equity, and Efficiency", New York: Columbia University Press.

Lancaster, K. (1990), "The Economics of Product Variety: A Survey", *Marketing Science*, 9(3): 189-206.

Marx, L. M., & Shaffer, G. (1999), "Predatory Accommodation: Below- Cost Pricing Without Exclusion in Intermediate Goods Markets", *The RAND Journal of Economics,* 30(1): 22-43.

Misra, S. and Mohanty, S. K. (2006), "Estimating Bargaining Games in Distribution Channels", *Working Paper.* Simon Graduate School of Business, University of Rochester.

Moorthy, K. S. (1984), "Market Segmentation, Self-Selection, and Product Line Design", *Marketing Science,* 3(4): 288-307.

Mussa, M. & Rosen, S. (1978), "Monopoly and Product Quality", *Journal of Economic Theory,* 18: 301-317.

Nevo, A. (2000a), "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry", *The RAND Journal of Economics,* 31(3): 395-421.

Nevo, A. (2000b), "A Practitioner's Guide to Estimation of Random Coefficients Logit Models of Demand", *Journal of Economics and Management Strategy,* 9(4): 513-548.

Petrin, A. (2002), "Quantifying the Benefits of New Products: The Case of Minivan", *Journal of Political Economy,*110 (4): 705-729.

Pinkse, J. & Slade, M. E. (2004), "Mergers, Brand Competition and the Price of A Pint", *European Economic Review,* 48(3): 617-643.

Quelch, J. A., & Kenny, D. (1994), "Extend Profits, Not Product Lines. Make Sure All Your Products are Profitable", 2nd Edition, Harvard Business Review On Point Collection.

Ratchford, B. (1990), "Commentary on "Marketing Applications of the Economics of Product Variety", *Marketing Science,* 9(3): 207-211.

Villas-Boas, S. B. (2007), "Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data", *Review of Economic Studies,* 74(2): 625 - 652.

Villas- Boas, J.M. (1998), "Product Line Design for a Distribution Channel", Marketing Science 17(2): 156-169.

Weinberger, M. (1996), "Salt Sensitivity and Blood Pressure in Humans", *Hypertension,* 27(3): 481-490.

Yang, Q., Zhang, Z., Gregg, E.W., Flanders, W.D., Merritt, R., & Hu, F. B, (2014), "Added Sugar Intake and Cardiovascular Diseases Mortality Among US Adults", *JAMA Internal Medicine,* 174(4): 516-524.

Chapter 2 - Introduction of Greek Yogurt and Its Market Impacts on U.S. Yogurt Industry

2.1 Introduction

New product introductions that extend the firm's product line have become a popular competition strategy. Yogurt is produced and consumed worldwide, and its popularity has increased in recent years. In the U.S., the per capita consumption of yogurt has risen from 3.6 pounds per person in the year 1984 to 14.9 pounds per person in the year 2014, a 313 percent increase. [10]

Greek yogurt is differentiated from regular yogurt during the straining process: It is 1.5 more time strained than regular yogurt on average, resulting in the removal of most liquid whey. Thus, compared to regular yogurt, Greek yogurt has more protein, fewer carbohydrates, and is thicker and stronger in flavor- making it more a healthy snack. In response to pro-health changes in tastes and preferences of consumers, producers have started supplying healthier food products. The dynamism of yogurt market, new flavors, packaging, production technologies, also kept consumers interested in this category, have helped broaden yogurt's appeal as a breakfast item, snack, dessert or a meal replacement.

With the entrance of Chobani in 2007, the popularity of Greek yogurt has risen widely in the United States. Although there has been an extensive amount of research regarding the impacts of the introduction of a new product/or brand in different types of industries, there has been no previous empirical research regarding the market impacts of the introduction and rise in popularity

---

[10] https://aei.ag/2020/02/23/u-s-dairy-consumption-trends-in-9-charts/, accessed (May 3, 2020).

of Greek yogurt. As such, a key objective of our study is to empirically analyze the market impacts that Greek yogurt has had on other types of yogurts.

To achieve our objectives, we first estimate the differentiated- products consumer demand using a discrete choice model. The estimated demand parameters and the assumption about the strategic behavior of competing firms in the industry are used to recover price elasticities and marginal cost. Similar in spirit to Petrin's (2002) work, we use the estimated model to perform counterfactual experiments designed to assess the market impact of Greek yogurt on other types of yogurt.

Our empirical model suggests that consumers tend to prefer Greek-type yogurts more compared to Non-Greek-type yogurts. In addition, consumers' socioeconomic status plays an important role in their yogurt consumption: Lower-income households consume more Greek-style yogurt than their high-income households. We find that, on average, consumers are responsive to changes in the price of yogurt products. In particular, consumers are more price-sensitive when consuming Greek-type yogurts.

The counterfactual analysis result shows that Greek-type products result in lower prices of Non-Greek-type products by a mean 39.85%. In addition, the introduction of Greek-type yogurt results in higher quantity demand for Non-Greek type yogurt products by a mean 45.22%. These findings are showing that the presence of Greek-type yogurt indeed increases the consumption of Non-Greek type yogurt products due to lower prices. In addition, the introduction of Greek yogurt decreases the fraction of consumers choosing not to purchase yogurt products by a mean 1.12%, which shows that the presence of Greek-type yogurt products has an expansionary market effect in the U.S. yogurt market.

A number of economic and marketing studies examined the yogurt industry. Most studies are applied to the U.S. yogurt market, based on consumer-level data and limited to some brands to answer questions regarding consumer demand and supply side (Villas-Boas and Winer (1999); Anderson and De Palma (2001); Chintagunta et al. (2001); Ackerbeg (2001)). Later, studies analyzing the yogurt industry adopt market level data to analyze consumer's multiple purchases to measure satiation of different offerings (Kim et al. (2002); Villas-Boas (2007); Giacomo (2008)). There are also studies using the yogurt industry to analyze product entry and exit (Rosetti (2018)). Given recent changes in the U.S. yogurt industry, our study focuses on a better understanding of the introduction and the rise in Greek yogurt's popularity on other types of yogurts in the market. Our paper also contributes to the existing set of empirical evidence on product introduction on market power in dynamic markets.

The rest of the paper is organized as follows: Section 2 provides a description of the data; Section 3 outlines the econometric model of the yogurt market; Section 4 explains the estimation and identification strategies; Section 5 discusses the results. Section 6 provides the main conclusions of the paper.

2.2 Data

This study primarily uses data made available by the U.S. marketing firm, Information Resources Inc. (IRI). IRI collected data by using scanning devices from a sample of stores belonging to different retail chains located in various areas of the U.S. The data consist of weekly prices and the total sales of almost all brands of yogurt sold in the U.S. We use data from year 2008 to 2012.[11]

---

[11] Data are available from 2001 to 2012.

We chose to delineate the geographic market areas by county, which is often a smaller geographic area compared to IRI designated geographic market areas. In our study, each market is defined as the unique combination of county, month, and year. Each product in the dataset is defined as a unique combination of non-price characteristics, such as yogurt style (Greek vs. non-Greek), brands, flavor/scent, organic information, and packaging type. We aggregate weekly data up to monthly sales and dollar value revenue from sales for each product in each market. The average retail product prices are computed by dividing monthly sales revenue by monthly unit sales.

We use a discrete choice demand model similar to Villas-Boas (2007), which requires computing product shares, as well as the share of an outside option in each market. First, we describe how potential market size is measured in this study, which is used in computing product shares and the share of the outside option in each market. Following Villas-Boas (2007), we assumed that per capita yogurt consumption for each individual in the U.S. is half of the per capita yogurt consumption per month. After obtaining the population of each county from the Bureau of Labor Statistics (BLS), we multiplied the number of the adult population with half of the per capita yogurt consumption, which yields the measure we use for potential market size for each defined market, respectively. The observed share associated with each product in a given market is computed by dividing the product's unit sales by the market's potential size measure. The observed share of the outside option is computed as one minus the sum of observed shares across products within a given market. Table 2.1 lists and defines the variables used in the analysis.

Table 2.1 Description of available variables

Name	**Description**
Price	Average monthly price in dollar per ounce.

Market Share (S_j)	Monthly market share for each product are computed as the total quantity sold divided by the potential market size.
Feature count	Counts feature(s) (i.e., frequent shopper program, large size advertisement) occurred for product during that month.
Display count	Counts the special display(s) (e.g. end aisle, lobby) occurred for each product during that month.
Sugar	Sugar price per ounce.
Milk	Milk price per ounce.
Yogurt Style	Dummy=1 if the product is Greek yogurt, zero otherwise.

For the empirical analysis, we need to supplement the IRI dataset with data on non-price product characteristics and consumer demographics. Assuming an individual's income and the number of kids in a household are presumably relevant to his/her demand for yogurt, we have drawn income and the number of children information of consumers from the U.S. Census Integrated Public Microdataset Sample (IPUMS). Our model considers the interactions of consumer demographics with the price and selected non-price product characteristics, such as yogurt style, i.e., Greek versus non-Greek style.

Table 2.2 provides descriptive statistics for single-pack, 6-ounces yogurt products over the years 2008 to 2012. The average price of yogurt per ounce is $0.145. Data on cost shifting variables, price of milk[12] and sugar[13], obtained from the United States Department of Agriculture (USDA) database. The cost-shifting variable relates more closely to manufacturers' cost.

[12] https://www.nass.usda.gov/Charts_and_Maps/graphics/data/pricemk.txt, accessed (February 23, 2020).

[13] https://www.ers.usda.gov/data-products/sugar-and-sweeteners-yearbook-tables.aspx, accessed (February 23, 2020).

Table 2.2 Descriptive Statistics of single-pack, 6-ounces yogurt products

Description	Mean	S.E.	Min	Max
Average price ($/ounce)	0.145	0.0005	0.05	0.55
Aggregate sales (ounces)	1430.75	17.93	6	274176
Sugar prices (cents/ounce)	63.3752	0.019	67.9	69.6
Milk prices (cents/ounce)	3.4687	0.0003	2.979	3.961
Feature	0.6962	0.0005	0	8
Display	0.0431	0.0007	0	8

2.3 Econometric Model of the Yogurt Market

We model the market for yogurt using a structural model of demand and strategic behavior of retailers and manufacturers. The empirical strategy is as follows. First, we estimate consumers' preferences in the yogurt market. Consumers in a market face a choice set that includes the offers of different yogurt products, and each product is defined as a combination of non-price characteristics. Using demand parameter estimates, along with an assumed static Nash equilibrium price-setting behavior of firms, we recover product level price-cost margins. In the final step of the empirical methodology, we perform a counterfactual experiment in which we artificially remove Greek-type yogurt products from the consumers' choice set and measure the model predicted price changes in Non-Greek yogurt products and consumers' Non-Greek type yogurt consumption.

2.3.1 Demand Model

We use a random coefficients logit model to estimate the demand and related price elasticities (Berry and Pakes (2001)). Suppose there are M markets, $m=1,...,M$ and in each market, there are L_m potential consumers. A typical consumer *i* can choose to either buy one of the *J* differentiated products, *j=1,. . .,J* or otherwise choose the outside good 0 (*j*=0), allowing for the possibility of consumer *i* not buying one of the *J* marketed goods. Therefore, consumer *i* chooses between *J+1* alternatives in market *m*. Consumer *i*'s conditional indirect utility for the outside good is $u_{i0} = \varepsilon_{i0m}$, while for products *j=1,. . .,J* it is:

$$U_{ijm} = x_{jm}\beta_i + \alpha_i p_{jm} + county_m + v_{month} + \tau_{year} + \rho(yogurt\_style * \tau_{year}) + product_j + \xi_{jm} + \varepsilon_{ijm} \quad (1)$$

where in equation (1), x_{jm} is a vector of observed non-price product characteristics. The parameter vector β_i contains consumer-specific valuations for the product characteristics. Parameter α_i captures consumer-specific disutility of price. p_{jm} is the price of yogurt per ounce; $county_m$ captures county-specific fixed effects; v_{month} captures month fixed effects; τ_{year} captures year fixed effects; $yogurt\_style * \tau_{year}$ is the interaction between zero-one dummy variable *yogurt_style* that takes a value of one when the relevant product is classified as "Greek yogurt" and year, with associated parameter vector ρ; $product_j$ captures product-specific fixed effects; and ξ_{jm} is the unobserved (by the econometrician) brand characteristics (i.e., quality, reputation, etc.) that have an impact on consumer utility, whereas ε_{ijm} is a mean-zero stochastic error term.

The distribution of consumer-specific taste parameters, β_i and α_i , is specified as follows

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \phi D_i + \Sigma\vartheta_i \quad (2)$$

In Equation (2), α and β parameters are the mean marginal utilities of respective observable product characteristics. D_i is an *m*-dimensional column vector of demographic variables, while ϑ_i is a *k*-dimensional column vector that captures unobserved consumer characteristics. ϕ is a $k \times m$ matrix of parameters that measure how taste characteristics vary with demographics, and Σ is a $k \times k$ diagonal matrix with the standard deviations, σ_k, on the diagonal that measures the variation in tastes due to random shocks. In our estimation, we consider income and the number of children residing within a household as demographic variables, and we expressed the demographic variables in deviation from their respective mean. Thus, the mean of D_i is zero. Following Nevo (2000b), we assume that ϑ_i has a standard multivariate normal distribution, $\vartheta_i \sim N(0,1)$. The assumptions regarding D_i and ϑ_i along with equation (2) imply that, the mean of α_i is α, and the mean of β_i is β, while variances of these consumer-specific marginal utilities are equal to the square of the elements on the main diagonal of Σ.

We can break down the indirect utility into a mean utility, $\delta_{jm} = x_{jm}\beta + \alpha p_{jm} + county_m + v_{month} + \tau_{year} + \rho(yogurt\_style * \tau_{year}) + product_j + \xi_{jm}$, and a deviation from this mean utility $\mu_{ijm}(x_{jm}, p_{jm}, D_i, \vartheta_i; \phi, \Sigma) = [p_{jm}, x_{jm}](\phi D_i + \Sigma\vartheta_i)$. As such, the indirect utility can be re-written as:

$$U_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm} \tag{3}$$

For computational tractability, the idiosyncratic error term ε_{ijm} is assumed to be governed by an independent and identically distributed extreme value density. Individual *i*'s probability of buying product *j* in market *m* is as follows:

$$s_{ijm} = \frac{\exp\,(\delta_{jm} + \mu_{ijm})}{\sum_{k=0}^{J_m} \exp\,(\,\delta_{km} + \mu_{ikm})} \tag{4}$$

The market share of product *j* in market *m* is given by:

$$s_{jm} = \int \frac{\exp\left(\delta_{jm} + \mu_{ijm}\right)}{\sum_{k=0}^{J_m} \exp\,(\,\delta_{km} + \mu_{ikm})} d\widehat{F(D)} dF(v) \tag{5}$$

where d$\widehat{F(D)}$ and $dF(v)$ are population distribution functions for consumer demographics and random taste shocks assumed to be independently distributed. For the integral in Equation (5), there is no closed-form solution. Thus, it must be approximated numerically by using random draws from $\widehat{F(D)}$ and $F(v)$.

Finally, the demand for product *j* is given by:

$$d_{jm} = L_m \times s_{jm}(x, p, \xi; \theta_d) \tag{6}$$

where in equation (6), L_m is a measure of market size in a given county; $s_{jmt}(x, p, \xi; \theta_d)$ is the model predicted share of product *j*; x, p, and ξ are vectors of observed non-price characteristics, price and the unobserved vector of product characteristics, respectively; and θ_d=(α, β, $\rho, county_m, v_{month}, \tau_{year}, \rho\left(yogurt\_style * \tau_{year}\right),\ product_j, \phi, \Sigma$) is a vector of demand parameters to be estimated.

2.3.2 Supply Side

Suppose there are $f = 1,2, \dots, F$ firms. Assuming that firms simultaneously choose prices as in static Bertrand-Nash model, where each firm f offers a subset of differentiated, F_f, of the *J* products. Thus, in each market, the firm *f*'s variable profit is given by

$$\pi_f = \sum_{j \in F_f} \left(p_{jm} - mc_{jm}\right) \times \; q_{jm}\,(\boldsymbol{p}) \tag{7}$$

in equilibrium the quantity of yogurt product *j* that gets sold in market *m*, q_{jm}, is exactly equal to the market of this product, i.e. q_{jm}= $L_m \times s_{jm}$ ($\boldsymbol{p}$). Recall that L_m is a measure of potential market size; $s_{jm}(\boldsymbol{p})$ is the predicted market share function for product *j*; and $\boldsymbol{p}$ is a vector of the prices for the *J* products in market *m*; mc_{jm} is the marginal cost of product *j* in market *m*.

The price of product *j* produced by firm *f* must satisfy the first- order condition:

$$s_j(\boldsymbol{p}) + \sum_{j \in F_f} \left(p_j - mc_j\right) \frac{\partial s_r(p)}{\partial p_j} = 0, \qquad \forall\, j \tag{8}$$

Market subscripts are suppressed in equation (8) and many subsequent equations to avoid a clutter of notation. The system of equations in equation (8) can be expressed in matrix form as follows:

$$\boldsymbol{s}(\boldsymbol{p}) + (\Omega * \Delta)(\boldsymbol{p} - \boldsymbol{mc}) = 0 \tag{9}$$

where $\boldsymbol{s(p)}$, $\boldsymbol{p}$, and $\boldsymbol{mc}$ are $J \times 1$ vectors of market share, prices and marginal costs respectively, whereas $\Omega * \Delta$ is an element- by- element multiplication of two matrices.

