Essays in Demand Estimation: Illicit Drugs and Commercial Mushrooms

A dissertation presented

By

Robert Bradley

to

The Department of Economics

In partial fulfillment of the requirements for the degree of
Doctor of Philosophy

In the field of

Economics

Northeastern University
Boston, Massachusetts
December 2020

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ABSTRACT OF DISSERTATION

Submitted in partial fulfillment of the requirements
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Abstract

This dissertation consists of two essays analyzing the various effects of market competition in the United States. The first chapter explores the impact of competition among drug dealers. Although opioid buyers are often addicted to the products they are purchasing, due to the competition among sellers, the buyers have a wide variety of opioid chemicals to choose from. The net result shows buyers to be price sensitive and without loyalty to any particular opioid compound. The second chapter shows that although Mushroom Council post market price and quantity information to all mushroom growers, it does not serve as a focal point for farmers to tacitly collude.

Acknowledgments

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To my sons, Abraham, Ezra, and Elijah: Thank you boys so much for always putting a smile on my face and being my motivation to finish. I love you and cannot wait to celebrate every one of your accomplishments as you grow. Remember there is nothing you can't do if you commit to doing it.

Finally, thank you to my wife, Cassie. Eight years ago I pitched a crazy idea of getting a Ph.D to you and you did not hesitate to support me. You have pushed me to do things I never would have had the

confidence to do on my own. Your belief in me became a belief in myself and I can never repay you for what that has meant. You put your own goals on hold so I could accomplish this one, and you have been my absolute rock every step along the way. The work you have done, the stress we have shared, and the unwavering enthusiasm for my work have made this possible. This degree is as much yours as it is mine. You have done all that while also raising our three incredible sons. All the good things in my life have only happened because you are by my side.

Table of Contents

Tables and Figures

CHAPTER ONE: Introduction

The opioid epidemic in the US has caused more than 350,000 death due to overdose since 1999.[1] The latest data from the Centers for Disease Control and Prevention (CDC 2018) show 70,689 people died of drug overdose in 2017.[2] Furthermore, the number of overdoses caused a strain on the US medical system: For example, from July 2016 to September 2017, emergency department visit rates for opioid overdose increased across the US, with the largest increase being in the Midwest (70%).[3] Treating opioid overdose can be dangerous to the health of the emergency responders especially when it involves fentanyl due to its potency.[4] Consequently, the economy takes a toll as more people are removed from the labor force and consume emergency health-care services. The total economic burden of this misuse of opioid prescriptions in the US is estimated to be $78.5 billion a year (Florence et al. 2013; Sullivan 2018). The rise in deaths from opioid overdose can be partially attributed to the exponential increase in the use of synthetic opioids, such as fentanyl.[5]

To understand why fentanyl is so dangerous, we provide a table below to illustrate.

Table 1.1
Opioid Equivalency across 3 Opioids

	Oxycodone	Heroin	Fentanyl
Q (mg)	80	24	1.6
P ($)	48	4	0.22
Duration (hr)	6-12	4-5	2-4

Three factors explain why fentanyl is so efficient at killing humans. One, it is extremely

[1]Wide -ranging online data for epidemiologic research (WONDER). Atlanta, GA: CDC, National Center for Health Statistics; 2017. Available at http://wonder.cdc.gov.

[2]https://www.cdc.gov/nchs/nvss/vsrr/drug-overdose-data.htm

[3]The largest increase was in the Midwest (70%), followed by the West (40%), Northeast (21%), Southwest (20%), and Southeast (14%). See CDC data from the National Syndromic Surveillance Program (NSSP) BioSense platform for more information.

[4]CDC and NIOSH publish a report specifically on preventing emergency responders from occupational exposures. See https://www.cdc.gov/niosh/topics/fentanyl/risk.htmlfor more information.

[5]National Vital Statistics System Mortality File, Centers for Disease Control and Prevention.

potent; 1.6mg of fentanyl is the same dosage as 24mg of heroin and 80mg of oxycodone. Two, it is cheap; to get the same high as 80mg oxycodone, consumers only needs to spend 25cents instead of US$48. Three, its duration is shorter than that of other opioids.[6] To achieve the same length of high, users have to dose more often.

One of the difficulties in studying the opioid epidemic is the concurrent wave of legalizing marijuana across the US. Jacobi and Sovinsky (2016) estimate that legalizing marijuana in Australia would lead to a 30% increase in usage for those under 30. Wen and Hockenberry (2018) and Bradford et al. (2018) show that legal marijuana leads to lower opioid prescrip-tions. The literature suggests that legalizing marijuana would prompt residents to use more marijuana and less opioids (Bachhuber et al. 2014). However, the increase in emergency vis-its due to opioid overdose in the Northeast—where states such as Maine, Massachusetts, and Vermont have legalized the recreational use of marijuana—conflicts with that hypothesis.

The other difficulty is the lack of data regarding the black market. Studies have also shown that mandatory access to a Prescription Drug Monitoring Program (PDMP) lowers opioid prescriptions (Buchmueller and Carey 2018; Dave et al. 2017). This certainly makes sense for preventing new patients from developing opioid addictions, but we are unsure if existing buyers seek out black-market opioids to fill their needs. Doleac and Mukherjee (2018) and Argys et al. (2017) disagree on whether naloxone (for treating opioid overdose) creates moral hazard. The results found may be distorted in the existing literature if they do not account for black-market activities.

Our study focuses on the black-market by collecting daily transaction data on the dark

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[6] Oxycontin duration info from New Zealand Medicines and Medical Devices Safety Authority (MED-SAFE), accessed on 9/2/18, http://www.medsafe.govt.nz/profs/Datasheet/o/OxyContintab.pdf.
Heroin duration info from Field, J. M., P. J. Kudenchuk, R. O'Connor, T. VandenHoek (2008): "The Text- book of Emergency Cardiovascular Care and CPR," *LWW*, 1st Edition.
Fentanyl duration info from Stanley T. H. (2014): "The Fentanyl Story," *The Journal of Pain*, 15, 12, 1215-1226.

web for all narcotics over a 10-month period. We can thus analyze policies in the context of the entire market for drugs, and account for overall consumer demand for narcotics in the US. Our research questions are the following:

1. How to reduce the number of opioid overdose?
2. What happens when the number of opioid prescriptions decreases?
3. What happens when law enforcement cracks down on narcotics in the black-market?

Using a comprehensive elasticity table based on consumer demand[7], we find opioid users to be extremely price sensitive. This makes the current policy on limiting the number of opioid prescriptions through mandatory access to PDMP ineffective in reducing the number of opioid overdose. Literature suggests that decreasing the number of opioid prescriptions in the legal market will increase the prices of prescription opioids in the illicit market (Mar- tin et al. 2018; Griffin and Miller 2011). We find that a 10% price increase in oxycodone (a prescription opioid) will lead to a 168mg decrease in oxycodone consumption, 32mg in- crease in buprenorphine, 62mg increase in fentanyl, 2mg increase in heroin, 4mg increase in methadone, and 199mg increase in tramadol.

To reduce the number of opioid overdose, policy makers should focus their effort on increasing the number of physicians able to prescribe buprenorphine, as fewer than half of US counties have physicians who are able to prescribe buprenorphine (Thomas 2018). Buprenorphine is an opioid partial agonist, when combined with naloxone, as is the case for Suboxone, makes it very difficult for users to overdose. The price sensitivity among opioid users is an effective mechanism in reducing the number of overdose through implementing treatment policies.

[7] See Appendix F for the full elasticity table for all narcotics.

Cracking down on narcotics sold in the black-market on the other hand, would also be ineffective in reducing the number of opioid overdose. Due to the price sensitivity of opioid users, when the price of heroin increase, they would switch to fentanyl or other cheaper synthetic drugs. This policy is also not future-proof, as sellers can produce other variants of synthetic opioid to skirt regulations and enforcements.

Our results also show that there is little correlation between opioid and marijuana us- age. Limiting the number of opioid prescriptions lead to a moderate increase in the use of marijuana bud, 12mg, which is not nearly sufficient to produce the average joint for smok-ing.[8] Thus, marijuana appears to have only a slight correlation with prescription opioid use. If anything, research shows marijuana use increases the risk of developing nonmedical prescription opioid use (Olfson et al. 2018).

The rest of the paper is organized as follows. Section 2 outlines the origin and history of this market. Section 3 explains our data. Section 4 describes the methodology and instruments. Section 5 provides the estimation results, and Section 6 concludes.

Background

The Onion Router

The online drug market was made possible by the development of strong encryption technology that allows anonymous communications and increases the complication for law enforcement to identify and intercept drug dealers. A technology known as The Onion Router (Tor) was originally developed in the mid-1990s at the United States Naval Research Laboratory by Paul Syverson, Michael Reed, and David Goldschlag (1996), whose goal was

[8] A typical marijuana joint contains about 660mg of bud (Mariani et al. 2011).

to protect US intelligence communications for the upcoming internet era. This technology was further developed by the Defense Advanced Research Projects Agency (DARPA) in 1997, and in 2003, Tor network was developed and the code released under the free and open MIT license.

Although Tor does not resolve the issue of anonymity completely, it makes tracing ac-tion and data back to users difficult for third parties. Consequently, this technology makes organizing political activities or exposing the wrong-doings of heads of state in oppressive regimes possible.[9] For example, the well-known Panama Papers and Paradise Papers lever-aged Tor technology.[10] On the other hand, as with any common tool or resource, criminals can and have incorporated Tor into their operations. Many crimes are committed using this technology. Our paper is concerned with the illicit drug sales coordinated using Tor.

Digital Drug Trade

In 2014, the global drug trade was estimated to be between US$426 billion and US$652 billion.[11] The number of drug users in the world in 2015 was estimated to be between 150 million and 350 million people aged 15 to 64 years old (UNODC 2017). Our interest, the online narcotics market, is a much smaller subset of the global drug trade. The main geo-graphic presence of the online market is in North America, Western Europe, and Australia. Each country we consider in this paper has multiple sellers for different categories of drugs, and we believe the online market we study to be competitive, because each type of product has at least three to five sellers (Bresnahan and Reiss 1991).

The different market dynamic leads us to expect that, initially, online prices will not nec-

[9] torflow.uncharted.software shows global traffic on Tor across time.

[10] The International Consortium of Investigative Journalists utilizes Tor for leaks to protect their sources.

[11] Channing May, "Transnational crime and the developing world," *Global Financial Integrity Washington D.C.*, March 2017.

essarily reflect local street prices. However, we expect that as online platforms increasingly coordinate buyers and sellers, online and street prices of narcotics will converge (Cavallo et al. 2014; Cavallo 2017). One can argue that information arbitrage and price discrimination were possible when the market first formed online, but this effect has likely disappeared. Consequently, we expect the law of one price to hold even in the illegal market and that any price discrepancies between online and offline can be attributed to market frictions. Some secondary analysis comparing online with street prices suggests the law of one price to hold, but we mention this finding cautiously, given the imprecise nature of narcotics price data.[12] Although online sales can be organized and managed anonymously and independently, local distribution tends to be controlled by criminal organizations that hold monopoly power (Decker et al. 2008; Densley 2013). We find the criminal distribution structure mirrors that of grocery stores in that both can be approximated as local monopolies. US court cases have shown that as we go further up the supply chain, the whole seller's market becomes even more concentrated (Colella's Super Market, Inc. v. SuperValu, Inc.; C&S Wholesale Grocers, Inc. 2017).

The first online drug bazaar, Silk Road, was launched in February 2011 and made international headlines when it was shut down by US law enforcement in 2013. FBI records showed approximately 1.2 million transactions completed on the site, with a total revenue of 9.5 million bitcoins or about US$1.2 billion based on valuation at the time. Site owner Ross Ulbricht (aka Dread Pirate Roberts), estimated to have made about US$79.8 million in commissions,[13] was sentenced to life imprisonment without parole and ordered to forfeit $183

[12] We have collected and organized local drug prices as a reference in Appendix C, which can be compared with online prices from Agora in Appendix D.