Ω is a $J \times J$ matrix that describes firms' ownership structure of the J products. Let Ω_{jr} denote an element in Ω, where

$$\Omega_{jr} = \begin{cases} 1 & \text{if there exists f: } \{\text{j, r}\} \subset F_f \\ 0 & \text{Otherwise} \end{cases}$$

In other words, Ω_{jr}=1 if products *j* and *r* are produced by the same firm, otherwise $\Omega_{jr} = 0$. Δ is a $J \times J$ matrix of first- order partial derivatives of product market shares with respect to prices, where element $\Delta_{jr} = \frac{\partial s_j(.)}{\partial p_r}$.

Using equation (9), product level markup estimates can be show as follows:

$$\boldsymbol{markup} = \boldsymbol{p} - \boldsymbol{mc} = -(\Omega * \Delta)^{-1}\boldsymbol{s(p)} \tag{10}$$

Equation (10) above implies that product level markup estimates depends on exclusively on demand side parameter estimates. Using the computed product- level markups and product prices, product-level marginal cost can be recovered as follows:

$$\widehat{\boldsymbol{mc}} = \boldsymbol{p} - [-(\Omega * \Delta)^{-1}\, \boldsymbol{s(p)}] \tag{11}$$

2.4 Estimation and Identification

To estimate the set of demand parameters, we use generalized methods of moments (GMM) following the previous literature [Berry (1994); Berry, Levinson and Pakes (1995) (BLP); Nevo (2000a); and Petrin (2002)]. The general strategy is to derive parameter estimates such that the observed product shares S_{jm} are equal to predicted product shares s_{jm}.

Instruments

To obtain consistent estimates of price coefficients, α_i, instrumental variables are required because when firms are setting their prices, they consider not only the product characteristics observed by us the researchers, x_{jm}, but also the product characteristics, ξ_{jm}, that are not observed by us the researchers, but observed by all consumers. Firms also take into account any changes in the product characteristics and consumer valuations.[14] To mitigate the endogeneity problem, we include product and market fixed effects. However, instruments for retail product prices are needed to deal with endogeneity problems that may remain even after controlling for product and market fixed effects.

In constructing one set of retail product price instruments, we assume that input prices are uncorrelated with the unobserved econometric error, ξ_{jm}, but highly correlated with retail price. The justification for this assumption is that consumers' brand loyalty across yogurt products is most likely uncorrelated with the prices of inputs in the production of yogurt, e.g. prices of milk, sugar, strawberry, electricity etc., but these input prices do influence the retail price of yogurt

[14] Villas-Boas (2007).

[Villas-Boas (2007)]. In addition, the intensity with which each input is used is likely to vary across yogurt brands. For example, some yogurt brands may use relatively more sugar than others; some brands may use more electricity for extra processing; only some brands use strawberry etc. As such, a change in price of a given input is likely to differentially influence production cost and therefore retail prices across yogurt brands. To allow input price to have differential production cost effects across brands of yogurt, we interact input prices with product dummies, and use these interaction variables as instruments for retail price. In fact, the brand “Chobani” focuses on high protein Greek-style yogurt, which is likely to consume more milk in processing and less sugar than regular yogurt. Therefore, the milk and sugar consumption would be different between the Greek yogurt brands such as “Chobani” and the regular yogurt brands “Yoplait”. Thus, the monthly milk and sugar prices interacted with the brand dummies are instruments for the endogenous retail price of yogurt. The monthly price of milk and sugar information is obtained from the U.S. Department of Agriculture.

Further, as shown by Berry and Haile (2014), the heterogeneity in consumer preferences for product characteristics creates an endogeneity problem that arises from the interaction of unknown demand parameters with market shares. The mean utilities that equate observed shares to predicted shares and the income terms will also be correlated with the unobserved error term. To mitigate this source of endogeneity, first, we define "count" variables of advertising characteristics for each product, i.e. number of times within the relevant month each product has been featured and specially displayed. This type of advertising information can be obtained from the data for each product to construct BLP type instruments. Then, we compute mean advertising counts across yogurt-type (Greek versus non-Greek type) products within each market, which facilitates computation of the deviation of each product’s advertising characteristic count from the relevant mean across similar yogurt-type products. We use deviation of each product's advertising characteristic count as instruments in demand estimation. Deviation of each product's advertising characteristic count from the relevant mean across similar yogurt-type products are likely to be correlated with products' market shares because consumers' preferences are likely to be influenced by differences in advertising intensities across products.

To identify parameters governing consumer heterogeneity, we use the interaction of mean income with the input costs (price of sugar and milk) and brand dummies as instruments.

2.5 Empirical Results

2.5.1 Demand

Standard Logit Model of Demand

The first and second columns in Table 2.3 present the coefficient estimates from the linear regression of mean utility $\delta_j = \log(S_{jm}) - \log(S_{0jm})$ on various product and market characteristics, which is the standard logit specification of the demand model. Coefficient estimates of the standard logit specification of the demand model in columns 1 and 2 of Table 2.3 are obtained using ordinary least squares (OLS) and two-stage least squares (2SLS) estimation procedures, respectively. The estimates of price coefficients from OLS and 2SLS are negative and statistically significant. As mentioned before, price is an endogenous variable in demand estimation. Hence, OLS estimation in column 1 of Table 2.3 produces biased and inconsistent estimate of the price coefficient. To eliminate the endogeneity problem of price, we re-estimate the demand equation using 2SLS. The Wu-Hausman exogeneity test rejects the exogeneity of price at conventional levels of statistical significance, and suggests the instruments used are necessary.

Random Coefficients Logit Model of Demand

Results from the random coefficients logit (RCM) specification of the demand model are presented in columns (3), (4), (5) and (6) of Table 2.3. The coefficient estimate of price in the RCM model is negative and statistically significant at conventional levels of statistical significance. Column (4) reports parameters that capture consumer taste variation unobserved by the researchers for various product characteristics. The estimated effects are statistically and economically significant, suggesting that consumers are heterogeneous with respect to their marginal disutility for price changes of yogurt products.

Consumers tend to prefer yogurt products that are Greek within each year. This result is evident from the positive and statistically significant coefficient estimate on the *yogurt_style**τ_{year} interaction variable. Furthermore, the negative and statistically significant coefficient on the interaction variable of *yogurt_style* with household *income* suggests that lower-income consumers have relatively stronger preferences for Greek-style yogurt. The positive but not statistically significant coefficient estimate on the interaction of *the Greek* dummy with *Number of Children* indicates families with or without kids are indifferent in choosing between Greek versus Non-Greek type yogurt products.

The positive and statistically significant coefficient estimates on the advertising characteristics, *Feature* and *Display* suggest that advertised yogurt products are associated with higher levels of utility compared to not advertised yogurt products, *ceteris-paribus*.

Table 2.3 Demand estimation results

	Standard Logit		Random Coefficients Logit			
	OLS	2SLS	GMM			
	Mean Coef	Mean Coef	Mean Coef	Standard Deviations	Demographic Interactions	
	(α, β)	(α, β)	(α, β)	(σ)	(Income)	(N. Child)
Price	-11.018***	-18.809***	-30.973***	7.250***	2.324***	
	(0.064)	(0.0183)	(0.904)	(0.387)	(0.152)	
Constant	-10.064***	-8.803***	-7.576***	-0.093		
	(0.129)	(0.137)	(0.148)	(0.251)		
Yogurt Style (Greek=1)				0.237	-0.394***	0.147
				(0.323)	(0.179)	(311179.6)
Yogurt Style (Greek=1)*Year(=2008)	-0.307***	0.390***	0.491***			
	(0.059)	(0.063)	(0.142)			
Yogurt Style (Greek=1)*Year(=2009)	0.065*	0.976***	1.110***			
	(0.048)	(0.054)	(0.126)			
Yogurt Style (Greek=1)*Year(=2010)	0.422***	1.643***	1.594***			
	(0.100)	(0.108)	(0.270)			
Yogurt Style (Greek=1)*Year(=2011)	0.335***	1.060***	1.354***			
	(0.019)	(0.024)	(0.083)			
Yogurt Style (Greek=1)*Year(=2012)	0.335****	0.830***	1.161***			
	(0.048)	(0.023)	(0.179)			
Advertising						
Feature	0.521***	0.274***	0.226***			
	(0.018)	(0.019)	(0.0216)			
Display	1.476***	1.506***	1.471***			
	(0.048)	(0.050)	(0.0498)			
Fixed Effects						
County	yes	yes	yes			
Month	yes	yes	yes			
Year	yes	yes	yes			
Brand	yes	yes	yes			
Exogeneity Test for IVs						
Wu-Hausman		128703.848***				
		(p=0.000)				
Other Statistics						
R^2	0.934					
GMM Objective			29475.33			
# of Observations	188,074	188,074	188,074			

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.5.2 Elasticities:

Given the structural demand estimates, we compute price elasticities of demand for each differentiated product. Table 2.4 summarizes the estimated own-price elasticities by yogurt type. The average of own-price elasticities is -3.27, statistically significant at a 1% level. This result implies that a one percent increase in the price of yogurt products, on average, decreases the quantity consumed by 3.27%.

The estimated own-price elasticities are in line with previous studies. For example, Draganska and Jain (2006) estimated average own-price elasticities of -4.25, and Villas-Boas (2007) find average own-price elasticity estimates of -5.9. For consumption goods, Pinkse and Slade (2004) estimate average own-price elasticities equal to -2 for beer in the UK, Nevo (2000a) finds that own-price elasticities for ready-to-eat cereals are approximately -4 on average in the US, Chintangunta et al. (2001) report own-price elasticities that range between -2 and -4.

Table 2.4 Average Own- price Elasticities

All products	Own- Price Elasticity
Greek	-4.380 (0.004)
Non-Greek	-2.979 (0.002)
Average All	-3.237 (0.002)

Note: Standard error of the means reported in parentheses.

2.5.3 Estimated Markup and Marginal Cost:

Table 2.5 reports summary statistics on prices, computed markup and recovered marginal costs for a single pack, six-ounces yogurt. Each reported summary statistics in Table 2.5 has an associated sample standard error of mean reported in parentheses. The reported means of markup and marginal costs are statistically significant at the 1% level.

Table 2.5 Estimated marginal cost and markup for a single pack, 6-ounces yogurt

	Product Markup	**Marginal Cost**
yogurt type	Mean (SEM)	Mean (SEM)
Greek	0.0509 (0.0001)	0.1682 (0.0003)
Non-Greek	0.0419 (0.00002)	0.1283 (0.0002)
Average All	0.0435 (0.00002)	0.1015 (0.0001)

Note: Standard error of the means reported in parentheses.

On average, we observe the mean computed markup from Bertrand- Nash equilibrium is higher for Greek yogurt. The estimated marginal costs are on average $0.1015 per ounce and include retailers' costs and markup; which can be expected to be relatively high due to the short shelf life of the product.

2.5.4 Counterfactual Experiment

Product innovation is essential to the economic growth and development of accurate measures of the welfare gains from the introduction of new goods and the improvement in the quality of existing products is the aim of many studies.

From the firm side, the incentives to introduce new brands come from the possibility of enjoying some transitory market power. Arrow (1962) and Schmalensee (1978) argue that product proliferation can deter entry. On the other hand, a comprehensive theoretical analysis of the imperfect competition and new goods is incomplete ((Breshnahan and Gordon, 1997)). One can expect that the new good is going to decrease the prices of competing goods, but there are no obvious prevailing effects concerning the price of the other brands of the introducer: Those prices could either fall -a cannibalization effect prevails-, or rise -the new brands allow the firm to enjoy some market power ((Breshnahan and Gordon, 1997)).

In 2007, Chobani, currently one of the leading competitors in the U.S. yogurt market, introduced Greek-type yogurt. Within a few years, the company commands 37.6% of the Greek yogurt market and 19.8% of the total spoonable yogurt market.[15] Given the success of the introduction of a new type of yogurt, in this study, we would like to answer the question of "What would happen to the US yogurt market if we removed the Greek type yogurt?" and assess the impact of the introduction of Greek yogurt empirically on other types of yogurts. To find the answer, we perform a counterfactual analysis where we remove the Greek yogurt products artificially from the choice set of consumers.

Given the supply model in Section 2.3.2., let $\Omega^{counterfactual}$ be a matrix that describes the counterfactual ownership structure of the yogurt industry. Predicted counterfactual equilibrium prices, p^*, solve:

$$\boldsymbol{p}^* - \widehat{\boldsymbol{mc}} = -\left(\Omega^{counterfactual} * \Delta\right)^{-1}\boldsymbol{s}(\boldsymbol{p}^*) \tag{12}$$

Using the new equilibrium price vector, counterfactual predicted demand for Non-Greek type yogurts are calculated as follows:

$$\boldsymbol{d}^* = L \times \boldsymbol{s}(\boldsymbol{p}^*) \tag{13}$$

Interpretation of the Counterfactual Analysis

[15] http://www.smartbrief.com/s/2017/03/nielsen-chobani-leads-us-yogurt-market-share , accessed (May 3, 2018).

Table 2.6 shows the predicted mean price change among Non-Greek products, predicted change in the quantity of Non-Greek yogurt products, and predicted change in the quantity of outside option.

The prices of Non-Greek-type yogurt products are predicted to increase by a mean 39.85% when Greek-type yogurt products are counterfactually removed. This evidence suggests that the presence of Greek-type products results in lower prices of Non-Greek type products.

The counterfactual experiment results suggest that the expanded yogurt demand is shared by both types of yogurt products. In particular, our model predicts that markets experiencing a decrease in quantity demand for Non-Greek-type yogurt products by a mean 45.22% due to the counterfactual elimination of Greek-type yogurt products. This prediction implies that the presence of Greek yogurt products results in higher quantity demand for Non-Greek type yogurt products. With this finding in hand, rather than cannibalizes, the presence of Greek-type products expands the yogurt market.

The evidence of the market expansion effect is inferred from the predicted changes in quantity demanded for the outside option. Recall that the outside option is the fraction of consumers not choosing to purchase any yogurt products. The predicted increase in quantity demanded of the outside option by a mean 1.12% implies that the presence of Greek-type yogurt products results in lower quantity demand for the outside option. A lower quantity demand for the outside option implies an expanded demand for the yogurt products in our data. Therefore, the presence of Greek-type yogurt products has a market expansionary effect within markets in our data.

Table 2.6 Counterfactual Outcomes and their Interpretation

Predicted Mean Price Change among Non-Greek products	Predicted Change in Quantity of Non-Greek products	Predicted Change in Quantity of Outside Option	Evidence of Market Expansion Effect	Evidence of Cannibalizing effect of Non-Greek products presence on Greek Demand
Increase	**Decrease**	**Increase**	**Yes**	**No**
%Δ in Price	%Δ in Quantity	%Δ in Outside option		
39.8529 (3.1024)	-45.2293 (4.3817)	1.1156 (0.1576)		

Note: Standard error of mean percentage change in parentheses.

Demand Transfer Ratio

We may also use a measure we call a demand transfer ratio to interpret the counterfactual outcomes. The demand transfer ratio measures the change in quantity demand of the outside option as a proportion of the quantity of the product(s) counterfactually eliminated from the market. Let us recall the commonly known diversion ratio that measures the fraction of consumers who switches from a product to an alternative due to an increase in the product's price. Here, our demand ratio is not equivalent but similar in spirit to a diversion ratio. In the case of demand transfer ratio, the stimulus for the demand transfer is the elimination of product(s), rather than a marginal price increase of the eliminated product(s), and the demand transfer explicitly measured is to an outside option rather than to products that were not eliminated from the demand system.

The time series plot for the mean demand transfer ratio is shown in Figure 2.1. After the removal of Greek-type yogurt from the markets selling Greek-type yogurt, the change in quantity demand of outside option as a proportion of the quantity of Greek-type products artificially removed, demand transfer ratio (R), is greater than 1. Among all possible scenarios presented in

Table 2.7, our calculated mean demand transfer ratio satisfies Scenario 1. Let's examine the outcomes of a mean demand transfer ratio below:

Table 2.7 Using Demand Transfer Ratio, *R*, to Interpret Counterfactual Outcomes

Scenario	*Demand Transfer Ratio*: Predicted Quantity Change in Outside option divided by Quantity of Single-cup Products Eliminated	Evidence of Market Expansion Effect	Evidence of Market Shrinkage Effect	Evidence of Demand-increasing effect on Auto-drip Products due to the Presence of Single-cup products.	Evidence of Cannibalizing effect of Single-cup products presence on Auto-drip Demand
1	*R > 1*	*Yes*	*No*	*Yes*	*No*
2	*R = 1*	*Yes*	*No*	*No*	*No*
3	*0 < R < 1*	*Yes*	*No*	*No*	*Yes*
4	*R = 0*	*No*	*No*	*No*	*Yes*
5	*R < 0*	*No*	*Yes*	*No*	*Yes*

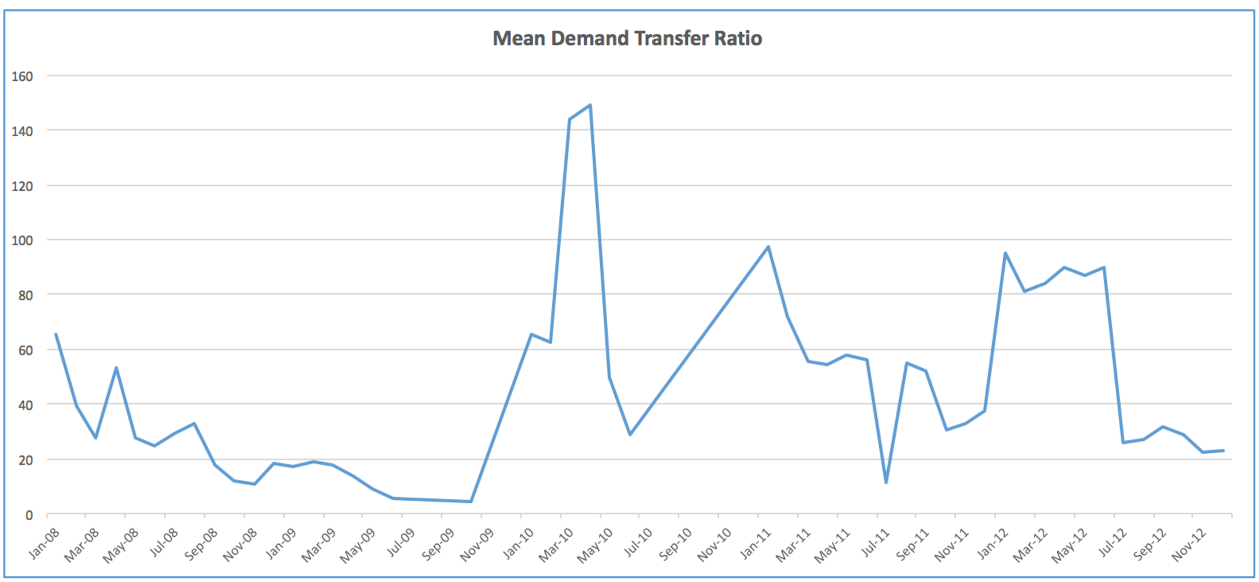


Figure 2.1 Mean demand transfer ratio by month and year over time

- **Evidence of market expansion effect**

A demand transfer ratio greater than one, i.e., R>1, means that the quantity of outside option is predicted to increase due to the counterfactual elimination of Greek-type yogurt products. In other words, the presence of Greek-type yogurt products causes the quantity of outside option to be smaller than it would be otherwise.

- **Evidence of Demand-increasing Effect on Non-Greek Products due to the Presence of Greek-type products**

When the demand transfer ratio is greater than one, i.e., R>1, there is evidence of the expanded yogurt demand shared by both types of yogurt styles, i.e., Greek versus Non-Greek. The portion of Non-Greek yogurt demand transferred to the outside option due to the counterfactual elimination of Greek-type products is a measure of the demand increasing impact the presence of Greek-type yogurts has on Non-Greek yogurt products. In other words, the presence of Greek yogurt products causes the demand for Non-Greek type products to be larger than it would be otherwise.

- **Evidence of cannibalizing effect of Non-Greek products on Greek-type demand**

When the demand transfer ratio is greater than one, i.e., R>1, there is no cannibalizing effects on Non-Greek yogurt demand associated with the presence of Greek-type yogurt products. The reason is that when Greek-type yogurt products are counterfactually eliminated, the demand transfer ratios greater than one implies that all the demand for Greek-type yogurt products is transferred to the outside option. In other words, no portion of the demand for Greek-type yogurt products displaces demand for Non-Greek-type yogurt products since none of the Greek-type demand switches to Non-Greek products when Greek-type yogurt products are counterfactually eliminated.

Overall, demand transfer ratio results are consistent with our findings with respect to change in predicted price, quantity demand, and outside option of Non-Greek products after the removal of Greek-style yogurt products.

2.6 Conclusion

This paper considers the recent introduction and rise in popularity of Greek yogurt in the U.S. yogurt industry and analyzes its market impacts on the yogurt industry with a structural econometric model. The empirical methodology begins with estimating the demand side parameters in a structural econometric model of differentiated products of consumer choice. With the consumer's preference parameters in hand, we then performed a counterfactual experiment in which we artificially removed Greek-type products from consumers' choice set and measured the model's predicted changes in prices and quantity demanded Non-Greek type products.

Our empirical model suggests that consumers tend to prefer Greek-type yogurts compared to Non-Greek type yogurts. In addition, consumers' socioeconomic status plays an important role in their yogurt consumption: Lower-income households consume more Greek-style yogurt than their high-income households. On average, consumers are more responsive to price changes in Greek yogurt products compared to non-Greek types.

The counterfactual analysis result shows that Greek-type products result in lower prices of Non-Greek-type products by a mean 39.85%. Due to the counterfactual elimination of Greek yogurt products, Non-Greek type yogurt products experience a decrease in their quantity demand by a mean 45.22%. This prediction implies that the presence of Greek yogurt products increases the quantity demand for Non-Greek type yogurt products. After the introduction of Greek yogurt, the outside option decrease by a mean 1.12%. A lower quantity demand for the outside option implies an expanded demand for yogurt products. Therefore, the presence of Greek-type yogurt products has an expansionary market effect.

Our analysis reveals that the introduction of Greek yogurt expanded the U.S. yogurt market, increased the consumption of Non-Greek type yogurt, and lowered yogurt prices.

2.7 References

Ackerbeg, D. (2001) “Empirically distinguishing informative and prestige effects of advertising.” *The RAND Journal of Economics,* 32:316-333.

Arrow, K. (1962) “Economic Welfare and the Allocation of Resources to Innovation.” *The Rate and Direction of Incentive Activity,* Universities- National Bureau Conference Series, No.14, New York: Arno Press.

Berry, S. (1994) “Estimating discrete choice models of product differentiation.” *RAND Journal of Economics,* 25:242-262.

Berry, S., & Pakes, A. (2001) “Additional information for: comments on alternative models of demand for automobiles by Charlotte Wojcik.” *Economics Letters,* 74:43-51.

Berry, S., & Pakes, A. (2007) “The pure characteristics demand model” *International Economic Review,* 48(4):1193-1225.

Berry, S., Levinsohn, J., & Pakes, A. (1995) “Automobile prices in market equilibrium.” *Econometrica,* 63:841- 890.

Bresnahan, T., & Gordon, R. (1996) “Valuation of New Goods under Perfect and Imperfect Competition. In The Economics of New Goods” *University of Chicago Press,* 207-248

Bresnahan, T., & Schmalansee, R. (1987) “The empirical renaissance in industrial economics: an overview.” *Journal of Industrial Economics,* 35: 371-378.

Chintagunta P., Kyriazidou E., Perktold J. (2001) “Panel data analysis of household brand choices.” *Journal of Economics,* 103:111–153.

Giacomo, M. D. (2008) “GMM estimation of a structural demand model for yogurt and the effects of the introduction of new brands.” *Empirical Economics,* 34:537-565.

Hausman, J. A., & Leonard, G. K. (2002) “The Competitive Effects of a New Product Introduction: A Case Study.” *The Journal of Industrial Economics,* 50(3): 237-263.

Hausman, J. (1999) “Cellular Telephone, New Products, and the CPI.” *Journal of Business and Economic Statistics,* 17 (2):188-194. 28

Kim, D. (2004) “Estimation of the Effects of New Brands on Incumbents’ Profits and Consumer Welfare: The U.S. Processed Cheese Market Case.” *Review of Industrial Organization,* 25:275–293.

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

Nevo, A. (2000b) “A Practitioner’s guide to estimation of random coefficients logit models of demand.” *Journal of Economics and Management Strategy*, 9:513-548.

Nevo, A. (2001) “Measuring market power in the ready-to-eat cereal industry.” *Econometrica*, 69:307-342.

Nevo, A. (2003) “New Products, Quality Changes, And Welfare Measures Computed from Estimated Demand Systems.” *The Review of Economics and Statistics*, 85 (2): 266–275.

Petrin, A. (2002) “Quantifying the benefits of new products: the case of Minivan.” *Journal of Political Economy*, 110:705-729.

Pinkse J., & Slade M.E. (2002) “Mergers, brand competition and the price of a pint.” *European Economics Review*, 48:617–643

Rosetti, J.(2018) “Product Variety in the U.S. Yogurt Industry.” Manuscript. *Ohio State University.*

Schmalansee, R. (1972) “Entry deterrence in the ready-to-eat breakfast cereal industry.” *The Bell Journal of Economics*, 9(2): 305-327.

Steven, B., Levinsohn, J., & Ariel, P. (1995) “Automobile Prices in Market Equilibrium.” *Econometrica*, 63: 841- 890.

Villas-Boas, J., & Winer, R. (1999) “Endogeneity in brand choice models.” *Management Science*, 45:1324–1338.

Villas-Boas, S. (2007) “Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data.” *Review of Economic Studies*, 74 (2):625-6

Chapter 3 - License Suspension for Default Laws, Cohort Default Rates, and Student's College Choice

3.1 Introduction

The amount of outstanding student loan debt continues to rise and currently stands at $1.71 trillion (The Board of Governors of the Federal Reserve System (2021a)). Student loan default is an important policy concern; for example, the *Coronavirus Aid, Relief, and Economic Security Act* (CARES Act) allows the U.S. Department of Education to suspend payments on student loans, stop collections on defaulted loans and use a 0% interest rate due to economic challenges surrounding the COVID-19 pandemic (Federal Student Aid (2021)). One policy aimed at reducing student loan default that has received little attention by researchers is the 1990 recommendation by the U.S. Department of Education that states should *"deny professional licenses to defaulters until they take steps to repayment"* (Farrell (1990)). Since this recommendation was made, several states have implemented policies to deny, revoke or suspend various licenses due to student loan nonpayment. These laws are referred to as *"License Suspension for Default Laws"* (LSD laws).[16] The types of licenses may include occupational licenses (for example, teaching or nursing), and in some states it even includes a driver's license.

Policymakers in states implementing LSD laws argue that the threat of losing a license is a powerful incentive to continue making timely student loan payments; hence, they are a way to decrease student loan default. Opponents of such laws argue that they are counterproductive, as

[16] Here after we use LSD laws and policy interchangeably for license suspension for default laws.

revoking occupational licenses or drivers' licenses will only make it harder to financially be able to repay and will thus increase student loan default. Thus, it is important to empirically estimate the impact of LSD laws on default behavior.

We first estimate the extent that cohort default rates (CDRs) of colleges influence students' school enrollment choice, and how LSD policies further influence this relationship. Since there are numerous costs associated with defaulting on a student loan, one may wish to attend colleges with lower CDRs since it may indicate that it will be easier to repay one's own student loan debt after leaving school.

Even though LSD laws may increase students' awareness of CDRs when making a college choice, the impact of LSD laws on CDRs is not determined solely by students' response to the policy, but also by schools' response. Bound and Turner (2017) show that larger cohorts have lower college completion rates because of reductions in per-pupil resources. These reductions in degree completion could then increase CDRs since Dynarski (2016) finds student loan default is an earnings problem and not a debt problem. So, even when students respond to LSD laws by being more diligent to avoid loan default, school's response (or lack thereof) in relation to per-pupil resources can counter students' response, causing the net impact of the LSD policy on cohort default rates to be either negative or positive, a feature of LSD policy that has not been studied and documented in the literature. Thus, the relative strength of the behavioral responses of students and schools will determine the impact of the policy on CDRs. We therefore contribute to the literature by estimating a behavioral model of the impact of LSD laws that considers both student and school responses.

Our analysis relies heavily on tools and techniques popularly used in the empirical industrial organization literature. We first estimate the preference parameters of a structural empirical model of students' college choice. We use variation across states and across times in implementation of LSD laws to identify structural preference parameters that capture the impact of LSD laws on students' school choice. Our empirical finding suggests that a colleges' cohort default rate negatively influences students' choice of attending the college. This is consistent with Cellini, Darolia, and Turner (2020) which shows large negative impacts on enrollment resulting from CDR related sanctions being imposed. Furthermore, mean elasticity estimates from our school choice model reveal that in making their college enrollment choice, students become almost 75% more sensitive to schools' cohort default rate when LSD laws are active compared to if these laws were repealed. Our model estimates also suggest that the socioeconomic status of students plays a significant role in their college choice. Based on our findings, students from high-income households have a stronger preference for enrolling in colleges with relatively lower cohort default rates compared to their low-income peers.

The estimated structural model is then used to perform counterfactual policy analyses in which we repeal the LSD laws from adopting states and measure the predicted impact on schools' CDRs. Our empirical findings suggest that the policy has mixed results on CDRs as we would theoretically expect. In some states, schools' response to the policy counters and dominates the students' response, causing an increase in their cohort default rates by a mean 5.57%. While, in other states, students' response to the policy counters and dominates the schools' response, causing a decrease in their cohort default rates by a mean 29.42%. From a policy efficacy perspective, our results suggest that it is important that policymakers consider behavioral responses of both students and schools when evaluating LSD laws' effect on cohort default rates.

Our analysis contributes to the literature on why people default on student loans. Abraham, Filiz-Ozbay, Ozbay and Turner (2020) and Cox, Kreisman and Dynarski (2020) focus on the role of the choice of repayment plan in experimental settings. Abraham et al. (2020) find that framing of plans matters for whether income-based plans are more appealing than the standard plan and Cox et al. (2020) find that people pick sub-optimal plans due to automatically being defaulted into a plan and staying with the default. Herbst (2020) also studies the role of income-based repayment plans but instead focuses on the role of student loan servicing companies. Using a leave-one-out IV strategy he finds that having a more helpful customer service representative leads to increases in income-driven repayment plans and reductions in delinquencies. Barr, Bird and Castleman (2019) conduct an experiment at a community college in which students could have one-on-one assistance from a loan counselor. While it was successful at reducing student loan debt, the intervention led to increased student loan default as well. This finding of lower amounts of student loans leading to increased default is consistent with the findings in Black, Denning, Dettling, Goodman, and Turner (2020) which used variation in student loan limits across time to estimate effects. We thus contribute to this literature by documenting that LSD laws impact default.

Another strand of the higher education literature studies school choice and its relationship to socioeconomic status using empirical industrial organization tools (Hastings et al (2009); Brand and Xie (2010); Dillon and Smith (2013); Ajayi (2011)). While sharing a similar methodological approach to this strand of the higher education literature, our study differs in the following ways: (*i*) use of state-level varying policy adoption on student loan default; (*ii*) consideration of cohort default rate as a school attribute that influences students' college choice; (*iii*) the inclusion of household income, race, and gender as observed sources of students' preference heterogeneity; and (*iv*) using institution-level data as oppose to individual-choice data to draw inference on preference parameters that drive students' school choice behavior.

The rest of the article is organized as follows. Section 2 provides background on License Suspension for Default Laws, consequences of student loan default and CDRs. Section 3 introduces the College Scorecard data set. Section 4 describes both the difference-in-differences strategy that motivates the structural model and the structural model. Section 5 explains the estimation and identification strategies. Section 6 discusses the results. Section 7 provides the main conclusions of the paper.

3.2 Background

3.2.1 License Suspension for Default Laws

In the 1990s, the U.S. Department of Education recommended that states adopt laws requiring regulatory boards to suspend professional licenses, and even drivers' licenses, if the board received notice from an education commission informing them an applicant held outstanding student loans that were not being paid. Since then, 23 states have implemented some form of license suspension for default (LSD) law (National Consumer Law Center (2014)). Some states have since repealed their law. Table 1 provides a list of states implementing and some subsequently repealing LSD laws with effective dates.

The National Conference of State Legislators (NCSL) and National Consumer Law Center report that some states only revoke licenses for defaulting on a state student loan. In contrast, other states using LSD laws consider default on any federal or state student loan as a trigger for applying punitive consequences under these laws. For example, in Alaska, Georgia, Hawaii, Iowa, Kentucky, Massachusetts, Tennessee, and Texas, LSD laws require all occupational boards to revoke licenses for defaulting on any federal or state education loan. In contrast, Louisiana, and Mississippi only revoke licenses if the professional has defaulted on an education loan issued by the state (Wagner (2018)). This is an important distinction given the recent federally proposed legislation to end these practices. Sibilla (2019) reports that Senator Rubio and Senator Warren re-introduced the Protecting JOBs Act which would ban states from revoking, denying, or suspending state licenses for defaulting on a student loan made, insured, or guaranteed under Title IV. Since state loans are completely separate from Title IV, defaulting on state loans would still be subject to these state laws.

The type of licenses that are impacted by LSD laws vary by the state. For example, Arkansas, California, Mississippi, Minnesota, and Florida revoke only health care professionals' licenses for defaulting on education loans. In Arkansas and Mississippi, the laws are applied to state health care education loans and scholarship agreements. On the other hand, Iowa and South Dakota suspend all the state-issued licenses, including drivers and recreational hunting licenses.