[13] Greenberg, A. "FBI Says It's Seized $28.5 Million In Bitcoin From Ross Ulbricht, Alleged Owner of Silk Road," *Forbes*, October 25, 2013, https://www.forbes.com/sites/andygreenberg/2013/10/25/fbi-says- its-seized-20-million-in-bitcoins-from-ross-ulbricht-alleged-owner-of-silk-road/#4752ed242765.

million in May 2015.[14] The harsh sentencing was meant to discourage similar crime, but subsequent online drug transactions show Ulbricht's sentence did not deter future criminals (Ladegaard 2017). Sales on the dark net spiked, likely due in part to media coverage.

Consider Figure 1.1, which comes from a government exhibit during the Silk Road trial[15] and illustrates in general transactions occur in this online market. Sellers set up listings similar to eBay, but unlike eBay, the listings are not auctions. Prices are set in a manner similar to prices for products sold on Amazon, and buyers browse the listings to find their desired products. To make a purchase, buyers must exchange their local currency for bitcoins, which they then deposit into their account with the website. Assuming no issues with the delivery, and the product being received as advertised, the website takes a commission before releasing funds to the seller. In the case of fraud or intercepted delivery, the website arbitrates the case and most likely splits the payment between the buyer and seller.

Our research exploits the fact that buyers were required to leave a comment in the check-out process. This requirement allowed us to identify when an online transaction occurred. We collected our data after US law enforcement shut down Silk Road.[16] By that time, the availability of online markets had been widely covered in American and international media and was presumably known to incumbent and potential consumers.

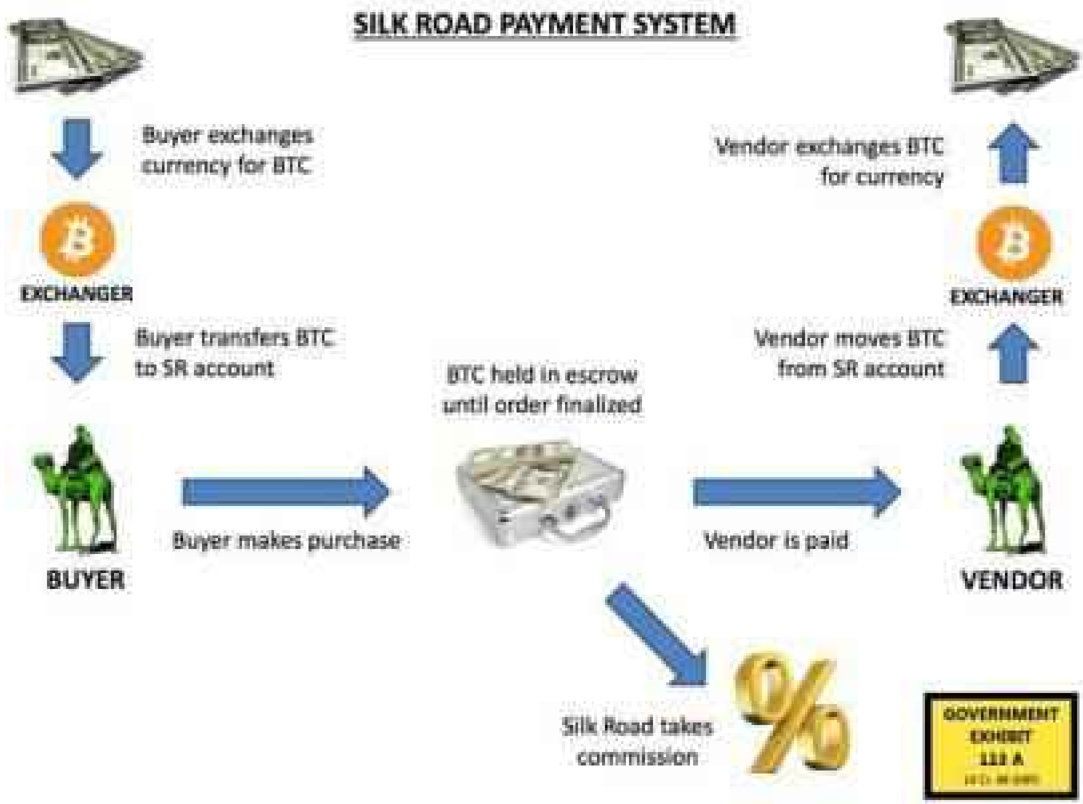
Accordingly, by the time of our data collection, rating norms on the online platforms had developed. Our observations suggest leaving a five out of five for a satisfactory transaction

[14] U.S. Attorney's Office "Ross Ulbricht, aka Dread Pirate Roberts, Sentenced in Manhattan Federal Court to Life in Prison," *Southern District of New York*, May 29, 2015, https://www.fbi.gov/contact-us/field- offices/newyork/news/press-releases/ross-ulbricht-aka-dread-pirate-roberts-sentenced-in-manhattan-federal- court-to-life-in-prison.

[15] Government exhibit from United States of America v. Ross Ulbricht 14 Cr. 68 (KBF) United States District Court Southern District of New York 2015.

[16] Greenberg, A. "End of The Silk Road: FBI Says It's Busted The Web's Biggest Anonymous Drug Black Market," *Forbes*, October 2, 2013, https://www.forbes.com/sites/andygreenberg/ 2013/10/02/end-of-the-silk-road-fbi-busts-the-webs-biggest-anonymous-drug-black-market/ #2258a2a75b4f.

Figure 1.1
Online Payment System



was common practice. A low rating usually corresponded to a comment regarding a scam. Online transactions of drug-purity testing kits lead us to suspect scrupulous consumers were able to detect a scam. Consumers had other ways to verify their purchased products. Many European countries have non-profit organizations that offer free testing of illicit drugs (Caudevilla 2016). Additionally, extensive reviews are available online.[17]

The behavior demonstrated on Agora (a website on the dark web for trafficking illicit products) reflects the way information, price discovery, and market coordination have been

[17] Appendix A shows a sample of an online review.

transformed by websites like Amazon and eBay in recent years. The dark net's current clients / participants are unlikely to represent overall drug users. However, Amazon's influence on modern markets suggests the dark net is increasingly relevant to drug enforcement. This study gives us insight into the potential future illicit drug trade pertinent to today's policy makers.

Data

Our dataset comes from the Agora Marketplace, which following the shutdown of Silk Road, launched in 2013. This platform was unaffected by Operation Onymous,[18] a cyber counternarcotics sting launched in November 2014 involving law-enforcement efforts in 17 countries to shut down online markets. At the time, market leaders such as Agora and Evolution escaped the international effort, and later, in March 2015, Agora rose to become one of the largest markets remaining when Evolution pulled off an exit scam.[19] However, only months later, in August 2013, Agora shut down its operation due to compromised security.[20] Before this self-dissolution, we were able to scrape Agora and obtain 481,138 illicit drug transactions collected during the 10-month period between November 4, 2014, and Septem-ber 5, 2015. Data scraping began daily starting at 9am, although due to technical difficulties, the process started later on some days. The data obtained include sales-transaction infor-mation for cannabis, dissociative drugs, ecstasy, opioids, prescription opioids, psychedelics, steroids, and stimulants. For our research we choose to focus on sales related to cannabis,

[18] "Operation Onymous," *Europol*, accessed April 18, 2018. https://www.europol.europa.eu/ activities-services/europol-in-action/operations/operation-onymous.

[19] Woolf, N. "Bitcoin 'Exit Scam': deep-web market operators disappear with $12m," *The Guardian*, March 18, 2015, https://www.theguardian.com/technology/2015/mar/18/ bitcoin-deep-web-evolution-exit-scam-12-million-dollars.

[20] See Appendix B for Agora's last warning to users before closing down the site.

ecstasy, opioids, prescription opioids and stimulants. We expect that these narcotics' high-inducing properties and the chemical addiction will allow our analysis to detect some of the substitutability between cannabis and harder drugs.

Table 1.2 shows the number of transactions and values for each broad drug category by region.[21] Overall, North America has the largest market share for marijuana, stimulants, and opioids. Oceania countries have the smallest market share for all drugs. Ecstasy seems to be Europeans' preferred drug.

Table 1.2
Agora Data Summary Statistics

	Marijuana		Stimulant		Ecstasy	
	Transactions	Value ($)	Transactions	Value ($)	Transactions	Value ($)
North America	64,385	16,557,707	22,392	5,168,305	20,255	4,146,234
EU	58,150	8,798,286	39,699	5,876,576	37,220	10,061,285
Oceania	9,470	1,382,277	10,742	3,860,875	6,485	2,262,883
Total	132,005	26,738,270	72,833	14,905,756	63,960	16,470,402

	Opioid		Prescription Opioid	
	Transactions	Value ($)	Transactions	Value ($)
North America	16,663	2,440,969	12,932	1,467,788
EU	7,730	675,317	3,801	221,576
Oceania	2,690	468,345	913	94,905
Total	27,083	3,584,631	17,646	1,784,269

Buyers can request large-quantity orders, but this type of transaction is not typical in our data, as reported in Aldridge and Decary-Hetu (2014). In that study, data from Silk Road show the site was mainly used by street vendors to reup their supply, because retail purchase was the norm. Once the world learned about Silk Road through the US court case, smaller-quantity orders became the norm.

Anyone could access this website, including law enforcement. Consequently, buyers and sellers did not provide any information that could be used to identify them.[22] Therefore, the

[21] For more detailed information on price and quantity for different countries please see Appendix D.
[22] "Dark Net Market Buyer Bible", *Reddit Post*, Accessed April 18, 2018.
https://www.reddit.com/r/ darknetmarketsnoobs/wiki/bible/buyer.

only information we could collect other than product specifics was the country where the transactions occurred. Sellers were required to disclose where they were located and where they felt comfortable shipping their products. On the other hand, buyers tend to be wary of international shipments, because the shipments have to go through customs. The risks of doing business internationally are explained in more detail in Aldridge (2016). Consumers can be reasonably expected to purchase more than a day's worth of supply to account for shipping time, and other transaction costs. However, we expect consumers to be repeat customers due to the addictive nature of the product.

Empirical Strategy

Nested Logit

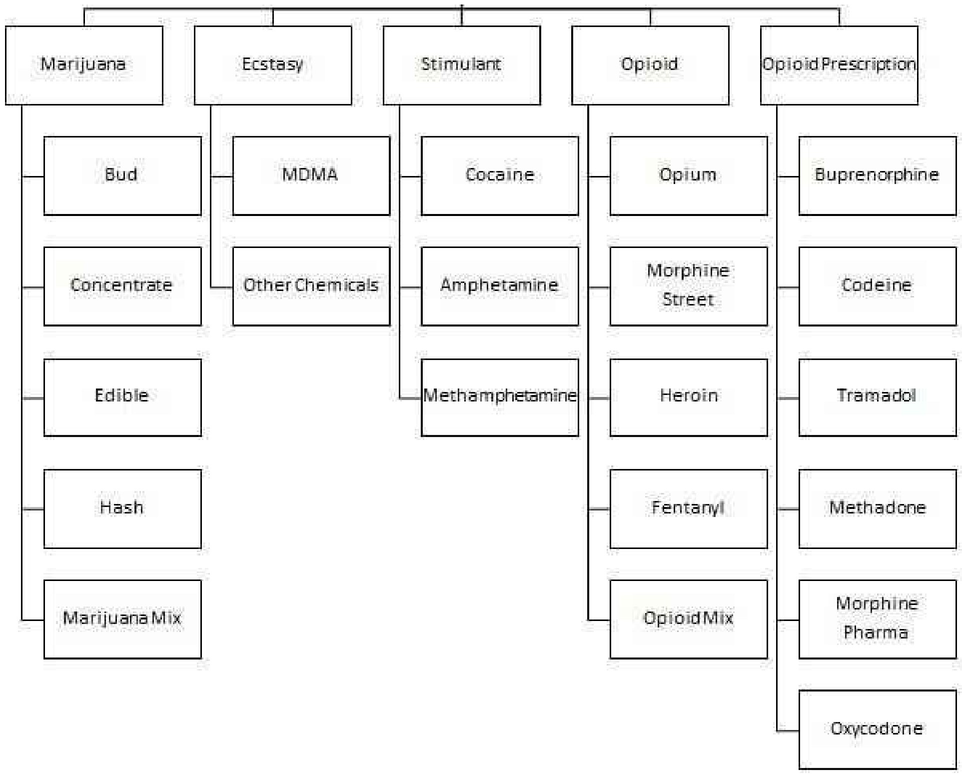
We assume black-market prices are endogenously set by the firms (drug dealers). The unobserved product characteristics (error term) in the demand equation are then correlated with price. This issue can be addressed using the instrumental variable (IV) method. In studies with homogeneous goods, the unobserved product characteristics enter the demand equation in a linear fashion. In addition, the number of product characteristics to keep track of is minimal. As such, the IV method will suffice in estimating demand. Our market contains heterogeneous goods, so the unobserved product characteristics enter the demand equation nonlinearly, which requires us to use market share to uncover the mean utility level of products as shown in Berry (1994). The mean utility levels can then be related to product characteristics and price using IVs. We choose to estimate demand in our market using nested logit. Imposing structure on the choice set consumers face can reduce the number of parameters and avoid the dimensionality issue.