Table 3.1 States that revoke licenses for unpaid student loans

States	Law is active since	Law is repealed
Alaska	2011	2018
Arkansas	2012	-
California	2003	-
Florida	2016	-
Georgia	2010	-
Hawaii	2002	-
Illinois*	1996	2018
Iowa	2013	-
Kentucky	2002	2019
Louisiana	1990	-
Massachusetts	2006	-
Minnesota	2001	-
Mississippi	1999	-
Montana	1999	2015
New Jersey	1999	2016
New Mexico	1993	2020
North Dakota	2014	2018
Oklahoma	2014	2016
South Dakota	2015	-
Tennessee#	1999	2018
Texas	2005	-

Virginia	2003	2018
Washington	1996	2018

Note: *Silver-Greenberg, Cowley and Kitroeff (2019) report Illinois started their policies in the 1980s while the National Consumer Law Center reported the start being 1996. Bregel (2011) reports Tennessee only started enforcing their law in 2009 after an audit required them to do so.

There is also variation in how strictly LSD laws are enforced. The National Conference of State Legislator (NCSL)[17] and Wagner (2018) reported that "Boards in Louisiana, Tennessee and Texas, are considered to be more aggressive with enforcement, while officials in Alaska, Iowa, Hawaii, and Massachusetts have said their LSD laws are not being enforced." Unfortunately, available data are not sufficient to show how many of these default notices result in license suspension, as enforcement is up to state boards. Silver-Greenberg, Cowley, and Kitroeff (2017) report using public records requests to get some information about LSD law usage. They were able to find 8,700 instances of the laws being used in recent years, although caution that this measure is likely underestimating the true impact.

3.2.2 Costs to Non-payment Aside from LSD Laws

Students may try to avoid schools with higher CDRs even in the absence of LSD laws because of numerous costs to defaulting on a student loan. For example, when borrowers default on their federal student loan, the federal government can garnish their wages, seize their tax refunds, impose collection costs, initiate litigation, and restrict borrowers from receiving additional federal student aid or Social Security benefits (Looney (2019)). Gaulke and Reynolds (2020) show that becoming delinquent on a student loan (missing a payment) results in a drop in Equifax Risk

[17] https://www.ncsl.org/research/labor-and-employment/license-suspension-for-student-loan-defaulters.aspx, accessed (February 18, 2021).

Scores (Equifax's version of a credit score) of around 50-60 points. This means that it will be much harder to get a new line of credit and would also be considerably more costly to do so.

Internet search data provide some evidence that individuals are interested in knowing the negative consequences of defaulting on student loans. For example, Figure 3.1 shows the "interest over time" of Google searches looking up: "What happens when you default on a student loan?" [18] Google Trend, measured on the vertical axis, captures the "interest over time" in the search phrase described above, with the highest value being 100, corresponding to peak popularity; a value of 50 corresponding to half of peak popularity, and a value of zero meaning not enough internet data for the searched phrase.

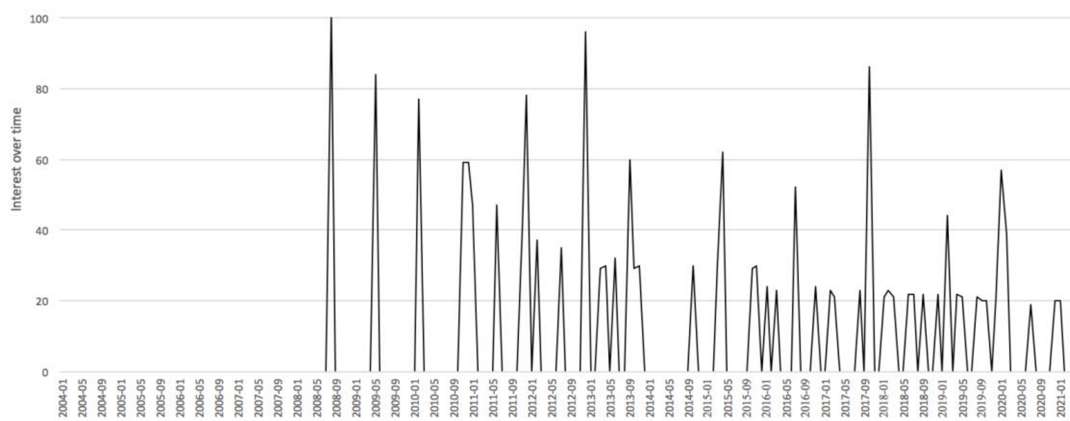


Figure 3.1 Google search trend for "What happens when you default on a student loan?" since 2004.

[18] https://trends.google.com/trends/explore?date=all&geo=US&q=what%20happens%20when%20you%20default%20on%20a%20student%20loan, accessed (April 3, 2021).

3.2.3 Why Schools Care about Student Loan Default: Cohort Default Rates

(Two-year) CDRs are calculated as the percentage of federal student loan borrowers who enter repayment in a fiscal year and default by the end of the next fiscal year.[19] The United States Department of Education releases CDR data once per year. Nationally, CDRs average around 9 percent and have steadily increased since 2005 (Looney (2011)).

College and universities should care about their CDRs. Having too high of a CDR can result in their students losing access to federal financial aid. For example, if a college's cohort default rate hits 30% for three consecutive years, or 40% in a given year, then students at that institution would no longer be able to receive federal Pell Grants or borrow federal student loans, which could substantially increase the cost of attendance (Webber and Rogers (2014); Hillman (2015); Jaquette and Hillman (2015)). Second, Cellini, Darolia, and Turner (2020) use variation in CDR related sanctions across schools and time to show that it negatively impacts student enrollment. Specifically, after a for-profit school receives a sanction there is a 68% decrease in annual enrollment and much of that is offset by students attending public schools instead.

3.3 Data

The dates for states implementing and repealing LSD laws come from a variety of sources. While the National Consumer Law Center (2014) had dates through 2014, to obtain more recent dates we had to compile information from many other sources. These sources include Justia (2006), Justia (2014), New Jersey Legislature (2016), Montana Legislature (2015), House of

[19] https://www2.ed.gov/offices/OSFAP/defaultmanagement/cdr.html, accessed (April 3, 2021).

Washington State (2017), North Dakota Legislature (2014), Sibilla (2019), Gettings, St. George, Piepgrass, Wingfield and Shachmurove (2018), Wagner (2018), Dieterle, Weissman and Watson (2018), Walker (2017), and Hicks (2015).

The rest of the data come from the College Scorecard, which is available through the United States Department of Education College Scorecard database.20 This database was developed during the Obama Administration, and debuted in 2015 as a website tool to provide additional information to potential college students. The Department of Education provides underlying university-level data dating back to the 1996-1997 academic year and updates the data annually. The data on student loans are aggregated based on the National Student Loan Data System, which is used by the federal government to administer financial aid. General information about the universities come from the Integrated Postsecondary Education Data System (IPEDS). IPEDS is an annual survey of institutions that are eligible, or applying to be eligible, for federal financial aid. A unit of observation in our data sample is a school in a particular year.

In terms of sample selection, we focus on schools that are offering four-year tertiary education programs mainly because of the way we construct the market share. Since we assume the set of potential students is based on the number of high school graduates in each state across time, this assumption is more realistic for the four-year sector than the two-year sector in which there are many more non-traditional students. We drop observations for which an institution's total student enrollment is not reported, as this prevents constructing the observation value of a key outcome variable for our empirical model. In addition, we remove observations that do not report cohort default rate, as this is a key control variable of interest in our empirical model. As previous

[20] https://collegescorecard.ed.gov/data/, accessed (February 18, 2021).

research has shown that for-profit schools are associated with higher rates of student loan default, implying that it is important to know the type of school, we drop observations that do not report the level of control with respect to public, private, or for-profit. Lastly, we remove universities that aggregate payment outcomes across multi-branch campuses, and universities that do not receive financial aid. The resulting sample contains 2,045 universities across 50 states and the District of Colombia, of which, 581 are public four-year, 1,222 are private non-profit, and 242 are private for-profit universities.

Due to concerns over schools `gaming the system' related to two-year CDRs, starting in FY2009 the Department of Education began evaluating universities based on three-year cohort default rates. After this change, the College Scorecard continued to report the two-year cohort default rate through FY2010; however, the subsequent years only included the three-year cohort default rate. Due to the change in the cohort default metric, we restrict our sample to years in which the two-year cohort default rate in the available - years FY1996 to FY2010.

Given the years of data available to us, the states that are identifying the treatment effects of LSD laws are California, Georgia, Hawaii, Kentucky, Massachusetts, Minnesota, Mississippi, Montana, New Jersey, Tennessee, Texas, and Virginia. In other words, these are the states that have implemented LSD laws at some point during the time span of our sample period.

Gross et al. (2009), Kelchen and Li (2017), Scott-Clayton (2018), Hillman (2014) show that students' household income, parental education level, and race/ethnicity influence their school choice. To consider the influence of socioeconomic status on college choice, we supplement the College Scorecard data with demographic data on household income, race, and gender from the U.S. Census Integrated Public Microdataset Sample (IPUMS). Table 2 provides descriptive statistics on our variables, and Table 3 shows summary statistics for school characteristics by type in our sample.

In our study, students are facing a choice set that includes alternate 4-year colleges within their state, *s*, at time, *t*. Thus, each choice set, or tertiary educational market, is defined as a unique combination of state and year. Given 14 years of data and 50 states with the District of Columbia, there are 714 defined tertiary educational markets. Each student chooses whether to enroll in a college by observing various characteristics of each school that includes its type (public, private for-profit, private non-profit), cohort default rate, and various attributes observable to the student but unobservable to us the researchers.

We use a discrete choice model similar to discrete choice models of demand found in the Empirical Industrial Organization literature (for example, see Berry (1994); Berry, Levinsohn and Pakes (1995); Nevo (2000); and Villas-Boas (2007)). In our setting, the discrete choice model requires computing school enrollment market shares, as well as the share of students who choose the outside option in each state for a given year. The outside option includes choosing not to attend a 4-year college within the defined tertiary educational market in which the student's household is located. Since we want to capture the extent to which students' school choice is influenced by colleges' cohort default rate, and the state's implementation of LSD laws, we restrict our focus to samples of students choosing to remain within the state after college graduation. The logic is that if student *i* choosing college *j* in state *s* when LSD law is active in time *t*, then LSD law would bind and have an impact on the student after graduation. To obtain the percentage of students staying within the state after graduation, we use IPUMS data and focus on individuals within age group 21- 24 with a college degree, and their residency information five years prior.

To define the potential enrollment size within a defined tertiary educational market, we follow the scaling factor methodology used by Ivaldi and Verboven (2005), which involves computing the potential enrollment size by scaling up the actual state by year student enrollment by a factor. Using the fact that from year 2000 through year 2017, 44% of high-school graduates enrolled in four-year institutions, we set our scaling factor to 2.272 (= 1/0.44), and use this scaling factor for computing the potential enrollment size in each defined tertiary educational market. The observed enrollment share associated with each school in a given state and year is computed by dividing the school's total undergraduate within-state enrollment level by the potential enrollment. After calculating the observed enrollment shares of each school (i.e., the observed probability of choosing each school within a given state in a given year), the share of the outside option is simply one minus the sum of the observed shares across schools within a given state and year.

3.4 Econometric Model of the Education Market

Our empirical methodology begins by using reduced-form regression equations to investigate whether schools in states with LSD laws differ in their cohort default rates. The reduced-form regression equations rely on a difference-in-differences identification strategy driven by variations in states' timing of LSD policy implementation. Motivated by evidence from the reduced-form regression analyses, we then formally specify and estimate a structural model of students' college preferences, where each student faces a choice set that includes different type colleges with varying cohort default rates, as well as the outside option of not choosing one of the colleges within the student's tertiary educational market. With the estimated school choice preference parameters in hand, we then recover the elasticity of students' college enrollment choice with respect to cohort default rate. In the final step of the empirical methodology, we perform counterfactual policy analyses in which we artificially remove the LSD laws in states that have them and measure the model-predicted changes in CDRs and responsiveness of students' college enrollment with respect to the cohort default rate.

Table 3.2 Summary statistics

Description	Mean	S.D.	Min	Max
Federal Student Loan Interest Rate	6.626	1.922	3.28	8.99
Inflation Rate	2.403	0.93	-0.355	3.839
Unemployment Rate	5.579	1.838	2.5	13.7
Per Capita Income	33589.17	7345.532	18836	63582
Household Income	89317.33	100.9213	55496.89	179202.2
Gender	0.513	0.49	0	1
Race	0.77	0.42	0	1

Notes: For the zero-one dummy variable, Gender, females are coded as 1. The zero-one dummy variable, Race, categorizes individuals as either being white or non-white, with white being coded as 1.

Table 3.3 Institution Characteristics by type

	All Institutions (n=2045)		Public (n=581)		Private Non-profit (n=1222)		Private For-profit (n=242)	
Description	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Default Rate	0.0528	(0.044)	0.0552	(0.0381)	0.0464	(0.0444)	0.0949	(0.0519)
Undergraduate Enrollment	4325.88	(5932.20)	9331.554	(7642.51)	1982.51	(2346.76)	1671.17	(3940.57)
%Women	0.5667	(0.1513)	0.5541	(0.0961)	0.5834	(0.1562)	0.4853	(0.2456)
%Men	0.4332	(0.1513)	0.4458	(0.0961)	0.4165	(0.1562)	0.5146	(0.2456)
Undergraduate Enrollment (Within State)	2992.274	(4120.814)	6473.319	(5333.997)	1370.904	(1610.247)	1079.027	(2579.392)

3.4.1 Reduced-form Regression Analysis: Difference-in-Differences

We first use reduced-form regressions to test whether the implementation of LSD laws impacts schools' cohort default rates. The identification comes from differences across states regarding whether and when they implement the law. Specifically, we are comparing differences in schools' cohort default rate over time in the treated states with differences in schools' cohort default rate over time in the control states. We use the following reduced-form regression model specification:

$$CDR_{jst} = \pi LSD_{st} + M_{st}\rho + year_t + school_j + \theta_s t + \varsigma_{jst} \qquad (1)$$

where in equation (1), CDR_{jst} represents the cohort default rate at school j located in state s in year t. LSD_{st}, our main variable of interest, is a state-by-year dummy variable that switches from "0" to "1" in the year of LSD law implementation and remains a "1" in the years after implementation provided the laws are not repealed. π is our reduced-form parameter of interest that captures the impact of LSD laws on CDR rates. $school_j$ captures school-specific fixed effects; M_{st} is a vector of controls including state-by-year unemployment rates, state-by-year per capita income, and state-by-year merit scholarship status, with associated parameter vector ρ. Macroeconomic conditions could also impact student loan default, so we also include year fixed effects ($year_t$). We also control for state-specific linear time trends with ($\theta_s t$). Standard errors are clustered at the state given that is the level at which these licensing policies took effect.

It is important to recognize that the reduced-form parameter, π, in equation (1) nests the behavioral responses of both students and schools to implementation of the LSD policy. In the event that schools' behavioral response to the policy counters students' response, then the sign of π may be either negative or positive depending on the relative strengths of the behavioral responses from the two groups. A key reason for expanding the analysis to include a structural model is to disentangle the behavioral responses of students from schools to allow for a better understanding of the impacts of the policy. However, a good starting point is to get a sense of what the reduced-form parameter estimates of π look like.

Our methodological framework is analogous to a typical demand and supply model used for analyzing equilibrium market outcomes resulting from simultaneous shifts in demand and supply. For example, consider $Q^d = f(p, X^d; \Theta_d)$ and $Q^s = f(p, X^s; \Theta_s)$ as representing the structural market demand and supply equations, respectively, where Q^d and Q^s represent quantity demand and quantity supply, respectively; p represents price; X^d a vector of demand shifting variables; Θ_d a vector of structural demand parameters; X^s a vector of supply shifting variables; and Θ_s a vector of structural supply parameters. Imposing the market equilibrium condition, $Q^d = Q^s$, allows us to equate the structural demand and supply equations, the result of which can yield a reduced-form price equation, $p = f(X^d, X^s; \pi)$, where π is a vector of reduced-form parameters that nests combinations of the structural parameters, i.e., $\pi = f(\Theta_d, \Theta_s)$.

In applying the market demand and supply modelling framework to our present study, CDR_{jst} is the equivalent of market price, and therefore $p = f(X^d, X^s; \pi)$ is analogous to reduced-form equation (1) above. In addition, $Q^d = f(p, X^d; \Theta_d)$ is analogous to the student school choice side of the structural model we subsequently specify, while $Q^s = f(p, X^s; \Theta_s)$ analogous to the school attribute choice side of the structural model. A situation of importance for our study is that X^d and X^s share a common variable, which in our study is the LSD policy variable. Furthermore, the LSD policy variable impacts $Q^d = f(p, X^d; \Theta_d)$ based on a subset of structural parameters in Θ_d, while impacting $Q^s = f(p, X^s; \Theta_s)$ based on a subset of structural parameters in Θ_s. As such, when we obtain an estimate of reduced-form parameter, π, from equation (1) above, it nests the structural impacts of the LSD policy through $\pi = f(\Theta_d, \Theta_s)$. Therefore, subsequently obtaining estimates of all parameters in Θ_d and Θ_s should provide deeper insights on the impacts of the LSD law policy.

The results from the difference-in-differences reduced-form regressions are shown in Table 4. In column (1) of Table 3.4, we report the average effect of the LSD laws on the CDRs for schools located in states with active LSD laws. The reduced-form parameter estimate capturing the average policy effect in column (1) does not reveal any evidence of average difference in changes in schools' CDR in states with LSD laws versus states without LSD laws. In column (2), we break out the average policy effect by states. These results now show clear heterogeneity across states such that some states have overall higher CDRs after LSD implementation and other states have overall lower CDRs after implementation. As such, the reduced-form estimates reveal that the LSD policy has mixed results on impacting CDR, which is contrary to a key goal of the policy of reducing student loan default. To better understand reasons for these mixed reduced-form results, we now turn to our structural model of students' school choice.

Table 3.4 Differences- in- differences on CDR

	(1)	(2)
	CDR	CDR
On Average	0.00268	
	(0.00312)	
California (LSD=1)		0.00354*
		(0.00195)
Georgia (LSD=1)		0.00866***
		(0.00208)
Hawaii (LSD=1)		0.00967***
		(0.00292)
Kentucky (LSD=1)		-0.00638***
		(0.00184)
Massachusetts (LSD=1)		-0.000698
		(0.0021)

Minnesota (LSD=1)		0.0575*
		(0.00326)
Mississippi (LSD=1)		0.00736***
		(0.00268)
Montana (LSD=1)		0.0236***
		(0.00292)
New Jersey (LSD=1)		-0.00469**
		(0.00216)
Tennessee (LSD=1)		-0.0179***
		(0.0027)
Texas (LSD=1)		0.0146***
		(0.00192)
Virginia (LSD=1)		0.00593***
		(0.00181)
Constant	5.597***	5.519***
	(0.998)	(1.009)
Fixed Effects		
Year	yes	yes
School	yes	yes
State specific linear time trends	yes	yes
Observations	21,552	21,552
R-squared	0.786	0.787

Note: The regression above includes controls for state-level per capita income, unemployment rate, and merit scholarship status. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.4.2 Structural Model of Students' School Choice

We use a random coefficients logit model to estimate students' enrollment decisions and related cohort default rate elasticities (Berry (1994); Berry, Levinsohn, and Pakes (1995)). For the schools located in state s during time t, there are L_{st} potential students who may enroll in a college. A typical student i can choose to either enroll in one of the J_{st} schools, where schools are indexed by $j = 1, \dots, J_{st}$, or otherwise choose the outside option $(j = 0)$, allowing for the possibility of student i not enrolling in one of the J_{st} colleges in the state. Therefore, student i chooses between $J_{st} + 1$ alternatives in state s during time t. Student i's conditional indirect utility for the outside good is $u_{i0t} = \varepsilon_{i0st}$, while for schools $j = 1, \dots, J_{st}$ it is:

$$U_{ijst} = \alpha_i CDR_{jst} + \gamma LSD_{st} + \beta(CDR_{jst} \times LSD_{st}) + X_{st}\Phi + year_t + \theta_s t + school_j + \xi_{jst} + \varepsilon_{ijst}, \quad (2)$$

where CDR_{jst} is the two-year cohort default rate. The parameter, α_i, captures student-specific valuations for schools' cohort default rate characteristic. LSD_{st} is a zero-one dummy variable that takes a value of '1' in the year of LSD laws implementation in state s, and remains '1' in subsequent years provided the laws are not repealed. γ is a parameter that captures students' mean valuation of LSD laws. Parameter β captures the extra mean valuation students place on the cohort default rate attribute of colleges when choosing to enroll in a college that is in a state with active LSD laws. $CDR_{jst} \times LSD_{st}$ is the interaction variable of interest that enables identification of β. X_{st} is a vector of controls including state-by-year unemployment rates, state-by-year per capita income, and state-by-year merit scholarship status, with associated parameter vector Φ; $year_t$ captures time (year) fixed effects; $\theta_s t$ represents state-specific linear time trends; $school_j$ captures school-specific fixed effects; and ξ_{jst} captures time-varying school characteristics (i.e., quality, reputation, opportunities for scholarships and grants, various initiatives schools may implement that directly or indirectly subsidize students' education costs, etc.) that are unobserved by us the researchers, but observed by students and therefore impact students' utility. For example, Kansas State University facilitates a program called "Textbooks 2.0" that incentivizes instructors to choose "open source type" digital textbooks for their course in an attempt to reduce the cost of textbooks to students.[21] In addition, Kansas State University offers "The Presidential Scholarship ($20,000

[21] https://stories.ksufoundation.org/503161-raised-for-textbooks-2-0-through-all-in-for-k-state/, accessed (April 5, 2021).

per year)" to incoming freshman students with exceptional leadership and academic success.[22] These are examples of potentially time-varying school-specific attributes captured in the composite term ξ_{jst} , which are intended to lower the cost of education for students; and in turn lessen the amounts students may need to borrow to attend college. ε_{ijst} is a mean-zero stochastic error term.

The distribution of student-specific taste parameter, α_i , is specified as follows:

$$\alpha_i = \alpha + \phi D_i + \sigma \vartheta_i, \tag{3}$$

where in equation (3), α is the mean marginal valuation students place on schools' cohort default rate attribute. D_i is an m-dimensional column vector of demographic variables, while ϑ_i is an unobserved student's preference draw for schools' cohort default rate attribute. ϕ is a $1 \times m$ vector of parameters that measure how students' valuation of schools' cohort default rate attribute vary with demographics, and parameter, σ, measures the variation in students' heterogeneous valuations for schools' cohort default rate attribute.

Given the findings in Kelchen and Li (2017) and Scott-Clayton (2018), we consider household income, gender, and race as demographic variables in our estimation. Following the empirical industrial organization literature, we expressed the demographic variables in deviation from their respective means. Thus, the mean of D_i in equation (3) is zero. As in Nevo (2000), we assume that ϑ_i has a standard normal distribution, $\vartheta_i \sim N(0,1)$. The assumptions regarding D_i and ϑ_i along with equation (3) imply that, the mean of α_i is α, while the variance of α_i is σ^2.

[22] https://www.k-state.edu/sfa/scholarships-aid/scholarships/future-students/additional-opportunities/freshman/competitive/presidential-scholarship.html, accessed (April 5, 2021).

We can break down the indirect utility into a mean utility, $\delta_{jst} = \alpha CDR_{jst} + \gamma LSD_{st} + \beta\left(CDR_{jst} \times LSD_{st}\right) + X_{st}\Phi + year_t + \theta_s t + school_j + \xi_{jst}$, and a deviation from this mean utility $\mu_{ijst}\left(CDR_{jst}, D_i, \vartheta_i; \phi, \sigma\right) = CDR_{jst}(\phi D_i + \sigma\vartheta_i)$. As such, the indirect utility can be re-written as:

$$U_{ijst} = \delta_{jst} + \mu_{ijst} + \varepsilon_{ijst}. \tag{4}$$

For computational tractability, the idiosyncratic error term ε_{ijst} is assumed to be governed by an independent and identically distributed extreme value density. Individual student i's probability of choosing school j in education market state s at time t is:

$$s_{ijst} = \frac{\exp\left(\delta_{jst}+\mu_{ijst}\right)}{1+\sum_{k=1}^{J_{st}} \exp\left(\delta_{kst}+\mu_{ikst}\right)} \tag{5}$$

The student enrollment share of school j in state s at time t is given by:

$$s_{jst} = \int \frac{\exp\left(\delta_{jst}+\mu_{ijst}\right)}{1+\sum_{k=1}^{J_{st}} \exp\left(\delta_{kst}+\mu_{ikst}\right)} d\widehat{F(D)} dF(v), \tag{6}$$

where $d\widehat{F(D)}$ and $dF(v)$ are population distribution functions for student demographics and random taste shocks assumed to be independently distributed. For the integral in equation (6), there is no closed-form solution. Thus, it must be approximated numerically by using random draws from $\widehat{F(D)}$ and $F(v)$.[23]

Finally, the enrollment for school j is given by:

$$d_{jst} = L_{st} \times s_{jst}(CDR, (LSD \times CDR), X, \xi; \Theta_d), \tag{7}$$

---

[23] Following much of the Empirical Industrial Organization literature, we numerically approximate the integral by obtaining random draws from $\widehat{F(D)}$ and $F(v)$. In the actual estimation of the discrete choice model, we use 300 individual draws from the U.S. Census Integrated Public Use Microdata Sample (IPUMS) dataset. The integral is approximated by the following simulator: $s_{jst} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp\left(\delta_{jst}+\mu_{ijst}\right)}{1+\sum_{k=1}^{J_{st}} \exp\left(\delta_{kst}+\mu_{ikst}\right)}$, where ns is the number of random draws from the distribution of D and v.

where in equation (7), L_{st} is a measure of potential college enrollment in a given state s at time t; $s_{jst}(CDR, (LSD \times CDR), X, \xi; \Theta_d)$ is the model-predicted share of school j; CDR, $(LSD \times CDR)$, X and ξ are vectors of cohort default rate, cohort default rate and LSD law interaction, other control variables we previously describe, and the vector of school characteristics unobserved to us but observed by students, respectively; and Θ_d=($\alpha, \beta, \gamma, \Phi, \theta, year_t$, $school_j, \phi$, σ) is a vector of school choice model parameters to be estimated.

Equilibrium Determination of Schools' CDR

Even though it is unreasonable to think that schools directly choose the cohort default rates we observe them to have, it is reasonable to think that schools' cohort default rates are indirectly influenced by the choices schools make on several school attributes under their control. For example, schools do make choices on fundraising efforts to provide students with opportunities for scholarships and grants, which reduce students' reliance on loans to cover the cost of their education. In addition, schools may pursue various initiatives that may directly or indirectly impact graduation rates and thus ability to repay loans. For examples, universities use first-year courses or communities aimed at helping students make the transition to college, provide tutoring and mentoring opportunities, and have programs aimed at improving retention of first-generation students or non-traditional students, etc. Schools may also invest in improving the quality of education they provide, as well as invest in building their reputation for consistently delivering a desirable standard of education, which in turn improve the competitiveness of their graduates in labor markets, and consequently lowers cohort default rate among the school's graduates.

In an effort to approximate schools' choices to lower the effective cost to students of acquiring education, which influences a school's cohort default rate, we adopt a simplified model in which we assume schools optimally choose their cohort default rate conditional on the cohort default rates of competing schools. Specifically, suppose each school solves the following optimization problem:

$$\max_{CDR_{jst}} NV_{jst} = \max_{CDR_{jst}} \left[\psi\left(1 - CDR_{jst}\right)q_{jst} - mc_{jst}\left(CDR_{jst}\right)q_{jst}\right], \qquad (8)$$

where NV_{jst} is the net value to school j from producing non-defaulting graduates who pursue successful careers; ψ is a parameter that measures the per student shadow value in monetary terms to the school from producing a non-defaulting graduate who pursues a successful career; q_{jst} represents number of students choosing to enroll at school j during period t; $\psi\left(1 - CDR_{jst}\right) * q_{jst}$ is the expected value in monetary terms to the school from producing non-defaulting graduates who pursue successful careers; and $mc_{jst}\left(CDR_{jst}\right)$ is the marginal cost per student, in monetary terms, the school incurs to reduce its cohort default rate, which we assume is a decreasing and convex function of the cohort default rate, i.e. $\frac{\partial mc_{jst}}{\partial CDR_{jst}} < 0$ and $\frac{\partial^2 mc_{jst}}{\partial CDR_{jst}^2} > 0$.

Let the marginal cost function be specified as:

$$mc_{jst} = -ln\left(CDR_{jst}\right) + c_{jst} \qquad (9)$$

where c_{jst} is a composite of marginal cost components that do not vary with CDR_{jst}. The specified marginal cost function in equation (9) has the desired properties of $\frac{\partial mc_{jst}}{\partial CDR_{jst}} = -\frac{1}{CDR_{jst}} < 0$ and $\frac{\partial^2 mc_{jst}}{\partial CDR_{jst}^2} = \frac{1}{\left(CDR_{jst}\right)^2} > 0$ since $0 < CDR_{jst} < 1$.

Even though the composite component of marginal cost captured by c_{jst} is not influenced by CDR_{jst}, we do allow this composite cost component to be influenced by the LSD policy. Formally, we specify that:

$$c_{jst} = \lambda(LSD_{st}) + school_j + year_t + \theta_s t + \epsilon_{jst}^{mc} \qquad (10)$$

where, as previously defined, LSD_{st} is a zero-one dummy variable for whether state s at time t has LSD law. Therefore, parameter λ captures the impact of LSD laws on the marginal cost per student a school faces to reduce its cohort default rate. Other included controls are: (i) $school_j$, representing school fixed effects that control for unobserved school characteristics; (ii) $year_t$, representing year fixed effects that control for time-varying macroeconomic conditions that may affect the marginal cost; and (iii) state-specific linear time trends, $\theta_s t$, which could be picking up things like changes in state support to public schools over time. Last, ϵ_{jst}^{mc} captures random shock components of the marginal cost that are unobserved to us the researchers but observed by schools and students. We assume that shock components captured by ϵ_{jst}^{mc} are independently and identically distributed across schools, states, and time, with a mean of zero and a constant variance.

The rationale guiding the specification of equation (10) is that with LSD laws in effect, schools may face a greater marginal cost per student to reduce its cohort default rate. There are numerous potential reasons for this. First, the students who have marginally greater access to resources outside the educational system will likely be incentivized by the LSD policy to increasingly tap these resources to mitigate the chances of student loan default. For example, Lochner, Stinebrickner, and Suleymanoglu (2021) show that parental support greatly reduces student loan repayment problems so students with higher income parents may further rely on their parents as insurance against non-payment after LSD laws are implemented. If students from higher income families are more likely to receive help from family resources after implementation of LSD laws, then the remaining students from lower income families who have less resources to fall back on in the case of a negative shock to their ability to repay will drive up schools' marginal cost per student to help those students avoid default. Second, the supply of higher education is not perfectly elastic and therefore increased demand cannot always be accommodated without impacts on quality of education provided (Bound and Turner (2007)). Bound, Lovenheim and Turner (2010) decompose the reason for reductions in college completion into changes in student preparation and changes in college characteristics and find that college characteristics play an important role, especially in the four-year sector. Overall, they find that reductions in student resources account for one third of the decline in completion rates. Thus, schools would face an increased marginal cost to have their students avoid default due to the reduced graduation rates and earnings potentials of their students.

The arguments above suggest that $\lambda > 0$. If LSD laws serve to increase the marginal cost per student a school faces to reduce its cohort default rate, then optimizing behavior of the school would prescribe that it marginally reduces investments targeted at lowering its cohort default rate. In other words, schools' optimal response to LSD laws may be counter to the objective of these laws, which is to reduce cohort default rates.

We impose the equilibrium condition that the number of students who actually enroll in school j during period t is exactly equal to the number of student enrollees predicted by our discrete school choice model previously described. Therefore, we have $q_{jst} = d_{jst} = L_{st} \times s_{jst}(CDR, (LSD \times CDR), X, \xi; \Theta_d)$ from equation (7).

The schools' optimization problem in equation (8) implies that each school's optimal cohort default rate must satisfy the following first-order conditions in a Nash equilibrium of cohort default rates:

$$\left[\psi\left(1 - CDR_{jst}\right) - mc_{jst}\right] \frac{\partial s_{jst}}{\partial CDR_{jst}} - \left[\psi + \frac{\partial mc_{jst}}{\partial CDR_{jst}}\right] s_{jst} = 0, \ \forall j. \quad (11)$$

The system of first-order conditions in (11) can be represented using matrix notation as follows:

$$(\mathbf{I} * \boldsymbol{\Delta}) \times [\psi(\mathbf{1} - \boldsymbol{CDR}) - \boldsymbol{mc}] - [\psi\mathbf{I} + \boldsymbol{\Gamma}]\boldsymbol{s}(\boldsymbol{CDR}) = \mathbf{0} \quad (12)$$

where $\mathbf{1}$, $\mathbf{0}$, $\boldsymbol{s}(\cdot)$, $\boldsymbol{CDR}$ and $\boldsymbol{mc}$ are $J \times 1$ vectors of ones, zeros, school enrollment shares, cohort default rates, and marginal costs, respectively; $\mathbf{I}$ is a $J \times J$ identity matrix; $\boldsymbol{\Delta}$ is a $J \times J$ matrix of first-order derivatives of predicted school enrollment shares with respect to cohort default rates; $\mathbf{I} * \boldsymbol{\Delta}$ is an element-by-element multiplication of the two matrices; and $\boldsymbol{\Gamma}$ is a $J \times J$ diagonal matrix with the j^{th} diagonal element being $\frac{\partial mc_j}{\partial CDR_j}$.

The system of first-order conditions represented in equation (12) can be re-arranged as follows:

$$(\mathbf{1} - \boldsymbol{CDR}) = \frac{1}{\psi}\boldsymbol{mc} + (\mathbf{I} * \boldsymbol{\Delta})^{-1} \times [\mathbf{I} + \boldsymbol{\Gamma}]\boldsymbol{s}(\boldsymbol{CDR}) \tag{13}$$

Equation (13) reveals that the shadow value parameter ψ is not separately identified from marginal cost. As such, in what follows we assume a normalized value of 1 for ψ.