Our reasoning for choosing nested logit is as follows. In a logit regression, consumers will switch to the product with the largest market share. In our study, the regression method would lead us to observe buyers switching from all illicit narcotics to marijuana, instead of what actually happens in the real world. We decided against using a random coefficient logit model as demonstrated in Berry, Levinsohn and Pakes (1995) for two reasons. One, we cannot identify individual characteristics regarding our market. We can resolve this issue by interacting product characteristics with fake individual characteristics drawn from an arbitrary random normal distribution, but this approach would seem to complicate our regression without offering any ties to the real world. Second, we do not have any continuous variable that links all products together. Nevo (2001) pours milk over cereal and counts how long the cereal takes to become soggy. We could run a similar experiment by hiring a group of research assistants and have them take various illicit narcotics, and then count the minutes to see how long the effects take to wear off. This approach would, of course, be unethical and illegal.

For the nested logit estimation, we closely follow Berry (1994) and Goldberg (1995). Un-like Goldberg, for the reasons discussed above, we were unable to obtain detailed household surveys to interact at each level of the nest. For the nesting structure, we have two levels as shown in Figure 1.2.[23] We maintain the same structure as to how a consumer would browse on the website. The categories and products within our nesting structure are as listed on the webiste. We keep prescription opioids separated from opioids manufactured by non-pharmaceutical firms, because dosage is important. An 80mg oxycodone pill will contain exactly 80mg, whereas a batch of heroin may be more or less potent than another batch simply because of the lack of quality control wherever they are produced.

[23]For alternative specification on the nesting structure, see Appendix G.

Figure 1.2
Illicit Drug Choice Model



We keep the various product types separated within each drug category as structured on the website to better differentiate consumer preference. From a consumer's point of view, a price reduction is a non-event, because she simply purchases more of whatever drug she had been using. A price increase, however, will help us better understand cross-price elasticity. For example, when the price of marijuana concentrate increases, consumers will likely switch to buy marijuana bud that is at a lower price bracket, before switching to a different drug category altogether.

One main criticism of nested logit estimation is that the researcher must choose the nests, when letting the data speak for themselves would in general be better. Consumers in the automotive market, for example, are not restricted to first deciding whether they want a foreign or a domestic car and then deciding which model they would like. As a result, the rigid structure of the nests may lead to cross-price elasticity that does not reflect the real world. However, that scenario is unlikely to happen in this market. As mentioned previously, a customer will likely look for a similar product within the nest first before jumping nests. Ultimately, we believe the rigid structure of our nests reflect the real-world decision-making process, and that is the appropriate framework for our analysis.

We define our market as each country pair. We aggregate our transaction data by country, day, and product characteristics. The destination country is recorded for each transaction. As mentioned before, the destination country is often the same as where the seller is from, to avoid additional custom screening.

In our data set, we observe $t = 1, \ldots, T$ markets. Because our main objective is consumer preference within the US, T denotes the daily US market on Agora. The conditional indirect utility u from product j at market t is

$$u_{ijt} = x_j \beta - \alpha p_{jt} + \xi_{jt} + \zeta_{igt} + (1 - \sigma)E_{ijt}$$

Assume the errors are distributed type-I extreme value, and the covariance matrix is re-stricted so that goods within the same nest have correlation coefficient $(1 - \rho^2)$, and goods across nests have 0. We get the following:

$$ln(s_{jt}) - ln(s_{0t}) = x_j \beta - \alpha p_{jt} + \sigma ln(\bar{s}_{jt|gt}) + \xi_{jt}$$
$$j = 1, \ldots, J_t;\ t = 1, \ldots, T,$$

where x_j is a vector of observable product characteristics, p_{jt} is the price of product j in market t, and ξ_{jt} is the error term to account for the variations unobserved to the econo-metrician, but known to consumers. The estimates for β, α and σ are obtained from linear

instrumental variables regression.[24] The term $ln(\bar{s}_{jt|gt})$ denotes the sub-group j within each nest g. In this case, j denotes the drug type within category and g for each category of drugs.

Each product's market share can thus be used as proxy for conditional indirect utility as per Berry (1994). To construct the market share, we define our outside good as illicit drug users who did not purchase their products from Agora. UNODC's "World Drug Report 2017" provides rough information on the number of past-year users in 2015, which we use for our construction of the outside good, that is, the number of users in the US.[25] Finally, the parameters for the utility equation are estimated using the GMM estimator (Hansen et al. 1996; Newey and Smith 2004) with the two-stage least-squares method for IV as described below.

Instrument

We propose two methods to instrument for price. One is to exploit our panel data similar to Hausman (1996) and Nevo (2001). The demand in each country is independent from the others, but the global supply tends to come from the same locations. For example, most of the world's supply of cocaine originates in Colombia, and fentanyl (China White) from China. The average prices of each narcotic in other countries are therefore a valid instrument

[24] For more in-depth discussion on product characteristics, see Appendix E.

[25] This information is cross-checked with CDC data on illicit drug use in "Health United States Report 2016" table 50, https://www.cdc.gov/nchs/data/hus/hus16.pdf#050.

after controlling for time invariant differences with country fixed effects.

The other method is to use a cost-based approach. The United Nations Office on Drugs and Crime publishes data on narcotics seizures. These data include the location of the seizure, date, drug name, and amount, which we organized into our respective categories. The data also have information on the precise location of the seizure and the destination of the shipments. The location of the seizure and destination is less important for our needs, because the seizure itself causes an exogenous shock to the global supply. Because the bulk of the cost for illicit drugs is for transportation, we believe the seizure of shipments presents a valid instrument.

We need an additional instrument for the nested logit estimation. The market share of product j within nest g is endogenous. We calculate the number of products within each nest to instrument for the $ln(\bar{s}_{jt|gt})$ term.

Results

The results of our nested logit estimation are presented in Appendix F for the five cat-egory nesting specification and Appendix G for the four category nesting specification. As explained above, we use two instruments for price and one to identify within nests. In the five category specification, the estimator for codeine is insignificant. Few codeine transactions take place in the US. In the four category specification, the estimators for codeine, edible marijuana, crystal meth, and marijuana mix are insignificant. We believe the insignificance is due to how we specify the nesting structure. Fortunately, other than the estimator for codeine, the rest of the estimators are not relevant to answering our questions. The following analyses are compiled based on results from the five category nesting structure.

Table 1.3 below shows what happens when the price of drugs increases by 10% to simulate the likely implications of increasing law enforcement in the black market. We observe a moderate increase in treatment opioids when the price of heroin increases, but no change when the price of fentanyl increases. Buyers seem to purchase more heroin when the price of fentanyl rises. This finding implies substitution behavior will thwart efforts to combat the opioid epidemic unless policy and law enforcement simultaneously target all forms of illicit opioids.

Table 1.3
Treatment Opioid Quantity Change When Prices Increased by 10%

10% up P on Q(g)	buprenorphine	codeine^^	fentanyl	heroin	methadone	morphineStreet
buprenorphine	-1.352	0.043	0.171	0.006	0.012	0.000
codeine^^	0.003	-0.257	0.005	0.000	0.000	0.000
fentanyl	0.000	0.000	-1.405	0.021	0.000	0.000
heroin	0.011	0.005	72.095	-5.968	0.001	0.016
methadone	0.008	0.004	0.015	0.001	-0.171	0.000
morphineStreet	0.000	0.000	0.038	0.001	0.000	-0.025

The existence of dark-net transactions of buprenorphine and methadone suggests buyers find conventional channels to treatment either inaccessible or unaffordable (Hettema and Sorensen 2009; Parran et al. 2017). The inaccessibility of conventional treatment due to long waiting lists[26] (Chun et al. 2008) or high-cost rehabilitation services[27] (upwards of $9,000 per month[28]) becomes an increasingly plausible explanation when one recalls the risks and additional costs associated with purchasing products on the dark net.

We assume a decrease in the number of opioid prescriptions will drive up the black-market price. Table 1.4 shows that buyers use more tramadol and illicit opioids to supplement their habits when faced with and price increase. It also shows no appreciable correlation between

[26]Elkins, C. "Addicts Grow Frustrated by Wait Times for Addiction Treat- ment," *DrugRehab.com*, January 20, 2016, https://www.drugrehab.com/2016/01/20/ addicts-grow-frustrated-wait-addiction-treatment/.

[27]Segal, D. "In Pursuit of Liquid Gold," *The New York Times*, December 27, 2017, https://www.nytimes.com/interactive/2017/12/27/business/urine-test-cost.html.

[28]Segal, D. "City of Addict Entrepreneurs," *The New York Times*, December 12, 2017, https://www.nytimes.com/interactive/2017/12/27/business/new-drug-rehabs.html.

opioid and marijuana use, as a typical joint consists of 660mg of marijuana bud, demonstrated by the estimated cross-price elasticity.

Table 1.4
Opioids and Marijuana Quantity Change When Prices Increased by 10%

10% up P on Q (g)	bud	buprenorphine	fentanyl	heroin	methadone	oxycodone	tramadol
bud	-11.025	0.362	57.679	1.928	0.049	0.074	2.220
buprenorphine	0.032	-1.352	0.171	0.006	0.012	0.018	0.544
fentanyl	0.003	0.000	-1.405	0.021	0.000	0.000	0.001
heroin	0.325	0.011	72.095	-5.968	0.001	0.002	0.068
methadone	0.003	0.008	0.015	0.001	-0.171	0.002	0.048
oxycodone	0.012	0.032	0.062	0.002	0.004	-0.168	0.199
tramadol	0.223	0.626	1.206	0.040	0.084	0.128	-3.649

There are a couple reasons for the asymmetric cross-price elasticities. In the marijuana versus opioid case, when marijuana price increases, buyers will purchase more opioid prod-ucts, but not vice versa. This is because a patient addicted to opioid is similar to a diabetic patient. Human body produce both opioid and insulin endogenously. In the case of a dia- betic patient. When the body stop producing endogenous insulin, the patient have to take exogenous insulin. A patient addicted to opioid is the same. When the body stop producing endogenous opioid, the patient have to take exogenous opioid. Marijuana is not a substitute to opioid addiction. On the other hand both chemicals can treat pain, so in this case mar- ijuana and opioid are substitutes. The reason why asymmetric cross-price elasticities exist within different opioid compounds is due to drug potency and human tolerance. When a patient is used to using fentanyl and the price went up, it is difficult to switch to heroin because fentanyl is more potent. A patient with high tolerance to opioid will need a lot more heroin to get the same effect.