To estimate parameters in the marginal cost function, we substitute in equation (13) the assumed functional form for marginal cost and rearrange the resulting equation as follows:

$$ln(\boldsymbol{CDR}) + (\mathbf{1} - \boldsymbol{CDR}) - [\mathbf{I} * \boldsymbol{\Delta}]^{-1} \times [\mathbf{I} + \boldsymbol{\Gamma}]\boldsymbol{s}(\cdot) = \boldsymbol{c}(\boldsymbol{LSD}, \boldsymbol{\epsilon^{mc}}; \boldsymbol{\lambda}) \tag{14}$$

The left-hand-side of equation (14) is the computed dependent variable of the linear regression, while the right-hand-side of equation (14) has the specification described in equation (10).

3.4.3 Measuring the responsiveness of students to cohort default rate when choosing a college

With the arguments from the literature in hand (please see the Introduction section), we use our random coefficients logit model estimates to calculate the elasticity of enrollment to each school with respect to cohort default rate in states with LSD laws.

The own-school cohort default rate elasticity is defined by:

$$\eta_j = \frac{\partial s_j}{\partial CDR_j} \times \frac{CDR_j}{s_j} = \frac{CDR_j}{s_j} \int (\alpha_i + \beta)\, s_{ij}\big(1 - s_{ij}\big)\, d\widehat{F_D^*(D)}\, dF_v^*(v) \tag{15}$$

Given the negative consequences for defaulting on student loan repayment sanctioned by LSD laws, in this study, we answer the following question: "How sensitive are students to cohort default rates when making college enrollment decisions?" To answer this question, we use the students' preference parameter estimates from our discrete school choice model along with equation (15) to compute own-school cohort default rate elasticities in states during periods when their LSD laws are active. We then re-compute the own-school cohort default rate elasticities for schools in the same set of states but counterfactually set to zero the LSD dummy variable, which allows for comparing factual cohort default rate elasticity estimates when LSD laws are active to model-predicted cohort default rate elasticity estimates when LSD laws are counterfactually inactive. Thus, we can test whether LSD laws result in students becoming more sensitive to student loan default and change their behavior in a way that would reduce student loan default.

3.5 Estimation and Identification

To estimate the set of school choice preference parameters, we use generalized methods of moments (GMM) following the previous literature (Berry (1994); Berry, Levinson and Pakes (1995) (BLP); Nevo (2000); and Petrin (2002)). The general strategy is to derive parameter estimates such that the observed school enrollment shares, S_{jst}, are equal to school enrollment shares predicted by the model, s_{jst}.

Instruments

The cohort default rate of a given college depends not only on the school characteristics observed by students and us the researchers, but also school characteristics observed by the students but not observed by us the researchers, i.e., school characteristics captured in ξ_{jst}. School-specific characteristics in ξ_{jst} include, but not limited to: (*i*) potential earnings after graduating from the relevant school, which is positively correlated with the schools' known quality of education and reputation; (*ii*) opportunities the school provides for scholarships and grants; and (*iii*) various school initiatives that directly or indirectly subsidize students' education costs. As such, the components captured in ξ_{jst} are likely correlated with a school's cohort default rate, making the CDR_{jst} variable in our discrete school choice model endogenous.

To mitigate the endogeneity problem, we include school fixed effects, state-specific linear time trends, and year fixed effects controls in the mean utility function when estimating the discrete school choice model. However, instruments for cohort default rates are needed to deal with endogeneity problems that may remain even after controlling for school, state-specific linear time trends, and year fixed effects.

In constructing one set of cohort default rate instruments, we assume that the determinants of the cost of borrowing is uncorrelated with the unobserved econometric error, ξ_{jst}, but highly correlated with cohort default rate. The justification for this assumption is that school's reputation and quality of education across colleges are most likely uncorrelated with the cost of borrowing, i.e., inflation rates, interest rates, etc., but these determinants of the cost of borrowing do influence the cohort default rate of colleges. In addition, depending on the school type and financial aid status, the cost of attending college varies across schools. For example, some schools require students to borrow less compared to other schools due to available financial support programs. As such, a change in the determinants of the cost of borrowing is likely to differentially influence the cost of attending, and therefore differentially influence cohort default rates across schools. To allow for changes in borrowing costs to differentially influence cohort default rates across schools, we interact the determinants of borrowing cost with school dummies, and use these interaction variables as instruments for cohort default rates. Data on yearly inflation rates are obtained from the World Bank Data[24] and the federal student loan interest rates extracted from Kantrowitz (2020)[25].

The cost of attending college also depends on the socioeconomic status of students. For example, students from high-income households may need less federal, state and school financial aid; hence their cost of attending college would be quite different from a student from a low-income family. By constructing and using as instruments three-way interaction variables of mean student characteristics, i.e., average household income, gender, and race, with the determinants of borrowing cost and with school dummies, we identify preference parameters governing consumer heterogeneity. This way, considering the variation in socioeconomic status, we allow the determinants of the cost of borrowing to differentially influence attendance cost across schools and across students' socioeconomic status.

Parameters in the marginal cost function described in equations (10) and (14) are estimated using ordinary least squares. The identification comes from differences across states regarding whether they implement the law and differences in timing of implementation. Specifically, we are

---

[24] https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?locations=US, accessed (February 18, 2021).

[25] https://www.savingforcollege.com/article/historical-federal-student-interest-rates-and-fees, accessed (February 18, 2021).

comparing differences in schools' marginal cost over time in the treated states with differences in marginal cost over time in the control states.

3.6 Results

3.6.1 Students' School Choice Model

Standard economic theory would suggest that rational individuals weigh the marginal cost and marginal benefit from defaulting on student loans in order to maximize their utility. The state policies of interest, LSD laws, create an additional cost of defaulting on a student loan, and are thus expected to increase students' sensitivity to schools' cohort default rate in choosing whether and which college to attend. We therefore hypothesize that, all else equal, potential students are less likely to enroll in colleges with relatively high cohort default rates.

The first and second columns in Table 3.5 present the coefficient estimates from the linear regression of mean utility $\delta_{jst} = \log(S_{jst}) - log(S_{0st})$ on various school, state and year characteristics, which is the standard logit specification of the students' school choice model. Coefficient estimates of the standard logit specification of the school choice model in columns 1 and 2 of Table 3.5 are obtained using ordinary least squares (OLS) and two-stage least squares (2SLS) estimation procedures, respectively. The estimates of cohort default rate coefficients across columns 1 and 2 are negative as expected, but the OLS and 2SLS estimates of these coefficients are of different magnitudes. As mentioned before, cohort default rate is an endogenous variable in the school choice model. Hence, OLS estimation in column 1 of Table 3.5 produces biased and inconsistent estimate of the cohort default rate coefficient. The 2SLS estimates in column 2 is an attempt to address the endogeneity problem of cohort default rate. Furthermore, the Wu-Hausman exogeneity test rejects the exogeneity of cohort default rate at conventional levels of statistical significance, and suggests the instruments are necessary.

Results from the random coefficients logit (RCM) specification of the school choice model are represented in columns (3), (4), (5), (6) and (7) of Table 3.5. The coefficient estimate for the cohort default rate (*CDR*), as well as the coefficient estimate for the interaction variable, $LSD \times CDR$, in the RCM model are negative and statistically significant at conventional levels of statistical significance. The negative coefficient estimate for CDR suggests that students are less likely to choose to attend schools with relatively high cohort default rates. This finding is consistent with Cellini, Darolia, and Turner (2020) which finds that CDR-related sanctions for schools lead to large and significant decreases in enrollment. The negative coefficient estimate for $LSD \times CDR$ suggests that students making school choice in states with active LSD laws are even more likely to avoid schools with relatively high cohort default rates. The results are consistent with our hypotheses that, all else equal, potential students are less likely to enroll in colleges with relatively high cohort default rates, and active LSD laws serve to magnify this choice behavior of students.

Table 3.5 Students' enrollment choice estimation results for 4-year colleges

	Standard Logit		Random Coefficients Logit				
	OLS	2SLS	GMM				
	Mean Coef (α, β)	Mean Coef (α, β)	Mean Coef (α, β)	Standard Deviations (σ)	Demographic Interactions (Income)	(Gender)	(Race)
CDR	-2.0241***	-1.3905***	-3.0393***	-1.1523	-0.9907***	-0.3292	-0.1012
	(0.1747)	(0.3364)	(0.4598)	(1.4112)	(0.1767)	(1.0731)	(1.0731)
$LSD \times CDR$	-1.3043***	-1.3539***	-1.4178***				
	(0.3174)	(0.5198)	(0.4331)				
Constant	-1.7490***	-1.7854***	-1.8219***	-2.0813***			
	(0.2207)	(0.2216)	(0.3441)	(0.1444)			
LSD	0.1847***	0.1683***	0.1751***				
	(0.0327)	(0.0396)	(0.0378)				
Fixed Effects							
Year	yes	yes	yes				
School	yes	yes	yes				
State specific time trend	yes	yes	yes				
Exogeneity Test for Ivs							
Wu-Hausman		14168.8413***					
		(*p=0.000*)					
Other Statistics							
GMM			1539.727				
#of observations	21,552	21,552	21,552				

Note: The Standard Logit and Random Coefficients Logit models above include controls for state-level per capita income, unemployment rate, and merit scholarship status. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Column (4) in Table 3.5 reports the parameters that capture student preference variation unobserved by the researchers for various school characteristics. In this column, the estimated parameter associated with schools' cohort default rate is statistically insignificant, suggesting that preference heterogeneity for the cohort default rate is mostly explained by the included demographics. The parameter estimates across columns (5), (6) and (7) reveal that an important driver of students' preference heterogeneity in school choice with respect to cohort default rate is their level of household income. Specifically, the negative and statistically significant coefficient estimate on the interaction variable of CDR with student household income suggests that students from higher-income households have relatively stronger preferences for schools with low cohort default rates compared to their low-income peers. Since Wagner (2019) finds evidence that financial literacy[26] is strongly associated with household income and education, it is not surprising that model estimates suggest students from high-income households are more likely to choose schools with relatively low cohort default rates. Hoxby and Avery (2012) also find evidence that high-income and low-income students have very different college application patterns, even when they have similar levels of academic achievement.

The positive and statistically significant coefficient estimate on *LSD* dummy variable suggests that students in states with active LSD laws are more likely to enroll in a four-year college, *ceteris-paribus.*

Table 3.6 shows the schools' marginal cost per student, defined in equation (10), before and after the implementation of LSD laws. Column (1) of Table 3.6 shows that across the treatment states, on average, marginal cost increases significantly after the implementation of the policy. In

---

[26] https://www.stlouisfed.org/on-the-economy/2018/september/how-americans-rate-financial-literacy, accessed (February 18, 2021).

column (2) of Table 3.6, we break down the effect of LSD laws on the marginal cost by state. Based on the results, except Georgia, we observe an increase in school's marginal cost after the LSD policy adoption by their states. Overall, the results reported in Table 3.6 suggest that it is important to consider the impact of LSD laws on schools' marginal cost when constructing the structural equilibrium model.

Table 3.6 Estimation results for parameters in the marginal cost function

	(1)	(2)
	Marginal cost	Marginal Cost
On Average	3.720***	
	(1.244)	
California (LSD=1)		4.053***
		(1.906)
Georgia (LSD=1)		-4.108**
		(1.592)
Hawaii (LSD=1)		9.358***
		(1.861)
Kentucky (LSD=1)		7.465***
		(1.82)
Massachusetts (LSD=1)		1.928
		(2.777)
Minnesota (LSD=1)		-1.417
		(1.662)
Mississippi (LSD=1)		5.723***
		(1.225)
Montana (LSD=1)		12.43***
		(1.164)
New Jersey (LSD=1)		3.481**
		(1.208)
Tennessee (LSD=1)		5.542***
		(1.201)
Texas (LSD=1)		4.527***
		(1.342)
Virginia (LSD=1)		10.83***
		(2.097)
Constant	-922.4***	-921.2***
	(52.00)	(52.75)
Fixed Effects		
Year	yes	yes
School	yes	yes
State specific linear time trends	yes	yes

Observations	21,552	21,552
R-squared	0.133	0.133

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.6.2 Elasticities

Given the structural school choice model parameter estimates, we compute the responsiveness of students' college enrollment choice with respect to colleges' cohort default rates. Our school choice model yields an average own-school cohort default rate elasticity of -0.1573 across all schools in the sample; and an average own-school cohort default rate elasticity of -0.1357 across schools in states with LSD laws. These mean elasticity estimates suggest that students in states without LSD laws are on average more sensitive to schools' cohort default rates compared to students in states with active LSD laws. However, an important question is whether students in states with active LSD laws become even less sensitive to schools' cohort default rates if the state's LSD laws were repealed.

To test our hypothesis that "The absence of LSD laws decreases the "sensitivity" of students to cohort default rates when making school enrollment choices," we conduct a counterfactual experiment in which we remove the LSD laws from states that are actively imposing the policy in the sample. Table 3.7 shows the results from this counterfactual experiment. Mean elasticity estimates in the table reveal that in making their college enrollment decision, students become almost 75% more sensitive to schools' cohort default rate, an elasticity increase in absolute terms from 0.0778 to 0.1357, when LSD laws are active compared to if these laws were repealed.

The results in Table 3.7 suggest that license suspension for default laws increases students' awareness of schools' cohort default rates when choosing a college. Given that active LSD laws serve to increase potential students' awareness of schools' cohort default rates when choosing a college, these laws could improve timely repayments of student loans.

Table 3.7 Own-school cohort default rate elasticity for schools in states with LSD law

Description	Mean	Standard Error of Mean	Min	Max
Factual Elasticity(LSD=1)	-0.1357	0.0010	-0.6152	-0.0052
Counterfactual Elasticity (LSD=0)	-0.0778	0.0005	-0.2839	-0.0003

3.6.3 Equilibrium Counterfactual Analyses

A useful feature of the full structural model outlined above, which captures both the optimizing behavior of students' school choice and schools' efforts to influence their cohort default rates, is that it can be used for performing equilibrium counterfactual analyses. The following equilibrium counterfactual analysis is designed to help us better answer to the following question: *How are schools' cohort default rates impacted by their state's adoption of LSD laws?* To answer this question, we begin by using the first-order conditions from the optimal cohort default rate-setting part of our model to recover estimates of the composite components of marginal costs that are invariant to schools' cohort default rates, i.e., re-arranging equation (12) and inserting the specified marginal cost function we obtain:

$$\hat{\boldsymbol{c}} = ln(\boldsymbol{CDR}) + (\boldsymbol{1} - \boldsymbol{CDR}) - [\mathbf{I} * \boldsymbol{\Delta}(\boldsymbol{CDR}, \boldsymbol{LSD})]^{-1} \times [\mathbf{I} + \boldsymbol{\Gamma}]\boldsymbol{s}(\boldsymbol{CDR}, \boldsymbol{LSD}), \qquad (16)$$

where the right-hand-side of equation (16) is evaluated using the actual values in the data for all variables, including $\boldsymbol{CDR}$ and $\boldsymbol{LSD}$; as well as the parameter estimates from the discrete school choice model reported in Table 5. Also, note that the recovered components of marginal cost captured by $\hat{\boldsymbol{c}}$ are influenced by LSD laws according to the right-hand-side of equation (14), $\boldsymbol{c}(\boldsymbol{LSD}, \boldsymbol{\epsilon}^{\boldsymbol{mc}}; \boldsymbol{\lambda})$.

Second, with estimates of marginal cost components, $\hat{\boldsymbol{c}}$, in hand, and estimates of marginal cost parameters, $\boldsymbol{\lambda}$, we purge $\hat{\boldsymbol{c}}$ from the impact of LSD laws, to obtain $\hat{\boldsymbol{c}}_{\boldsymbol{LSD=0}}$.

Third, we counterfactually set the LSD dummy variable to zero in states that have active LSD laws, and solve for the new Nash equilibrium set of cohort default rates, $\boldsymbol{CDR}^*$, that solves:

$$[\mathbf{I} * \boldsymbol{\Delta}(\boldsymbol{CDR}^*, \boldsymbol{LSD} = \mathbf{0})] \times \left[(\mathbf{1} - \boldsymbol{CDR}^*) - [-ln(\boldsymbol{CDR}^*) + \hat{\boldsymbol{c}}_{\boldsymbol{LSD=0}}]\right]$$
$$-[\mathbf{I} + \Gamma]\boldsymbol{s}(\boldsymbol{CDR}^*, \boldsymbol{LSD} = \mathbf{0}) = \mathbf{0} \qquad (17)$$

A comparison of $\boldsymbol{CDR}$ with $\boldsymbol{CDR}^*$will reveal the extent to which LSD laws impact schools' cohort default rates.

Last, note that the behavioral responses to LSD laws are captured by structural parameters γ and β from the student school choice side of the structural model (see equation (2)), as well as structural parameter vector $\boldsymbol{\lambda}$ (see equations (10) and (14)) from the school attribute choice side of the structural model. These are the structural parameters that drive the impact of a states' LSD law policy on its equilibrium CDRs.