Using data from the National Survey on Drug Use and Health (NSDUH), Alpert et al. (2017) show that consumers in states with decreases in prescription opioids substitute to other opioids, such as heroin and fentanyl. Although we do not disagree with the importance of increasing law enforcement in the black-market and reducing opioid prescriptions, we would also like to see a more patient- and community-level interventions as suggested in Dasgupta et al. (2018).

Conclusion

Using data collected from the dark web, we seek a solution to lower the number of opioid overdose induced deaths in the US. From our demand estimation analysis for all narcotics, we find the opioid users to be very price sensitive. This can explain why current policy such as mandatory access to PDMP has been ineffective in lowering the number of opioid overdose. Similarly, increasing law enforcement in the black-market will only lead to opioid users switching to cheaper and potentially more dangerous drugs. Policy makers should instead utilize the price sensitivity among opioid users as an effective mechanism in reducing the number of overdose through implementing treatment policies, such as increasing the number of physicians able to prescribe buprenorphine.

Many questions remain unanswered. Due to our estimation method, we are unable to accommodate product bundling. Consumers might use multiple drugs together. We leave this avenue for future research. We struggle to find a continuous variable to run our random coefficient logit properly. Two questions interest us, but we are unable to answer them using our data. The first involves the impact and effectiveness of treatment and rehab centers. The other involves calculating the social welfare surplus of the policies. We can calculate consumer surplus, but doing so tells us only that consumers are better off when prices of drugs decrease, because they can consume more, which is hardly an interesting finding. Our research contributes to the literature by studying the effects of the black market on the current opioid epidemic in the US.

Appendix A: Sample Review for Cocaine Sold on Agora

Source: https://www.reddit.com/r/DarkNetMarkets/comments/2ozy10/vendor_review_ columbiamagic_35g_cocaine_agora/

Vendor Review [Vendor Review] ColumbiaMagic - 3.5g Cocaine [Agora]
submitted 2 years ago by Free Fox

I am a seasoned vendor on the DNM. My usual is MDMA/LSD but I enjoy skiing with my girlfriend and really close friends. I do not sell coke and I don't intend to; I buy only for personal use, which means that I expect a good product. Here's a screenshot of the purchase: http://i.imgur.com/idcTRig.png

Shipping - 10/10: I ordered on a Monday and the 3.5g landed that Wednesday. I was blown away by how fast it arrived.

Stealth - 10/10: The stealth was great. I obviously can't describe all the methods used but the product was both vacuum sealed and heat sealed within a MBB (the gold standard). I can't imagine how this letter could ever get stopped domestically. The vendor did a great job here.

Product - 9/10: The product is fantastic. The first thing you notice upon opening the bag(s) is the smell - a BEAUTIFUL, strong cocaine smell. The coke cuts up great, flakes, and flattens when pressed (a sign of quality). It is also quite shiny - fishscale indeed! There's a very slight burn, but barely anything noticeable. Goes in great. When my girlfriend and I went out for a night of drinking and skiing, we came home and fucked for 8 hours. It was the best sex I've ever had.

The reason I am giving a 9/10 here instead of 10/10 is because I've had a lot of coke and it's important to me to leave a very honest review. I can't give 10/10 until I see a GC/MS lab result. You can't beat the quality of, let's say, Meerkovo, but his 3.5g bag is gonna cost you over $400 while only being 5-8% more pure (not worth it). At $280 for a a really potent, high quality 8-ball, ColumbiaMagic's coke is unbeatable. Also, neither of us experience much of a comedown - just a little boredom and that was it. No jitters or depression or anything like that. Here's a photo of the reagent test I did: http://i.imgur.com/Cx1CnUr.png

Please note on this test that the test asks for exactly 20mg to be accurate (since it's a semi-quantitative test). I accidentally only put in 10-15 mg so it's likely that the color would have been an even darker shade of coffee brown.

Communication - ?/10: I can't comment on this because there was no need for communication! haha. My order was shipped instantly and arrived at my door in 48 hours. who needs communication at that point? lol

Bottom line, check him out and try some yourself. He's got great reviews on Agora and when I tried to find reviews on here, I couldn't find any. I'm a long-time buyer and supporter of Bungee54 and as that team knows, I like to support my vendors who take their time to sell a good, honest product. This vendor is one of the good ones, people.

Figure 1.3
Sample Transaction on Agora

Order #[redacted]

Buying from: ColumbiaMagic 5.00/5, 100~150 deals

3.5g Uncut Fishscale cocaine

****

NEW ESCROW POLICY
Due to the high amount of orders in escrow, any new orders that are place today and tom ...

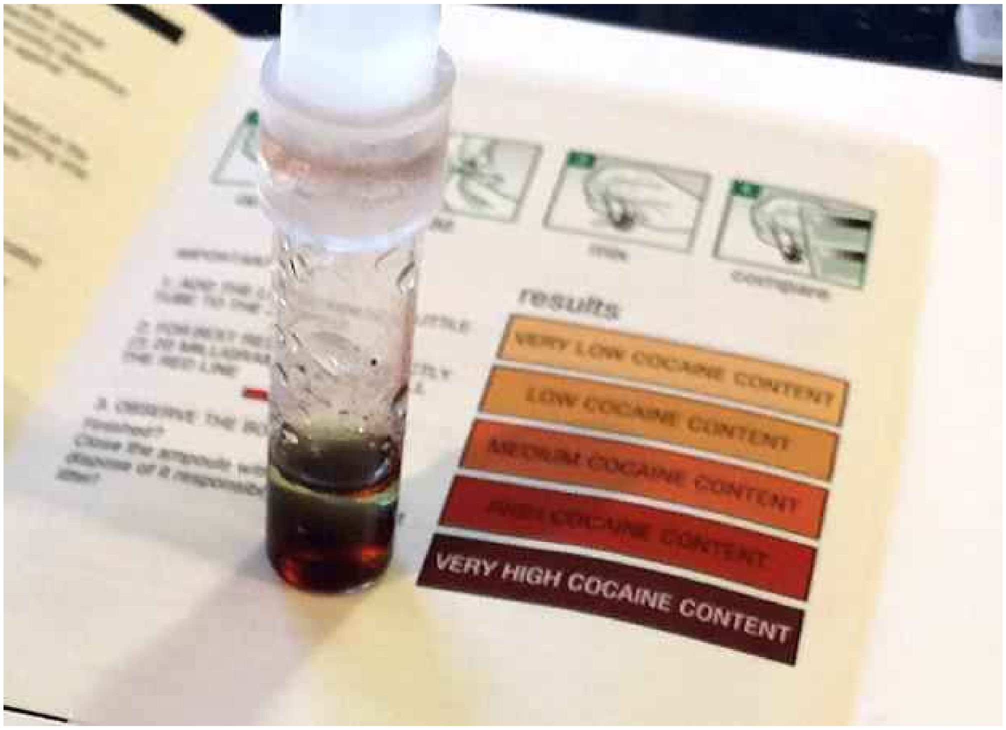
Price: 0.8083[redacted] BTC
Shipping: Priority Shipping
Amount: 1

This order is finalized. Nothing else can be done with it.
Total cost of this order: 0.825[redacted] BTC
Current status: [redacted]

Feedback

This order is finalized. You can add or update feedback for up to 6 weeks after finalization (new feedback replaces the old one for this order):

Figure 1.4
Sample Vendor Review on Agora



Appendix B: Agora Closing Statement

The message below was posted on Agora marketplace before its closure.

–––BEGIN PGP SIGNED MESSAGE––– Hash: SHA512 Recently research had come that shed some light on vulnerabilities in Tor Hidden Services protocol which could help to deanonymize server locations. Most of the new and previously known methods do require substantial resources to be executed, but the new research shows that the amount of resources could be much lower than expected, and in our case we do believe we have interested parties who possess such resources. We have a solution in the works which will require big changes into our software stack which we believe will mitigate such problems, but unfortunately it will take time to implement. Additionally, we have recently been discovering suspicious ac- tivity around our servers which led us to believe that some of the attacks described in the research could be going on and we decided to move servers once again, however this is only a temporary solution. At this point, while we don't have a solution ready it would be unsafe to keep our users using the service, since they would be in jeopardy. Thus, and to our great sadness we have to take the market offline for a while, until we can develop a better solution. This is the best course of action for everyone involved. In the mean time we shall do our best to clear all outstanding orders and we ask all of you users who have money on their accounts, withdraw them as soon as possible, because we don't want to be responsible for it during the time when the market will be offline. During this time, there might be some delays in payouts, since many people are expected to withdraw money at the same time, but we intend to resolve any such issues in the end. But we advice you to use only destination bitcoin addresses that do not expire when you send money out from Agora, as the payments to them might get delayed. While the market is offline, do not send any bitcoin to any of your deposit addresses on Agora. We do not gurantee the safety of any funds sent there. Vendors, we strongly advice you to abort any orders that haven't been sent out or processed yet, as we cannot gurantee what will happen with the orders in resolution. We shall try to resolve it on a case-by-case basis, but there might not be time to wait for orders that require long shipping times. We are going to handle the situation with the vendor bonds soon, we need some time to make sure that noone uses this as an opportunity to start scamming wildly. All of the market data will be kept intact and be available upon return, including all of the user history and profile data. Since our PGP key is nearing expiration date, here is a new PGP key which could be used to check authenticity of our messages in the future. - ——BEGIN PGP PUBLIC KEY BLOCK—

Appendix C: Street Prices from United Nations Office on Drugs and Crime

The street price data come from the United Nations Office on Drugs and Crime. The data provide a comparison to the online prices from Agora.

Table 1.5
Marijuana Street Prices

Year	Country	Type	Transaction	Typical $/g	Typical THC %	$/g (low)	THC % (low)	$/g (high)	THC % (high)
2013/2014	Australia	Herb	Retail	24.23	3.71	9.77	0.02	40.72	25.60
2013/2014	Australia	Herb	Wholesale	6.94	N/A	3.80	N/A	11.76	N/A
2014	Australia	Resin	Retail			32.57	N/A	40.72	N/A
2012	Australia	Resin	Wholesale			8.29	N/A	12.96	N/A
2015	Belgium	Herb	Retail	9.63	13.00	3.28	2.00	21.88	25.00
2015	Belgium	Herb	Wholesale	5.72	N/A	3.28	N/A	8.21	N/A
2015	Belgium	Resin	Retail	8.97	19.20	3.50	2.00	21.88	55.00
2015	Belgium	Resin	Wholesale	3.44	N/A	1.86	N/A	4.38	N/A
2014/2015	France	Herb	Retail	9.30	13.00	8.21	N/A	10.94	N/A
2014/2015	France	Herb	Wholesale	3.83	8.00	3.39	N/A	4.92	N/A
2014/2015	France	Resin	Retail	7.11	20.70	6.02	N/A	8.53	N/A
2014/2015	France	Resin	Wholesale	2.41	10.00	1.86	6.00	2.74	18.00
2015	Germany	Herb	Retail	11.05	0.60	5.80	0.10	17.61	22.30
2015	Germany	Herb	Wholesale	6.00	10.60	3.92	0.02	7.68	22.10
2015	Germany	Resin	Retail	8.97	14.90	4.49	0.40	13.68	45.60
2015	Germany	Resin	Wholesale	3.97	15.00	2.49	0.15	5.28	32.80
2014	Netherlands	Herb	Retail	12.91	15.30	11.90	6.40	14.44	22.80
2014	Netherlands	Resin	Retail	11.73	17.80	11.05	1.90	12.76	27.70
2007	Netherlands	Resin	Wholesale	2.60	N/A	N/A	N/A	N/A	N/A
2015	UK	Herb	Retail	4.23	N/A	4.23	N/A	6.35	N/A
2015	UK	Herb	Wholesale	1.48	N/A	1.33	N/A	2.67	N/A
2015	UK	Resin	Retail	4.23	N/A	4.23	N/A	6.35	N/A
2015	UK	Resin	Wholesale	1.48	N/A	1.19	N/A	2.67	N/A
2014/2015	USA	Herb	Retail	N/A	12.17	1.05	2.79	63.29	14.48
2014/2015	USA	Herb	Wholesale	N/A	4.20	0.66	2.97	15.38	5.42
2015	USA	Resin	Retail	N/A	N/A	5.27	N/A	12.31	N/A
2008/2015	USA	Resin	Wholesale	N/A	34.16	16.98	2.43	39.68	65.90

Notes: Herb refers to the flower part of the plant. The flowers are typically called bud and are sold after trimming and curing. Resin in this dataset refers to hash or hashish. It is made with only the trichome part of the flower. Low-quality hashish will have other plant materials mixed in.