An Estimate of Socially Optimal Cohort Default Rates

To help put in context the size of the impact of LSD laws on cohort default rates, we approximate socially optimal cohort default rates, $\boldsymbol{CDR^{so}}$, in the absence of LSD laws by assuming a social planner chooses $\boldsymbol{CDR^{so}}$ to maximize a social welfare function, i.e., the social planner solves the following problem:

$$\max_{CDR_{jst}} \{NV(CDR_{jst}) + EU(CDR_{jst})\}, \qquad (18)$$

where $NV = \left[(1 - CDR_{jst})q_{jst} - mc_{jst}(CDR_{jst})q_{jst}\right]$ is the previously described (see equation (8)) net value to schools from producing non-defaulting graduates who pursue successful careers; and $EU(CDR_{jst})$ is the mean expected utility students obtain from the options to acquire college education. Based on the school choice model we previously outlined in section 3.2, $EU(CDR_{jst})$ takes the following functional form:

$$EU = \frac{1}{ns}\sum_{i=1}^{ns} ln\left[1 + \sum_{k=1}^{J_{st}} \exp\left(\delta_{kst}(CDR) + \mu_{ikst}(CDR)\right)\right], \tag{19}$$

where equation (19) is the well-known functional form for expected utility obtained from the choice options when using a logit model to capture decision-making individuals' discrete choice problem.

In matrix notation, the system of first-order conditions implied by the optimization problem in (18) is the following:

$$(\mathbf{I} * \boldsymbol{\Delta}) \times [(\mathbf{1} - \boldsymbol{CDR^{so}}) - \boldsymbol{mc}] - [\mathbf{I} + \boldsymbol{\Gamma}]\boldsymbol{s}(\boldsymbol{CDR^{so}}) + \boldsymbol{\Delta}\mathbf{EU}(\boldsymbol{CDR^{so}}) = \mathbf{0} \tag{20}$$

where $\boldsymbol{\Delta}\mathbf{EU}(\cdot)$ is the extra term that appears in the first-order condition because students' welfare is accounted for in the social planner's optimization problem. $\boldsymbol{\Delta}\mathbf{EU}(\cdot)$ is a $J \times 1$ vector of first-order derivatives, where element j is: $\frac{\partial \mathrm{EU}_j}{\partial CDR_j} = \frac{1}{ns}\sum_{i=1}^{ns}\left(\frac{\partial \delta_j}{\partial CDR_j} + \frac{\partial \mu_{ij}}{\partial CDR_j}\right)$. With estimates of the LSD-adjusted marginal cost components, $\hat{\boldsymbol{c}}_{\boldsymbol{LSD=0}}$, in hand, we then counterfactually set the LSD dummy variable to zero in states that have active LSD laws, and solve for the socially optimal set of cohort default rates, $\boldsymbol{CDR^{so}}$, that solves:

$$\begin{aligned}&[\mathbf{I} * \boldsymbol{\Delta}(\boldsymbol{CDR^{so}}, \boldsymbol{LSD} = \mathbf{0})] \times \left[(\mathbf{1} - \boldsymbol{CDR^{so}}) - [-ln(\boldsymbol{CDR^{so}}) + \hat{\boldsymbol{c}}_{\boldsymbol{LSD=0}}]\right] \\ &\quad -[\mathbf{I} + \Gamma]\boldsymbol{s}(\boldsymbol{CDR^{so}}, \boldsymbol{LSD} = \mathbf{0}) + \boldsymbol{\Delta}\mathbf{EU}(\boldsymbol{CDR^{so}}, \boldsymbol{LSD} = \mathbf{0}) = \mathbf{0}\end{aligned} \tag{21}$$

The key difference between equation (21) and equation (17) is the added term, $\boldsymbol{\Delta}\mathbf{EU}(\boldsymbol{CDR^{so}}, \boldsymbol{LSD} = \mathbf{0})$.

The Impact of LSD laws on Cohort Default Rates

To answer "*How are schools' cohort default rates impacted by their state's adoption of LSD laws?",* we conduct a counterfactual in which we switch the value of the LSD dummy from 1 to 0 and then solve for the cohort default rates that satisfy the first-order conditions shown in equation (17).

Table 3.8 shows by state with LSD laws, the mean factual observed CDR, the mean counterfactual predicted Nash equilibrium CDR where we consider the behavioral responses of both schools and students to the implementation of LSD laws, "CDR_Nash_student_school", and the mean predicted percentage change in CDR. In addition, we report the counterfactual predicted Nash equilibrium CDRs where we only consider the behavioral response of students to the implementation of LSD laws, "CDR_Nash_student."

Table 3.8 State level CDR, predicted Nash CDR and percent changes

States with factual LSD = 1	Avg. CDR	Avg. CDR* considering only Students' Response	Avg. CDR* considering Students' & Schools' Responses	Percentage Change (CDR*_student-CDR)	Percentage Change (CDR*_student_school-CDR)
	(1)	(2)	(3)	(4)	(5)
California	0.0503	0.0558	0.0489	10.84	-2.79
				(0.0362)	(0.0297)
Georgia	0.0697	0.0717	0.0859	2.86	23.35
				(0.1407)	(0.2155)
Hawaii	0.0632	0.0748	0.0604	18.27	-4.52
				(0.1356)	(0.1179)
Kentucky	0.0683	0.0942	0.0715	37.86	4.69
				(0.085)	(0.0767)
Massachusetts	0.0432	0.0458	0.0438	6.13	1.47
				(0.0631)	(0.0506)
Minnesota	0.0326	0.0458	0.0557	40.67	71.12
				(0.1004)	(0.072)

Mississippi	0.0728	0.107	0.0888	46.91 (0.1313)	21.93 (0.1327)
Montana	0.0624	0.0886	0.1214	41.94 (0.1222)	94.39 (0.2996)
New Jersey	0.0504	0.0723	0.0563	43.45 (0.0748)	11.72 (0.0596)
Tennessee	0.0714	0.0999	0.0762	39.89 (0.0677)	6.67 (0.0422)
Texas	0.0776	0.0895	0.0742	15.38 (0.0517)	-4.33 (0.0392)
Virginia	0.0464	0.051	0.0415	9.9 (0.0714)	-10.64 (0.057)
Overall Means	0.059	0.0747	0.0687	26.18 (0.2731)	17.75 (0.3645)

Note: Standard error of mean percentage change in parentheses.

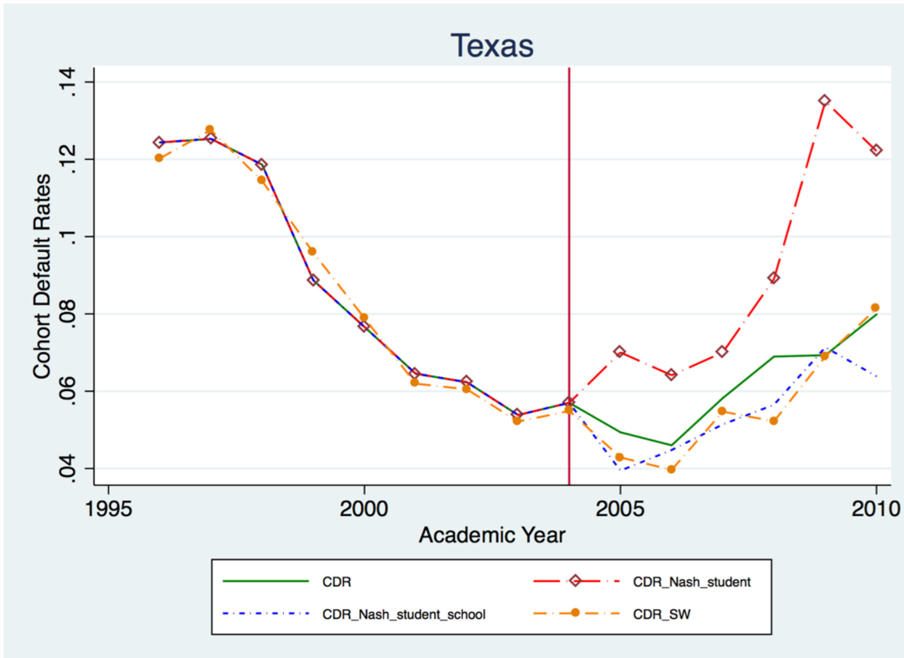
Overall, across the treatment states, model-predicted percent change in the last row and last column of Table 3.8 shows that implementation of LSD laws served to decrease CDRs of schools by a mean 17.75%. But this overall mean decline masks the mixed state-by-state results. Model-predicted percent changes throughout the last column in Table 3.8, column (5), reveal that the LSD law policy implementation has mixed results on CDRs by state. Across the twelve treated states, the model predicts that implementation of LSD laws served to increase schools' CDRs in California, Hawaii, Texas and Virginia by a mean 5.57%. While in Georgia, Kentucky, Massachusetts, Minnesota, Mississippi, Montana, Tennessee and New Jersey, the model predicts that implementation of LSD laws served to decrease schools' CDRs by a mean 29.42%.

In column (4) of Table 3.8, we consider model-predicted percent changes in CDR when only students respond to the LSD law policy. Based on results in column (4), CDRs decline unanimously across states by a mean 26.18% in response to the LSD law policy when we only consider students' response to the policy.

A comparison of the results in column (4) and column (5) clearly shows that it is important to consider both students' and schools' responses to the LSD laws policy. The comparison reveals that, in some states, schools' response to the policy counters and dominates the response of students, leading to higher CDRs. In contrast, in other states, students' response to the policy dominates schools' response, leading to the policy-intended goal of reducing CDRs.

Figure 3.2 shows time series plots of the factual observed CDR ("CDR"), the counterfactual predicted Nash equilibrium CDRs ("CDR_Nash_student school" and "CDR_Nash_student"), and estimated social welfare maximizing CDR in the absence of LSD laws ("CDR_SW") for schools in Texas, Virginia, Minnesota, and New Jersey. The vertical line in each time series plot shows the specific time period in which the relevant state implemented their LSD laws.

As an example of states in which our model predicts implementation of LSD law policy served to increase CDRs, we report time series plots for Texas and Virginia. The time series plots for Texas and Virginia clearly show that the implementation of LSD laws increased cohort default rates of schools ("CDR" compared to "CDR_Nash_student_school"). One way to interpret this result is that LSD laws served to increase the marginal cost per student schools face to reduce their CDR; therefore, facing higher marginal costs, schools optimally choose to marginally lower resources channeled towards decreasing their CDRs. Lowered efforts of schools to support initiatives that subsidize the cost students face of acquiring education will increase the likelihood of student loan defaults since students will increasingly need to borrow to finance their education. On the other hand, the time series plots for Texas and Virginia show that if the equilibrium model only focuses on student's response to the LSD policy ("CDR_Nash_student"), our model predicts that implementation of the LSD policy unambiguously serves to lower CDRs. Interestingly, the plots for Texas and Virginia show that the LSD policy served to increase CDRs even higher than our estimate of socially optimal levels of cohort default rates.



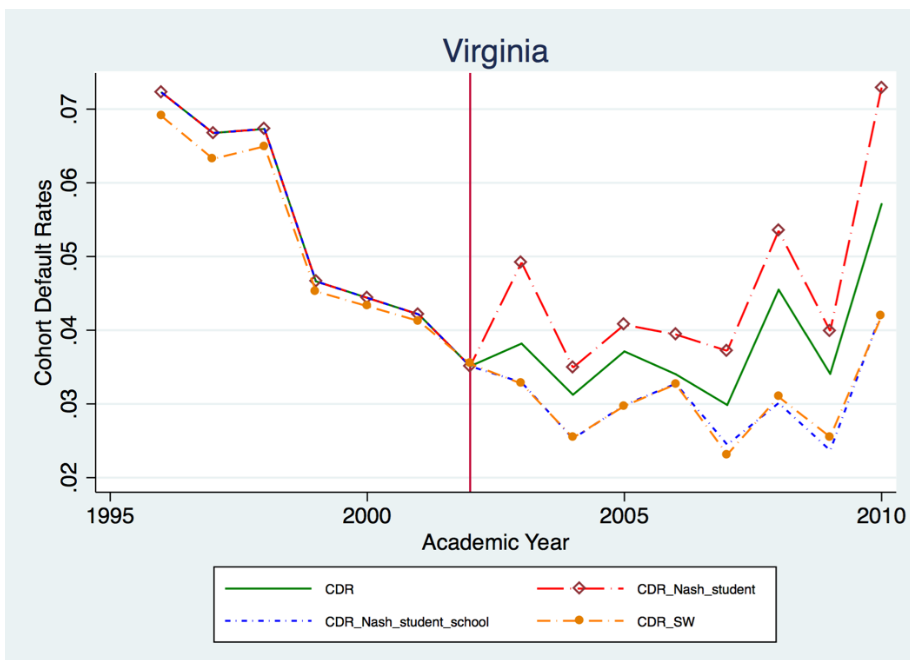
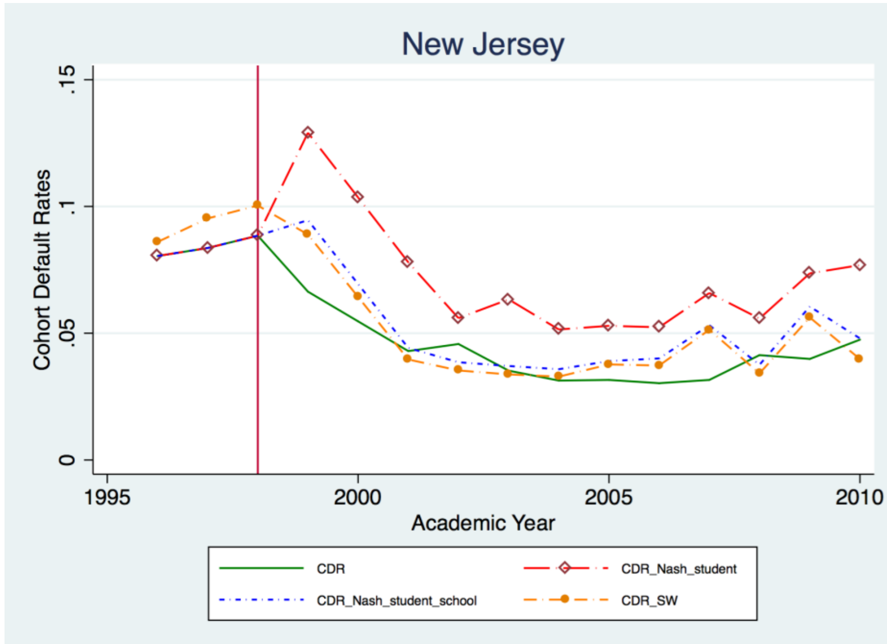


Figure 3.2 Factual Observed CDR ("CDR"), Counterfactual Predicted CDR considering only Students' response ("CDR_Nash_student"), Counterfactual Predicted CDR considering Students' & Schools' responses ("CDR_Nash_student_school"), and Estimated Social Welfare Maximizing CDR in the absence of LSD laws ("CDR_SW")



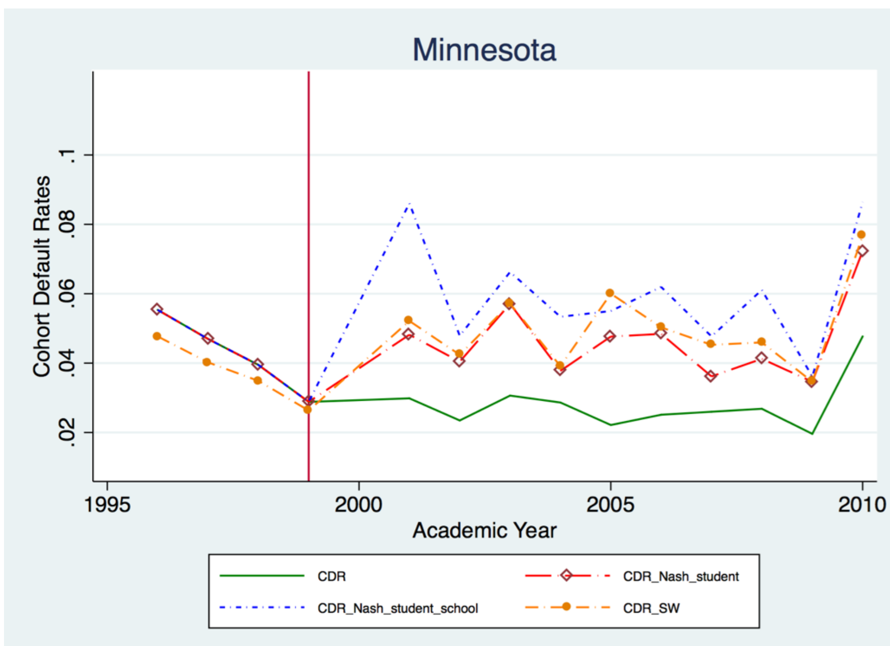


Figure 3.2 Contd.

Time series plots for schools located in Minnesota and New Jersey are examples in which our model predicts implementation of LSD law policy served to decrease CDRs. Comparing the time series plot of actual CDR to the time series plot of “CDR_Nash_student_school” in these diagrams clearly show that LSD laws decreased cohort default rates in these two states. As the proponents of LSD laws expect, in these states, the threat of losing a state or occupational license is a sufficiently powerful incentive for borrowers to keep up with loan repayments and avoid default on their student loans. Interestingly, the plots for Minnesota and New Jersey show that LSD law policy decreased CDRs even lower than our estimate of socially optimal levels of cohort default rates.