Table 1.6
Cocaine Street Prices

Year	Country	Type	Transaction	Typical $/g	Purity %	$/g (low)	Purity % (low)	$/g (high)	Purity % (high)
2014	Australia	Salt	Retail	414.80	34.40	201.58	7.70	651.47	79.70
2014/2015	Australia	Salt	Wholesale	176.44	62.90	146.58	8.50	203.58	92.10
2015	Belgium	Salt	Retail	58.53	64.00	21.88	50.00	127.68	90.00
2015	Belgium	Salt	Wholesale	31.80	N/A	13.68	N/A	49.23	N/A
2007	Belgium	Crack	Retail	54.80	N/A	6.85	N/A	82.20	N/A
2014/2015	France	Salt	Retail	71.12	52.00	65.65	N/A	82.06	N/A
2013/2015	France	Salt	Wholesale	38.29	62.00	32.82	50.00	43.76	75.00
2015	Germany	Salt	Retail	80.74	69.10	51.53	3.70	122.32	92.10
2015	Germany	Salt	Wholesale	46.85	65.50	32.93	11.24	59.90	92.70
2015	Germany	Crack	Retail	74.73	N/A	58.32	N/A	123.96	N/A
2014	Netherlands	Salt	Retail	69.35	59.00	26.32	N/A	131.59	N/A
2010	Netherlands	Salt	Wholesale	41.60	N/A	N/A	N/A	N/A	N/A
2015	UK	Salt	Retail	59.26	44.00	44.44	1.00	177.78	96.00
2015	UK	Salt	Wholesale	57.78	59.00	51.85	1.00	63.70	93.00
2015	UK	Crack	Retail	88.89	N/A	59.26	N/A	118.52	N/A
2015	UK	Crack	Wholesale	57.78	N/A	51.85	N/A	63.70	N/A
2015	USA	Salt	Retail	N/A	N/A	10.00	N/A	900.00	N/A
2015	USA	Salt	Wholesale	N/A	74.00	3.00	N/A	55.00	N/A
2015	USA	Crack	Retail	N/A	N/A	20.00	N/A	470.00	N/A
2015	USA	Crack	Wholesale	N/A	N/A	7.00	N/A	45.00	N/A

Notes: Salt is the most common form of cocaine sold. It has high melting point, so users tend to snort salts. Crack is the free base form of the salt. They are cooked with baking soda, have a lower melting point and can be smoked.

Table 1.7
Ecstasy Street Prices

Year	Country	Type	Transaction	Typical $/tablet	Purity %	$/tablet (low)	Purity % (low)	$/tablet (high)	Purity % (high)
2014	Australia	Ecstasy	Retail	26.82	20.80	5.70	1.70	40.72	81.10
2014/2015	Australia	Ecstasy	Wholesale	9.21	60.00	1.08	0.30	16.29	78.80

Year	Country	Type	Transaction	Typical $/tablet	mg/tablet	$/tablet (low)	mg/tablet (low)	$/tablet (high)	mg/tablet (high)
2015	Belgium	Ecstasy	Retail	6.24	125.00	1.09	75.00	10.94	250.00
2015	Belgium	Ecstasy	Wholesale	3.15	N/A	2.74	N/A	3.56	N/A
2013/2015	France	Ecstasy	Retail	9.30	66.00	6.56	N/A	10.94	N/A
2015	France	Ecstasy	Wholesale	2.19	N/A	1.64	N/A	3.17	N/A
2015	Germany	Ecstasy	Retail	8.32	103.00	4.49	2.60	13.89	1756.80
2015	Germany	Ecstasy	Wholesale	3.11	94.90	2.09	3.70	4.35	297.80
2014	Netherlands	Ecstasy	Retail	5.13	150.00	0.66	N/A	19.74	N/A
2015	UK	Ecstasy	Retail	7.41	N/A	2.96	N/A	14.81	N/A
2015	UK	Ecstasy	Wholesale	5.19	N/A	2.22	10.00	7.41	200.00
2014	USA	Ecstasy	Retail	N/A	N/A	1.00	N/A	70.00	N/A

Notes: The most common chemical compound in ecstasy is 3,4-Methylenedioxymethamphetamine (MDMA). Although other chemical compound with similar effects are sold as ecstasy as well. The highlighted cell shows unusually high concentration. That high of a dosage will kill a person. The recommended dosage is 80mg. People with higher tolerance may increase the dosage to 120mg. Pills with 200-300mg dosage are usually taken half at a time.

Table 1.8
Opioid Street Prices

Year	Country	Type	Specifics	Transaction	Typical $/g	Purity %	$/g (low)	Purity % (low)	$/g (high)	Purity % (high)
2014	Australia	Heroin		Retail	294.20	22.40	122.20	6.50	447.90	57.40
2014/2015	Australia	Heroin		Wholesale	234.12	56.70	228.01	0.40	240.23	0.40
2015	Belgium	Heroin		Retail	24.20	22.00	7.00	15.00	73.00	30.00
2015	Belgium	Heroin		Wholesale	17.51	N/A	13.13	N/A	21.88	N/A
2014/2015	France	Heroin		Retail	38.30	15.00	29.50	N/A	49.20	N/A
2015	France	Heroin		Wholesale	16.41	N/A	12.04	N/A	21.88	N/A
2015	Germany	Heroin		Retail	54.90	19.10	27.70	1.70	80.00	62.90
2015	Germany	Heroin		Wholesale	36.38	36.50	18.76	0.80	40.87	0.80
2008/2013	Netherlands	Heroin		Retail	46.70	N/A	N/A	0.10	N/A	65.00
2010	Netherlands	Heroin		Wholesale	22.08	N/A	N/A	N/A	N/A	N/A
2015	UK	Heroin	Heroin #2	Retail	74.10	44.00	59.30	1.00	88.90	96.00
2015	UK	Heroin	Heroin #2	Wholesale	40.00	49.00	35.56	1.00	44.44	1.00
2015	USA	Heroin	Black tar	Retail	N/A	17.00	20.00	N/A	300.00	N/A
2015	USA	Heroin	Black tar	Wholesale	N/A	45.00	12.00	N/A	100.00	N/A
2015	USA	Heroin	South American	Retail	N/A	35.00	25.00	N/A	400.00	N/A
2015	USA	Heroin	South American	Wholesale	N/A	60.00	10.00	N/A	100.00	N/A
2015	USA	Heroin	Southwest Asia	Retail	N/A	23.00	120.00	N/A	300.00	N/A
2015	USA	Heroin	Southwest Asia	Wholesale	N/A	34.00	50.00	N/A	85.00	N/A

Notes: Heroin #2 means heroin freebase. It is not a salt and has a lower melting point. Black tar is typically from Mexico, it has high contaminant counts due to the manufacturing process. USA is a large consumer of opioid, so imports come from around the world.

Appendix D: Online Prices from Agora Market

The online price data come from Agora. The data provide a comparison to the street- price data from the United Nations Office on Drugs and Crime. The quantity is measured in grams. In general, the online prices are higher, perhaps due to the better review and policing system online to ensure higher-quality products (Caudevilla 2016).

Table 1.9
Marijuana Online Prices

Year	Country	Type	avg Q	avg $/g	# strain available
2014	Australia	Bud	5.30	65.99	55
2015	Australia	Bud	4.79	64.00	116
2014	Belgium	Bud/Hash	36.25	187.67	3
2015	Belgium	Bud/Hash	30.72	139.39	7
2014	France	Bud/Hash	5.18	54.06	7
2015	France	Bud/Hash	5.28	54.63	22
2014	Germany	Bud/Hash	9.31	85.95	75
2015	Germany	Bud/Hash	15.96	84.47	162
2014	Netherlands	Bud/Hash	13.62	102.61	34
2015	Netherlands	Bud/Hash	10.61	129.94	79
2014	UK	Bud/Hash	5.96	63.95	72
2015	UK	Bud/Hash	13.4	58.21	254
2014	USA	Bud/Hash	18.28	141.2	258
2015	USA	Bud/Hash	31.02	139.48	712

Notes: The average price per gram is higher online than offline. This is due to online offering higher quality products (EMCDDA 2017) and buyers paying for convenience and safety from dealing with dealers face-to-face (Barratt et al. 2016). The staggering number of strain available may also be a factor to the higher prices.

Table 1.10
Cocaine Online Prices

Year	Country	Type	avg Q	avg $/g	Purity
2014	Australia	Cocaine	0.43	178.89	90%
2014	Australia	Crack	0.40	172.04	N/A
2015	Australia	Cocaine	1.04	304.75	90%
2015	Australia	Crack	0.77	281.09	N/A
2014	Belgium	Cocaine	3.79	308.76	90%
2014	Belgium	Crack	2.13	210.69	N/A
2015	Belgium	Cocaine	2.51	192.58	90%
2015	Belgium	Crack	1.32	148.80	N/A
2014	France	Cocaine	1.04	114.03	90%
2015	France	Cocaine	1.49	102.04	88%
2014	Germany	Cocaine	2.41	235.72	90%
2014	Germany	Crack	1.00	109.73	N/A
2015	Germany	Cocaine	2.73	208.73	88%
2015	Germany	Crack	3.62	306.07	N/A
2014	Netherlands	Cocaine	1.93	159.44	81%
2014	Netherlands	Crack	0.24	188.30	N/A
2015	Netherlands	Cocaine	2.08	152.8	86%
2015	Netherlands	Crack	0.77	84.27	N/A
2014	UK	Cocaine	2.21	195.31	84%
2014	UK	Crack	0.79	99.77	N/A
2015	UK	Cocaine	2.51	193.30	85%
2015	UK	Crack	1.91	109.73	62%
2014	USA	Cocaine	3.12	241.24	88%
2014	USA	Crack	1.20	151.85	N/A
2015	USA	Cocaine	4.70	287.43	92%
2015	USA	Crack	1.16	142.51	N/A

Notes: The online cocaine prices are much higher than the street. This is likely due to the high purity sold online.

Table 1.11
Ecstasy Online Prices

Year	Country	Type	avg Q	avg $/g
2014	Australia	MDMA	3.72	441.27
2015	Australia	MDMA	3.01	326.92
2014	Belgium	MDMA	28.30	393.55
2015	Belgium	MDMA	18.74	298.32
2014	France	MDMA	2.19	68.57
2015	France	MDMA	3.97	82.00
2014	Germany	MDMA	19.16	291.50
2015	Germany	MDMA	30.01	343.28
2014	Netherlands	MDMA	73.76	144.71
2015	Netherlands	MDMA	15.16	190.14
2014	UK	MDMA	4.97	142.54
2015	UK	MDMA	6.9	146.2
2014	USA	MDMA	4.49	185.98
2015	USA	MDMA	4.69	185.31

Notes: We excluded bulk purchase as they are unlikely to occur in street sales. The bulk sales are common in Belgium and Netherlands. Study conducted in Netherlands shows that online prices tend to be higher than the street (van der Gouwe 2017).

Table 1.12
Opioid Online Prices

Year	Country	Type	avg Q	avg $/g
2014	Australia	Heroin	0.55	249.83
2014	Australia	Fentanyl	0.34	289.69
2015	Australia	Heroin	0.57	171.07
2015	Australia	Fentanyl	0.29	178.07
2014	Belgium	Heroin	2.50	124.54
2015	Belgium	Heroin	2.43	118.05
2014	France	Heroin	0.49	57.93
2015	France	Heroin	0.72	98.63
2014	Germany	Heroin	1.23	107.04
2014	Germany	Fentanyl	0.007	159.54
2015	Germany	Heroin	1.39	89.60
2015	Germany	Fentanyl	0.005	102.82
2014	Netherlands	Heroin	3.53	207.42
2015	Netherlands	Heroin	1.82	111.33
2014	UK	Heroin	0.52	55.29
2015	UK	Heroin	0.67	68.06
2014	USA	Heroin	0.97	130.96
2014	USA	Fentanyl	0.74	175.79
2015	USA	Heroin	1.37	152.84
2015	USA	Fentanyl	0.50	204.12

Notes: Fentanyl is not listed in UNODC data, but is relevant to our analysis. We list it here for reference. We do not distinguish between black tar from regular heroin because they are the same compound. Black tar has more impurity, which we account for, hence the difference in color. We also do not distinguish between heroin #3 or #4 as we do not care about the intake method. Since there are no documented difference in the high produced, we treat snort, smoke and injection as the same. The low average quantity of fentanyl sold in Germany is the result of pharmaceutical patch sale, not raw powder from China.

Appendix E: Product Characteristics for Each Drug Category

We provide more background information on product characteristics and their importance to buyers' preference. The quality of the drugs is an important factor in the product pricing (Galenianos and Gavazza 2017). We therefore paid close attention to the types of compounds sold and the respective purity levels.

The online market is anonymous, but the sellers can maintain their reputation through their usernames. First-time sellers commonly provide free samples with the requirement that buyers leave a comment (Ladegaard 2017). The comments serve as a way for the community to police the sellers.

Although the product descriptions on Agora are rich and full of details, we do not incorporate all the information in our analysis. We focus only on the product characteristics that will help answer our questions. Below is the product information we excluded for each category and our reasons.

In the marijuana category, we excluded all the strain information. Hundreds of different strains are sold. We do not believe that all the consumers are knowledgeable enough to choose between the strains. We could group the different strains into three main plant types of sativa, indica, and hybrid. However, upon close inspection, most of the strains are hybrids of sativa and indica strains, or even hybrids of hybrids. The plants have been cross-bred so much that they no longer resemble the properties of a pure sativa or a pure indica plant.

For ecstasy, we excluded all the colors and the maker's mark information. The MDMA powder is often pressed into pills of different colors and designs. We cannot imagine a scenario where a consumer is so offended by the color yellow or the brand Audemars Piguet engraved on the pill that she decided to exit the market.

In terms of stimulants, we excluded the origin of the manufacturer. Often, cocaine listings will include whether the coca plants were farmed in Bolivia, Colombia, Ecuador, or Peru. Unlike wine, for which terroir matters, we do not believe that after so much processing the users will be able to detect where the plant was grown. The argument of the conscious consumer does not make sense either, because fair-trade cocaine does not exist. The cartels do not create trading partnership based on transparency, or respect, or seek greater equity in international trade.

In the opioid category, we excluded the brand names for prescriptions and the numbers for heroin. OxyContin has generic versions, but we ignore the brands. We believe the dosage in each pill is what buyers care about. Heroin is often labeled as either #3 or #4.[29] Heroin #3 is for smoking and is not suitable for injection. Heroin #4 has a higher purity than #3. We don't think the consumption method matters–only the purity. We describe below the characteristics that are relevant to our analysis.

<u>Marijuana</u>

This category has five main types of product: bud, concentrate, edible, hash, and mari-juana mix.[30] Synthetics are not popular, because purchasing cheap weed in the US is easy. These types of transactions do exist in our dataset, but they are rare. We therefore ig- nore them. We refer to a relevant article for reference on characteristics buyers care about (Bancroft and Reid 2016).

Most of the sales online are of higher-quality products. In the case of marijuana, most of the plant has some amount of tetrahydrocannabinol (THC). However, the flower part of

[29] PBS, "From Poppy to Heroin: Step 5: Heroin Purification," August 22, 2002, http://www.pbs.org/wnet/wideangle/uncategorized/from-poppy-to-heroin-step-5-heroin-purification/3172/.

[30] Cannabis information in this section provided by Leafly.com.

the female plant has the highest concentration. When dealers list buds for sale, they are referring to the flower section that has been trimmed of excess plant material and cured, ready to be ground up and rolled into joints.

New extraction techniques have been developed since the legalization of marijuana in the US. These new forms of production method allow manufacturers to extract THC concentrate from buds. Concentrates are generally sold at a higher value than bud because making them requires a lot of bud. They are typically smoked in specialized dab rigs because they need to withstand temperatures between 550 and 750 degrees Fahrenheit. Concentrates are also popular in e-cigarette-type vaporizers.

Edibles are usually cookies and cupcakes made from THC butter. The THC butter is usually made by mixing left-over plant materials with butter and cooking the mix on the stove on low heat for a period of time to extract the THC compound. Various baked goods can be made from THC butter.

Hash is popular in Europe because the Asian suppliers typically collect trichomes from the flower and press them into bricks. Hash is smoked just like concentrates.

Marijuana mixes or bundles are a combination of multiple product types. We often see sellers combining buds and concentrate as bundles and throwing in some cookies for good repeat customers.

We provide a conversion between the different product types within this category. All types are compared with bud, which is set to 1. It takes one gram of bud to produce one gram of bud. For example, edible takes the most amount of bud to produce. One gram of bud will only produce 0.05 grams of edible.

Table 1.13
Marijuana Gram Equivalency Conversion Chart

Marijuana	Potency
Bud	1.00
Concentrate	0.25
Edible	0.05
Hash	0.15
Mix	0.36

MDMA (Ecstasy)

This category has two types of products: MDMA and non-MDMA. Ecstasy is a type of stimulant, but consumers identify it as a separate category all on its own, mainly due to the fact that ecstasy compounds release serotonin that evoke euphoria and feelings of happiness. This product is typically used at electronic dance music festivals or similar events (Ridpath et al. 2014). A variety of compounds are sold as ecstasy. The most popular compound is 3,4-methylenedioxy-N-methylamphetamine (MDMA). It belongs to the amphetamine class and has a phenethylamine core. MDMA can be made from safrole, which is an oil extracted from the sassafras plant. Similar compounds with a phenethylamine core can be synthesized from other precursors. This compound is mostly made in the Netherlands[31] and the Belgium region of Europe where laws on the precursor materials are lax.[32] Other compounds pro- vide effects similar to those from MDMA. In our research, we grouped them as non-MDMAs.

<u>Stimulants</u>

[31] Walker, P. "Ingredients for one billion ecstasy pills seized in Netherlands by police," Independent, Febru- ary 10, 2017, https://www.independent.co.uk/news/world/europe/billion-ecstasy-pillls-seized-netherlands- dutch-police-lorry-zeeland-rotterdam-a7573716.html.

[32] Koerner, B. "What's With All the Dutch Ecstasy? Why it's not made in the USA," Slate, April 1, 2004, http://www.slate.com/articles/news_and_politics/explainer/2004/04/whats_with_all_ the_dutch_ecstasy.html.

This category has three types of products: cocaine, speed, and meth. Cocaine is made from coca leaves. Coca plants are typically grown and processed in Colombia, Bolivia, and Peru.[33] During the time when our data were collected, Sinaloa Cartel was the main organi- zation trafficking cocaine from South America to the US through Mexico (DEA 2015). As a chemical compound, amphetamine is a close cousin to MDMA, although its effect on users is different. Amphetamine stimulates the releases of dopamine, which can increase energy and mental alertness and suppress the appetite. Most of the world's amphetamine supplies are produced from the same location as MDMA due to a similar chemical compound. Metham-phetamine hydrochloride, commonly known as crystal meth, can be fully synthesized from precursor chemicals.

Prescription Opioids and Non-prescription Opioids

The prescription-opioid category has six types of products: buprenorphine, codeine, methadone, pharmaceutical morphine, oxycodone, and tramadol. The non-prescription-opioids category has five types of products: fentanyl, heroin, non-pharmaceutical morphine, opioid mix, and opium.

In terms of prescription opioids, India is the top producer of licit opium for pharmaceuti- cals.[34] Buprenorphine and methadone are prescription opioids marketed to treat addiction. The US currently has methadone clinics for addiction treatments, but buprenorphine is rel- atively new compare to country like France (Polomeni and Schwan 2014). We believe that treatment opioids are for sale on the black market because the US has a shortage of treat-

[33] Based on CIA's World Factbook, Colombia had 159,000 hectares under coca cultivation in 2015. Peru had 53,000 hectares and Bolivia had 36,500 hectares in the same year.

[34] Based on CIA's World Factbook, India is the "world's largest producer of licit opium for the pharma-ceutical trade."

ment centers (Hettema and Sorensen 2009; Chun et al. 2008; Parran et al. 2017). France introduced buprenorphine as a treatment for heroin addiction in 1995.[35] Over time, studies have been conducted regarding its effectiveness (Auriacombe et al. 2004). Reports show that buprenorphine can be crushed and injected to produce a high.[36] As such, this compound has been trafficked in the black market.[37] Codeine is a relatively weak opioid compound commonly found in cough syrups. Consumers abuse both pharmaceutical morphine and oxycodone. Tramadol is an opioid-like substance for treating pain.

Illicit poppy plants are grown in India, Afghanistan, Burma, Laos, Pakistan, Thailand, Vietnam, Mexico, and Colombia.[38] They are often processed into heroin, although they are also sold in the form of opium, morphine, and mixed product. Synthetic opioids are the common cause of overdose, because fentanyl is 75 times more potent than morphine. Figure 1.5 shows a picture from the New Hampshire State Police's Forensic Lab, illustrating how easy overdosing on fentanyl is compared to heroin.

Data show that at least 200,000 people died in the US from prescription-opioid overdose between 1999 and 2016. The number of prescription overdose deaths increased five times from 1999 to 2016.[39] CDC data show more than 19,000 deaths related to synthetic opioids in the US in 2016. In the same year, New Hampshire, West Virginia, and Massachusetts had the highest death rates from synthetic opioids, and the number of overdose deaths increased in 21 states.[40]

[35] Khazan, O. "How France Cut Heroin Overdoses by 79 Percent in 4 Years," The Atlantic, April 16, 2018, https://www.theatlantic.com/health/archive/2018/04/ how-france-reduced-heroin-overdoses-by-79-in-four-years/558023/.

[36] Niedowski, E. "Success, Setback in France," The Baltimore Sun, June 26, 2018, http://www. baltimoresun.com/news/nation-world/bal-te.bupe17dec17-story.html.

[37] Alouti, F. "Subutex – Where Heroin Addiction Therapy Meets High Profit Trafficking," Equal Times, June 18, 2015, https://www.equaltimes.org/subutex-where-heroin-addiction#.WzJgF1VKj3g.

[38] Information from CIA's World Factbook.

[39] Seth P, Rudd RA, Noonan RK, Haegerich. Quantifying the Epidemic of Prescription Opioid Overdose Deaths. American Journal of Public Health 108, no. 4 (April 1, 2018): pp. 500 -502.

[40] Seth P, Scholl L, Rudd RA, Bacon S. Increases and Geographic Variations in Overdose Deaths Involving

Figure 1.5
Lethal Dose of Heroin and Fentanyl

Due to the difference in potency levels between opioid compounds, we use Table 1.14 to make the transactions in this category comparable. All opioid potency levels are synchronized to multiples of morphine; thus, morphine = 1x morphine.

Opioids, Cocaine, and Psychostimulants with Abuse Potential – United States, 2015-2016. MMWR Morb Mortal Wkly Rep. ePub: 29 March 2018.