Overall, once we consider the behavioral responses of both schools and students, it is not surprising to find mixed results of the impact of LSD laws on cohort default rates. Indeed, the relative magnitude of schools’ and students’ responses to the policy implementation determines the impact of LSD laws on cohort default rates, a feature and result of LSD policy that have not been studied and documented in the literature.

3.7 Conclusion

We have shown how the implementation of state laws that deny, revoke, or suspend state licenses due to student loan default changes schools’ cohort default rates and student’s college choice. Using a structural econometric model, this paper provides answers to the following questions: *(i)* To what extent do cohort default rates of colleges influence students’ school enrollment choice, and how does LSD law policy further influence this relationship? and (*ii*) How are schools’ cohort default rates impacted by their state’s adoption of LSD laws? The empirical methodology begins with estimating preference parameters in a structural econometric model of students’ college choice. With the preference parameter estimates in hand, we then performed counterfactual policy analyses in which we artificially repeal the LSD laws from adopting states in the equilibrium model and measure the model-predicted changes in schools' CDRs and student's sensitivity to CDRs in their college decisions.

Regarding an answer to question (*i*) above, our empirical finding suggests that a colleges' cohort default rate negatively influences students' choice of attending the college. Furthermore, mean elasticity estimates from our school choice model reveal that in making their college enrollment choice, students become almost 75% more sensitive to schools' cohort default rate when LSD laws are active compared to if these laws were repealed. Our model estimates also suggest that the socioeconomic status of students plays a significant role in their college choice. Based on our findings, students from high-income households have a stronger preference for enrolling in colleges with relatively lower cohort default rates compared to their low-income household peers.

Even though LSD laws increase students' awareness of cohort default rates when making a college choice, the impact of LSD laws on cohort default rates is not only determined by students' response to the policy but also by schools' response. In fact, we find that schools' response to the LSD policy tends to counter students' response, a feature of LSD policy that has not been studied and documented in the literature. Thus, the relative strength of the behavioral responses of students and schools will determine the impact of the LSD policy on CDRs. Regarding an answer to question (*ii*) above, our empirical findings suggest that the LSD policy has mixed results on cohort default rates: In some states, schools' response to the policy counters and dominates students' response, causing an increase in these states cohort default rates by a mean 5.57%. While, in other states, students' response to the LSD policy counters and dominates schools' response, causing cohort default rates to decrease by a mean 29.42%.

From a policy efficacy perspective, LSD laws alter students' college decisions by increasing their sensitivity to schools with high cohort default rates. Hence, considering students' response to LSD law policy, the policy can improve timely repayments of student loans, which reduces CDRs. On the other hand, the impact of LSD laws on cohort default rates is not only determined by students' response to the policy but also by schools' response. Thus, the relative strength of the behavioral responses of students and schools will determine the policy's ultimate effect on CDRs. Therefore, we recommend policymakers consider both students' and schools' behavioral responses when evaluating this policy's impact on CDRs.

3.8 References

65th Legislative Assembly of North Dakota (2014), Senate Bill No. 2130. Legislation, Legislative Assembly of North Dakota.

Abraham, K., Filiz-Ozbay, E., Ozbay, E., & Turner, L. (2020), "Framing Effects, Earnings Expectations, and the Design of Student Loan Repayment Schemes", *Journal of Public Economics*, 183, 104067.

Ajayi, K.F. (2014). "Does School Quality Improve Student Performance? New Evidence from Ghana", Boston University Working Paper.

Avery, C. & Turner, S. (2012). "Student loans: Do College Students Borrow Too Much-or Not Enough?" *Journal of Economic Perspectives*, 26(1):165–92.

Barr, Andrew C., Kelli A. Bird, and Ben Castleman. (2019). The Effect of Reduced Student Loan Borrowing on Academic Performance and Default: Evidence from a Loan Counseling Experiment. (EdWorkingPaper: 19-89). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/gc0r-gv02

Black, Sandra E., Jeffrey T. Denning, Lisa J. Dettling, Sarena Goodman, and Lesley J. Turner. (2020). Taking It to the Limit: Effects of Increased Student Loan Availability on Attainment, Earnings, and Financial Well-Being. (EdWorkingPaper: 20-273). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/2np6-xq05

Brand, J. E., & Xie, Y. (2010), "Who Benefits Most from College?" *American Sociological Review*, *75*(2): 273–302.

Berry, S., Levinsohn, J. & Pakes, A., (1995), "Automobile Prices in Market Equilibrium", *Econometrica*, 841-890.

Berry, S.T. (1994). "Estimating Discrete-Choice Models of Product Differentiation", *The RAND Journal of Economics*, pp.242-262.

Bezmen, T., & Craig A. Depken, I. I. (1998), "School Characteristics and the Demand for College", *Economics of Education Review*, 17(2): 205–210.

Board of Governors of the Federal Reserve System (2021a). "Consumer Credit - G.19" https://www.federalreserve.gov/releases/g19/current/

Board of Governors of the Federal Reserve System (2021b). "Report on the Economic Well-Being of U.S. Households in 2019 - May 2020". https://www.federalreserve.gov/publications/2020-economic-well-being-of-us-households-in-2019-student-loans-other-education-debt.htm

Bound, John, Michael Lovenheim, and Sarah Turner. 2010. “Why Have College Completion Rates Declined: Marginal Students or Marginal College?” *American Economic Journal: Applied Economics*, vol. 2(3): 129-57 (July).

Bound and Turner (2007). “Cohort crowding: How resources affect collegiate attainment,” *Journal of Public Economics*, 91(5-6): 877-99

Bregel, E. (2011), “Loan Defaults Sting Tennessee Nurses”, News article, Times Free Press.

Butler, J. S., Carr, D. A., Toma, E. F., & Zimmer, R. (2013), “Choice in a World of New School Types”, *Journal of Policy Analysis and Management*, *32*(4): 785–806.

Cellini, Stephanie R., Rajeev Darolia, and Lesley J. Turner. (2020). "Where Do Students Go When For-Profit Colleges Lose Federal Aid?" *American Economic Journal: Economic Policy*, 12 (2): 46-83.

Chou, T., Looney, A., & Watson, T. (2017), “Measuring Loan Outcomes at Postsecondary Institutions: Cohort Repayment Rates as an Indicator of Students Success and Institutional Accountability”, NBER Working

Cox, J. C., D. Kreisman, and S. Dynarski (2020). “Designed to fail: Effects of the default option and information complexity on student loan repayment,” *Journal of Public Economics* 192, 104298.

Deming, D. J., Goldin, C., & Katz, L. F. (2012), “The For-Profit Postsecondary School Sector: Nimble Critters or Agile Predators?”, *Journal of Economic Perspectives*, 26(1): 139–164.

Dieterle, C. J., Weissmann, S., and Watson, G. (2018). “How States Use Occupational Licensing to Punish Student Loan Defaults”, Policy Study 148, R Street.

Dillon, E.W., & Smith, J. A. (2013), “The Determinant of Mismatch Between Students and Colleges”, *NBER Working Paper*, No.19286. pg. 1-50.

Dynarski, S. (2016), “The Trouble with Student Loans? Low Earnings, Not High Debt”, *Brookings Report.*

Farrell, M. (1990), “Reducing Student Loan Defaults: A Plan for Action”, *Viewpoints (120)*, Department of Education, Washington, DC. Office of Planning, Budget, and Evaluation.

Federal Student Aid (2021), “Coronavirus and Forbearance Info for Students, Borrowers, and Parents”. https://studentaid.gov/announcements-events/coronavirus

Florida Legislature (2016), Fla. Stat. 456.072, 456.074. Legislation, Florida Legislature.

Gaulke and Reynolds (2020), “Student Loan Repayment Prioritization”, working paper.

Georgia Secretary of State Office (2018), Professional licensing boards: Title 43. Professions and Businesses. Report, Georgia Secretary of State Office.

Gross, J. P., Cekic, O., Hossler, D., & Hillman, N. (2009), "What matters in student loan default: A review of the research literature", *Journal of Student Financial Aid*, 39(1): 19–29.

Hastings, J.S, Kane, T., J & Staiger, D., O. (2009), "Heterogeneous Preferences and the Efficacy of Public School Choice", NBER Working Paper: 2145.

Herbst, D. (2020). Liquidity and Insurance in Student-Loan Contracts: The Costs and Benefits of Income-Driven Repayment. Working paper.

Hillman, N. W. (2014), "College on Credit: A Multilevel Analysis of Student Loan Default", *The Review of Higher Education*, 37(2): 169–195.

Hillman, N. W. (2015). "Borrowing and Repaying Federal Student Loans", *Journal of Student Financial Aid,* 45(3): 35-48.

Hoxby, C., & Avery, C. (2012), "The Missing "One-Offs: The Hidden Supply of High-Achieving, Low-Income Students", NBER Working Paper: 18586.

Ivaldi, M., & Frank, V. (2005), "Quantifying the Effects from Horizontal Mergers in European Competition Policy", *International Journal of Industrial Organization*, 23 (9-10): 669-691.

Jackson, B. A., & Reynolds, J. R. (2013), "The Price of Opportunity: Race, Student Loan Debt, and College Achievement", *Sociological Inquiry*, 83(3): 335–368.

Jaquette, O. & Hillman, N.W. (2015), "Paying for Default: Change Over Time in the Share of Federeal Financial Aid Sent to Institutions with High Student Loan Default Rates", *Journal of Student Financial Aid*, 45(1): 3-25.

Kelchen, R., & Li, A. Y. (2017), "Institutional Accountability: A Comparison of the Predictors of Student Loan Repayment and Default Rates", *The Annals of the American Academy of Political and Social Science*, 671: 202–223.

Kelchen, R. (2019), "Do High Cohort Default Rates Affect Student Living Allowances and Debt Burdens? An Empirical Analysis", *Journal of Student Financial Aid*, 45(1): 3-25.

Lochner, L., & Monge-Naranjo, A. (2014), "Default and Repayment Among Baccalaureate Degree Earners", NBER Working Papers

Lochner, Lance, Todd Stinebrickner, and Utku Suleymanoglu. 2021. "Parental Support, Savings, and Student Loan Repayment." *American Economic Journal: Economic Policy*, 13 (1): 329-71.

Looney, S. M. (2011), “Cohort Default Rates in Context”, Institute for Higher Education Policy.

Looney, A. (2019), “A better way to provide relief to student loan borrowers”, Brookings.

Looney, A., & Yannelis, C. (2015), “A Crisis in Student Loans? How Changes in the Characteristics of Borrowers and in the Institutions They Attended Contributed to Rising Loan Defaults”, *Brookings Papers on Economic Activity*, 2015(2): 1–89.

Montana Legislature (2015), Montana HOUSE BILL NO. 363. Legislation, 2015 Montana Legislature.

National Consumer Law Center (2014), State laws and statutes that suspend professional licenses and certificates. Web article, National Consumer Law Center.

New Jersey 217th Legislature (2016), Assembly, No. 2926. Legislation, New Jersey Legislature.

Nevo, A. (2000), “A practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand”, *Journal of Economics & Management strategy*, 9(4): 513-548.

Scott-Clayton, J. (2018), “The Looming Student Loan Default Crisis is Worse Than We Thought”, *Economics Studies at Brookings*, *Evidence Speaks Reports*, 2(34)

Sibilla, N. (2019), New Bill By Rubio, Warren Would Stop States From Suspending Job Licenses Over Unpaid Student Loans. News article, Forbes.

Silver-Greenberg, J., Cowley, S., & Kitroeff, N. (2017), “When Unpaid Student Loan Bills Mean You Can No Longer Work”, *The New York Times*.

United States House of Representatives (2018), H.R.6156 - Protecting JOBs Act. Proposed legislation, 115th Congress (2017-2018).

United States Senate (2018), S.3065 - Protecting JOBs Act. Proposed legislation, 115th Congress (2017-2018).

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

Wagner, A. (2018), “The Debate Over Suspending Licenses for Student Loan Defaulters”, Legis-Brief 40, National Conference of State Legislatures.

Wagner, J. (2019), “Financial Education and Financial Literacy by Income and Education Groups”, *Journal of Financial Counseling and Planning*, 30(1), 132–141.

Webber, K. L., & Rogers, S. L. (2014), “Student Loan Default: Do Characteristics of Four-Year Institutions Contribute to the Puzzle?”, *Journal of Student Financial Aid*, 44(2).

Walker, M. (2017), State debt center suspends 1,500 driver's licenses. News article, Argus Leader, Part of USA Today.

Washington State House Committee on Higher Education Appropriations (2017), House Bill Report HB 1169. Legislation, House Committee on Higher Education & Appropriations.

Wiederspan, M. (2016), "Denying Loan Access: The Student-Level Consequences when Community Colleges Opt Out of the Stafford Loan Program", *Economics of Education Review*, 51:79 – 96.

Walker, M. (2017), "State Debt Center Suspends 1,500 Driver's Licenses", News article, Argus Leader, Part of USA Today.

Washington State House Committee on Higher Education Appropriations (2017), House Bill Report HB 1169. Legislation, House Committee on Higher Education & Appropriations.

Wiederspan, M. (2016), "Denying Loan Access: The Student-Level Consequences when Community Colleges Opt Out of the Stafford Loan Program", *Economics of Education Review,* 51: 79 – 96.

Appendix A

This Appendix contains three tables (Table A.1-Table A.3). Table A.1 presents the manufacturers and their available brands in year 2012. Table A.2 reports the results assessing the impact of manufacturer's characteristics on manufacturer's bargaining power under Assumption 2 *where each retailer carrying PL contracts with a unique outside manufacturer.* Table A.3 shows the results assessing the impact of manufacturer's characteristics on manufacturer's variable profit, mean price-cost margins and quantity sold under Assumption 2 *where each retailer carrying PL contracts with a unique outside manufacturer*.

Table A.1: Manufacturers and their available brands in year 2012

Manufacturer's Name	**Manufacturer's Brands**
Alpina Productos Alimenticious	Alpina Alpina Revive
Cascade Fresh	Amande Cascade Fresh
Chobani Inc.	Chobani
Dean Foods	Dean Land O Lakes
Emmi Roth USA Inc.	Emmi
Fage USA Dairy Industry Inc	Fage Total
General Mills Inc.	Yoplait Yoplait Greek Yoplait Light Yoplait Light Thick and Creamy Yoplait Original Yoplait Thick and Creamy Yoplait Vivant
Greece by Tyras S A	Olympus
Green Mountain Creamery	Green Mountain Creamery
Green Valley Organics	Green Valley Organics
Group Dannon	Brown Cow Dannon Dannon Activia Selects

	Dannon All Natural Dannon Light and Fit Stonyfield Farm Stonyfield Organic YoCrunch YoCrunch Fruit Parfait
H P Hood Inc	AxelRod Crowley
Johanna Foods Inc	La Yogurt La Yogurt Custard Classics
Kalona Organics	Cultural Evolution
Liberty Products Inc.	Liberte Liberte Mediterranee
Maple Hill Creamery	Maple Hill Creamery
Mehadrin Dairy Corp	Mehadrin Mehadrin Fit N Free
National Dairy Holdings	LaLa Weight Watchers
Prairie Farms Dairy	Prairie Farms
Private Label	Private Label
Redwood Hill Farm	Redwood Hill Farm
Schreiber Foods Inc	Schreiber Lactaid
Springfield Creamery Inc	Nancys
The Hain Celestial Group Inc	Almond Dream The Greek Gods
Tillamook County Creamery	Tillamook
Tula Foods Inc	Better Whey of Life
Turtle Mountain Inc	So Delicious
Wallaby Yogurt Company Inc	Wallaby Down Under Wallaby Organic
WhiteWave Foods Company	Silk Live
WholeSoy & Co	WholeSoy & Co

Table A.2: Bargaining power as a function of manufacturer's characteristics

	(1) Model 1	(2) Model 2
Product Line Depth (Maximum)	-0.00847	
	(0.0129)	
Product Line Depth (Average)		-0.0114
		(0.0186)
Product Line Width	-0.0167	-0.0288
	(0.0349)	(0.0285)
Constant	1.068***	1.093***
	(0.104)	(0.134)
Observations	29	29
R-squared	0.057	0.055

Notes: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1

Table A.3: Variable profit, Quantity sold and Price-cost Margins as a function of manufacturer's characteristics

	(1) Variable Profit	(2) Variable Profit	(3) Quantity sold	(4) Quantity sold	(5) Mean Price-cost Margins	(6) Mean Price-cost Margins
Product line depth (maximum)	41.23		1,738		0.0292**	
	(33.65)		(1,195)		(0.0121)	
Product line depth (average)		83.44*		3,326*		0.0460**
		(47.13)		(1,669)		(0.0171)
Product line width	20.91	76.08	1,050	3,400	0.0149	0.0555**
	(91.38)	(72.23)	(3,246)	(2,558)	(0.0329)	(0.0261)
Constant	-1,941***	-2,217***	-76,337***	-86,911***	-0.853***	-0.975***
	(271.4)	(340.8)	(9,642)	(12,067)	(0.0976)	(0.123)
Observations	29	29	29	29	29	29
R-squared	0.099	0.150	0.139	0.193	0.299	0.330

Notes: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1