Table 1.14
Opioid Potency Conversion Chart

Opioid	Potency
Buprenorphine	40
Codeine	0.3
Fentanyl	50-100
Hydrocodone	1
Heroin	2-5
Methadone	3
Morphine	1
Opium	0.1
Oxycodone	1.5

Notes: Keating, D. and Granados, S. "See How Deadly Street Opioids Like 'Ele- phant Tranquilizer' Have Become," The Washington Post, October 25, 2017, https://www.washingtonpost.com/graphics/2017/health/opioids-scale/?noredirect=on&utm_term=.4c9d4d347ffd.
Sources: Centers for Disease Control and Prevention information, Drug Enforcement Administration, National Institute on Drug Abuse including Congressional testimony, Maryland Poison Center at University of Maryland School of Pharmacy, Department of Justice Diversion Control Division, Dance Safe and the Substance Abuse and Mental Health Services Administration.

Appendix F: Nested Logit Estimation Results and Elasticities (5 Categories)

Table 1.15
Nested Logit Parameter Estimates (5 Categories)

w/ both Ivs	betaNL	SE
const	13.998	0.008
bud	-7.007	0.016
buprenorphine	16.782	0.111
cocaine	1.764	0.037
codeine^^	2.204	1.373
concentrate	-3.576	0.055
edible	-2.707	0.323
fentanyl	25.428	0.536
hash	-3.110	0.050
heroin	-0.789	0.178
meth	0.612	0.026
methadone	14.456	0.155
marijuanaMix^^	3.211	2.390
pharmaMorphine	8.361	0.243
streetMorphine	13.833	0.394
notMDMA	-5.192	0.733
opioidMix	5.373	0.156
oxycodone	14.153	0.096
speed	-3.773	0.060
tramadol	-5.798	0.181
lnsjg	0.673	0.003
p	-4.877	0.001

Notes: Past literature shows the more flexible frameworks to be preferable compared to OLS and instrumental variable method (Petrin 2002). The estimator for codeine and marijuana mix is not significant. In general consumers prefer buprenorphine over any other opioid varieties as it has the highest coefficient of all opioids. The coefficient for cross-nest term, lnsjg, is close to 1, which shows large correlation across different categories of drugs.

The elasticity calculations are as follows (Ackerberg and Crawford 2009):

$$\frac{\partial s_{jt}}{\partial p_{jt}} = -\alpha s_{jt} \left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} s_{jt|g} - s_{jt} \right)$$

$$\frac{\partial s_{jt}}{\partial p_{kt}} = \begin{cases} \alpha s_{kt} \left(\frac{\sigma}{1-\sigma} s_{jt|g} + s_{jt} \right), & \text{if j and k are in the same nest} \\ \alpha s_{jt} s_{kt}, & \text{otherwise} \end{cases}$$

$$\eta_{jjt} \equiv \frac{\partial s_{jt}}{\partial p_{jt}} \cdot \frac{p_{jt}}{s_{jt}} = -\alpha p_{jt} \left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} s_{jt|g} - s_{jt} \right)$$

$$\eta_{jkt} \equiv \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} \alpha p_{kt} \frac{s_{kt}}{s_{jt}} \left(\frac{\sigma}{1-\sigma} s_{jt|g} + s_{jt} \right), & \text{if j and k are in the same nest} \\ \alpha p_{kt} s_{kt}, & \text{otherwise} \end{cases}$$

Table 1.16 shows the own and cross price elasticities for illicit drugs in the US.

Table 1.16
Price Elasticities for Illicit Drugs in the US (5 Categories)

Elasticities	bud	buprenorphine	cocaine	codeine	concentrate
bud	-28.19	27.29	27.29	27.29	84.51
buprenorphine	24.41	-30805.07	24.41	2020.20	24.41
cocaine	9.33	9.33	-866.55	9.33	9.33
codeine	0.04	3.37	0.04	-703.95	0.04
concentrate	45.10	14.57	14.57	14.57	-437.48
edible	2.21	0.71	0.71	0.71	2.21
fentanyl	77.78	77.78	77.78	77.78	77.78
hash	11.02	3.56	3.56	3.56	11.02
heroin	11.21	11.21	11.21	11.21	11.21
meth	6.19	6.19	164.47	6.19	6.19
methadone	0.87	72.24	0.87	72.24	0.87
marijuanaMix	0.79	0.26	0.26	0.26	0.79
morphinePharma	0.19	15.39	0.19	15.39	0.19
morphineStreet	0.10	0.10	0.10	0.10	0.10
nonMDMA	0.10	0.10	0.10	0.10	0.10
opioidMix	1.08	1.08	1.08	1.08	1.08
oxycodone	6.60	546.25	6.60	546.25	6.60
speed	2.32	2.32	61.61	2.32	2.32
tramadol	1.00	82.49	1.00	82.49	1.00
yesMDMA	24.29	24.29	24.29	24.29	24.29

Elasticities	edible	fentanyl	hash	heroin	meth
bud	84.51	27.29	84.51	27.29	27.29
buprenorphine	24.41	24.41	24.41	24.41	24.41
cocaine	9.33	9.33	9.33	9.33	247.87
codeine	0.04	0.04	0.04	0.04	0.04
concentrate	45.10	14.57	45.10	14.57	14.57
edible	-202.56	0.71	2.21	0.71	0.71
fentanyl	77.78	-7038.55	77.78	3191.37	77.78
hash	11.02	3.56	-183.04	3.56	3.56
heroin	11.21	459.89	11.21	-1138.66	11.21
meth	6.19	6.19	6.19	6.19	-673.08
methadone	0.87	0.87	0.87	0.87	0.87
marijuanaMix	0.79	0.26	0.79	0.26	0.26
morphinePharma	0.19	0.19	0.19	0.19	0.19
morphineStreet	0.10	3.98	0.10	3.98	0.10
nonMDMA	0.10	0.10	0.10	0.10	0.10
opioidMix	1.08	44.14	1.08	44.14	1.08
oxycodone	6.60	6.60	6.60	6.60	6.60
speed	2.32	2.32	2.32	2.32	61.61
tramadol	1.00	1.00	1.00	1.00	1.00
yesMDMA	24.29	24.29	24.29	24.29	24.29

Elasticities	methadone	marijuanaMix	morphinePharma	morphineStreet	nonMDMA
bud	27.29	84.51	27.29	27.29	27.29
buprenorphine	2020.20	24.41	2020.20	24.41	24.41
cocaine	9.33	9.33	9.33	9.33	9.33
codeine	3.37	0.04	3.37	0.04	0.04
concentrate	14.57	45.10	14.57	14.57	14.57
edible	0.71	2.21	0.71	0.71	0.71
fentanyl	77.78	77.78	77.78	3191.37	77.78
hash	3.56	11.02	3.56	3.56	3.56
heroin	11.21	11.21	11.21	459.89	11.21
meth	6.19	6.19	6.19	6.19	6.19
methadone	-11710.91	0.87	72.24	0.87	0.87
marijuanaMix	0.26	-160.74	0.26	0.26	0.26
morphinePharma	15.39	0.19	-3422.76	0.19	0.19
morphineStreet	0.10	0.10	0.10	-11529.54	0.10
nonMDMA	0.10	0.10	0.10	0.10	-207.56
opioidMix	1.08	1.08	1.08	44.14	1.08
oxycodone	546.25	6.60	546.25	6.60	6.60
speed	2.32	2.32	2.32	2.32	2.32
tramadol	82.49	1.00	82.49	1.00	1.00
yesMDMA	24.29	24.29	24.29	24.29	433.09
Elasticities	opioidMix	oxycodone	speed	tramadol	yesMDMA
bud	27.29	27.29	27.29	27.29	27.29
buprenorphine	24.41	2020.20	24.41	2020.20	24.41
cocaine	9.33	9.33	247.87	9.33	9.33
codeine	0.04	3.37	0.04	3.37	0.04
concentrate	14.57	14.57	14.57	14.57	14.57
edible	0.71	0.71	0.71	0.71	0.71
fentanyl	3191.37	77.78	77.78	77.78	77.78
hash	3.56	3.56	3.56	3.56	3.56
heroin	459.89	11.21	11.21	11.21	11.21
meth	6.19	6.19	164.47	6.19	6.19
methadone	0.87	72.24	0.87	72.24	0.87
marijuanaMix	0.26	0.26	0.26	0.26	0.26
morphinePharma	0.19	15.39	0.19	15.39	0.19
morphineStreet	3.98	0.10	0.10	0.10	0.10
nonMDMA	0.10	0.10	0.10	0.10	1.78
opioidMix	-1197.37	1.08	1.08	1.08	1.08
oxycodone	6.60	-13885.45	6.60	546.25	6.60
speed	2.32	2.32	-211.60	2.32	2.32
tramadol	1.00	82.49	1.00	-78.35	1.00
yesMDMA	24.29	24.29	24.29	24.29	-234.84

Notes: Although this is the first in-depth analysis that includes all narcotics on the black market, there have been other studies done in the past. Chaloupka and Saffer (1999) shows the elasticities across multiple narcotic categories. Petry and Bickel (2002) uses a behavior set up to study change in quantity of heroin use when price changes. Jofre-Bonet and Petry (2006) focuses on heroin and cocaine. Hempstead and Yildirim (2014) includes fentanyl in their study. Our results are comparable to others in that the direction of substitutions match. However the magnitudes of the substitution varies from studies to studies. It is highly dependent on the fragmented markets.

Table 1.17
Change in Quantity for 10% Price Increase (5 Categories)

10% up P on Q (g)	bud	buprenorphine	cocaine	codeine	concentrate
bud	-11.025	0.362	0.647	0.177	6.204
buprenorphine	0.032	-1.352	0.002	0.043	0.006
cocaine	0.374	0.013	-2.109	0.006	0.070
codeine	0.001	0.003	0.000	-0.257	0.000
concentrate	4.147	0.045	0.081	0.022	-7.550
edible	0.181	0.002	0.004	0.001	0.034
fentanyl	0.003	0.000	0.000	0.000	0.001
hash	1.999	0.022	0.039	0.011	0.375
heroin	0.325	0.011	0.020	0.005	0.061
meth	0.295	0.010	0.475	0.005	0.055
methadone	0.003	0.008	0.000	0.004	0.001
marijuanaMix	0.192	0.002	0.004	0.001	0.036
morphinePharma	0.002	0.005	0.000	0.003	0.000
morphineStreet	0.000	0.000	0.000	0.000	0.000
nonMDMA	0.017	0.001	0.001	0.000	0.003
opioidMix	0.039	0.001	0.002	0.001	0.007
oxycodone	0.012	0.032	0.001	0.016	0.002
speed	0.196	0.007	0.317	0.003	0.037
tramadol	0.223	0.626	0.014	0.307	0.042
yesMDMA	1.420	0.048	0.086	0.024	0.267

10% up P on Q (g)	edible	fentanyl	hash	heroin	meth
bud	18.990	57.679	8.792	1.928	0.687
buprenorphine	0.018	0.171	0.008	0.006	0.002
cocaine	0.215	2.023	0.100	0.068	0.641
codeine	0.001	0.005	0.000	0.000	0.000
concentrate	2.382	7.236	1.103	0.242	0.086
edible	-9.507	0.315	0.048	0.011	0.004
fentanyl	0.002	-1.405	0.001	0.021	0.000
hash	1.148	3.488	-8.834	0.117	0.042
heroin	0.187	72.095	0.086	-5.968	0.021
meth	0.169	1.593	0.078	0.053	-2.064
methadone	0.002	0.015	0.001	0.001	0.000
marijuanaMix	0.110	0.335	0.051	0.011	0.004
morphinePharma	0.001	0.010	0.001	0.000	0.000
morphineStreet	0.000	0.038	0.000	0.001	0.000
nonMDMA	0.009	0.089	0.004	0.003	0.001
opioidMix	0.022	8.675	0.010	0.290	0.003
oxycodone	0.007	0.062	0.003	0.002	0.001
speed	0.113	1.061	0.052	0.035	0.336
tramadol	0.128	1.206	0.059	0.040	0.014
yesMDMA	0.816	7.675	0.378	0.257	0.091

10% up P on Q (g)	methadone	marijuanaMix	morphinePharma	morphineStreet	nonMDMA
bud	0.049	12.340	0.120	0.013	5.413
buprenorphine	0.012	0.012	0.029	0.000	0.016
cocaine	0.002	0.140	0.004	0.000	0.190
codeine	0.000	0.000	0.001	0.000	0.000
concentrate	0.006	1.548	0.015	0.002	0.679
edible	0.000	0.067	0.001	0.000	0.030
fentanyl	0.000	0.001	0.000	0.000	0.001
hash	0.003	0.746	0.007	0.001	0.327
heroin	0.001	0.121	0.004	0.016	0.165
meth	0.001	0.110	0.003	0.000	0.149
methadone	-0.171	0.001	0.003	0.000	0.001
marijuanaMix	0.000	-14.472	0.001	0.000	0.031
morphinePharma	0.001	0.001	-0.397	0.000	0.001
morphineStreet	0.000	0.000	0.000	-0.025	0.000
nonMDMA	0.000	0.006	0.000	0.000	-17.396
opioidMix	0.000	0.015	0.000	0.002	0.020
oxycodone	0.004	0.004	0.011	0.000	0.006
speed	0.001	0.073	0.002	0.000	0.100
tramadol	0.084	0.083	0.208	0.000	0.113
yesMDMA	0.006	0.530	0.016	0.002	12.839

10% up P on Q (g)	opioidMix	oxycodone	speed	tramadol	yesMDMA
bud	0.493	0.074	1.196	2.220	1.280
buprenorphine	0.001	0.018	0.004	0.544	0.004
cocaine	0.017	0.003	1.115	0.078	0.045
codeine	0.000	0.001	0.000	0.015	0.000
concentrate	0.062	0.009	0.150	0.279	0.161
edible	0.003	0.000	0.007	0.012	0.007
fentanyl	0.005	0.000	0.000	0.001	0.000
hash	0.030	0.004	0.072	0.134	0.077
heroin	0.617	0.002	0.036	0.068	0.039
meth	0.014	0.002	0.878	0.061	0.035
methadone	0.000	0.002	0.000	0.048	0.000
marijuanaMix	0.003	0.000	0.007	0.013	0.007
morphinePharma	0.000	0.001	0.000	0.033	0.000
morphineStreet	0.000	0.000	0.000	0.000	0.000
nonMDMA	0.001	0.000	0.002	0.003	0.035
opioidMix	-2.013	0.000	0.004	0.008	0.005
oxycodone	0.001	-0.168	0.001	0.199	0.001
speed	0.009	0.001	-2.009	0.041	0.024
tramadol	0.010	0.128	0.025	-3.649	0.027
yesMDMA	0.066	0.010	0.159	0.295	-1.647

Appendix G: Nested Logit Estimation Results and Elasticities (4 Categories)

The figure below shows the specification for the nesting.

Figure 1.6
Nested Logit Nesting Structure (4 Categories)

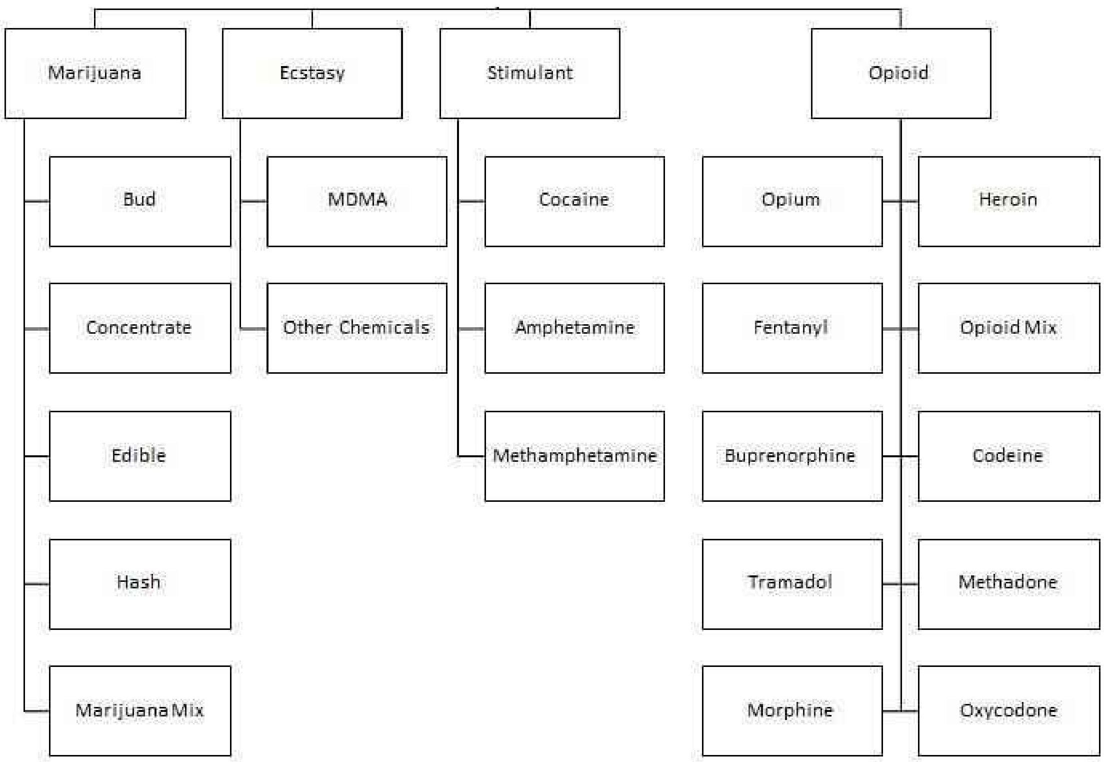


Table 1.18
Nested Logit Parameter Estimates (4 Categories)

w/ both Ivs	betaNL	SE
const	13.80	1.31
bud	-7.40	0.67
buprenorphine	25.19	1.48
cocaine	2.61	0.16
codeine^^	2.37	1.83
concentrate	-0.79	0.07
edible^^	-2.50	0.66
fentanyl	14.50	0.57
hash	-7.40	0.32
heroin	6.36	0.34
meth^^	0.10	0.16
methadone	13.36	1.07
marijuanaMix^^	8.74	3.57
morphine	11.89	0.59
notMDMA	-6.09	0.44
opioidMix	4.74	0.19
oxycodone	14.56	1.16
speed	-5.16	0.33
tramadol	-6.98	0.50
lnsjg	0.55	0.03
p	-4.75	0.36

Notes: The estimator for codeine, marijuana edible, methamphetamine, and marijuana mix are not significant.

Table 1.19
Price Elasticities for Illicit Drugs in the US (4 Categories)

Elasticities	bud	buprenorphine	cocaine	codeine	concentrate
bud	-25.20	27.38	27.38	27.38	70.03
buprenorphine	19.68	-26881.98	19.68	414.82	19.68
cocaine	8.94	8.94	-734.23	8.94	8.94
codeine	0.04	0.78	0.04	-628.17	0.04
concentrate	37.55	14.68	14.68	14.68	-364.86
edible	0.73	0.28	0.28	0.28	0.73
fentanyl	96.45	2032.83	96.45	2032.83	96.45
hash	9.53	3.73	3.73	3.73	9.53
heroin	11.29	237.94	11.29	237.94	11.29
meth	6.05	6.05	121.97	6.05	6.05
methadone	0.96	20.26	0.96	20.26	0.96
marijuanaMix	0.68	0.26	0.26	0.26	0.68
morphine	0.26	5.53	0.26	5.53	0.26
nonMDMA	0.10	0.10	0.10	0.10	0.10
opioidMix	1.09	22.99	1.09	22.99	1.09
oxycodone	4.34	91.46	4.34	91.46	4.34
speed	2.31	2.31	46.67	2.31	2.31
tramadol	0.90	18.94	0.90	18.94	0.90
yesMDMA	24.83	24.83	24.83	24.83	24.83

Elasticities	edible	fentanyl	hash	heroin	meth
bud	70.03	27.38	70.03	27.38	27.38
buprenorphine	19.68	414.82	19.68	414.82	19.68
cocaine	8.94	8.94	8.94	8.94	180.34
codeine	0.04	0.78	0.04	0.78	0.04
concentrate	37.55	14.68	37.55	14.68	14.68
edible	-104.27	0.28	0.73	0.28	0.28
fentanyl	96.45	-8052.06	96.45	2032.83	96.45
hash	9.53	3.73	-159.88	3.73	3.73
heroin	11.29	237.94	11.29	-1078.34	11.29
meth	6.05	6.05	6.05	6.05	-586.38
methadone	0.96	20.26	0.96	20.26	0.96
marijuanaMix	0.68	0.26	0.68	0.26	0.26
morphine	0.26	5.53	0.26	5.53	0.26
nonMDMA	0.10	0.10	0.10	0.10	0.10
opioidMix	1.09	22.99	1.09	22.99	1.09
oxycodone	4.34	91.46	4.34	91.46	4.34
speed	2.31	2.31	2.31	2.31	46.67
tramadol	0.90	18.94	0.90	18.94	0.90
yesMDMA	24.83	24.83	24.83	24.83	24.83

Elasticities	methadone	marijuanaMix	morphine	nonMDMA	opioidMix
bud	27.38	70.03	27.38	27.38	27.38
buprenorphine	414.82	19.68	414.82	19.68	414.82
cocaine	8.94	8.94	8.94	8.94	8.94
codeine	0.78	0.04	0.78	0.04	0.78
concentrate	14.68	37.55	14.68	14.68	14.68
edible	0.28	0.73	0.28	0.28	0.28
fentanyl	2032.83	96.45	2032.83	96.45	2032.83
hash	3.73	9.53	3.73	3.73	3.73
heroin	237.94	11.29	237.94	11.29	237.94
meth	6.05	6.05	6.05	6.05	6.05
methadone	-9947.31	0.96	20.26	0.96	20.26
marijuanaMix	0.26	-133.39	0.26	0.26	0.26
morphine	5.53	0.26	-3895.96	0.26	5.53
nonMDMA	0.10	0.10	0.10	-172.45	0.10
opioidMix	22.99	1.09	22.99	1.09	-994.95
oxycodone	91.46	4.34	91.46	4.34	91.46
speed	2.31	2.31	2.31	2.31	2.31
tramadol	18.94	0.90	18.94	0.90	18.94
yesMDMA	24.83	24.83	24.83	311.33	24.83

Elasticities	oxycodone	speed	tramadol	yesMDMA
bud	27.38	27.38	27.38	27.38
buprenorphine	414.82	19.68	414.82	19.68
cocaine	8.94	180.34	8.94	8.94
codeine	0.78	0.04	0.78	0.04
concentrate	14.68	14.68	14.68	14.68
edible	0.28	0.28	0.28	0.28
fentanyl	2032.83	96.45	2032.83	96.45
hash	3.73	3.73	3.73	3.73
heroin	237.94	11.29	237.94	11.29
meth	6.05	121.97	6.05	6.05
methadone	20.26	0.96	20.26	0.96
marijuanaMix	0.26	0.26	0.26	0.26
morphine	5.53	0.26	5.53	0.26
nonMDMA	0.10	0.10	0.10	1.29
opioidMix	22.99	1.09	22.99	1.09
oxycodone	-11504.31	4.34	91.46	4.34
speed	2.31	-180.53	2.31	2.31
tramadol	18.94	0.90	-115.60	0.90
yesMDMA	24.83	24.83	24.83	-219.77

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Chapter two: Are Mushroom Farmers a Government Assisted Oligopoly? An Analysis on a Government Imposed Focal Point

CHAPTER TWO: Introduction

Collusion among either buyers or sellers can be harmful to society, as it creates dead weight loss when prices of goods are manipulated away from market equilibrium. As a con- sequence, detecting collusion is an important aspect of the industrial organization literature. For example, Bajari and Summers (2002) discuss how to detect collusion when buyers solicit bids from suppliers, and Porter (2005) offers an excellent survey on literature related to collusion.

There exist numerous examples on collusion in various industries from both the buy and the sell side. Bresnahan (1987) provides the earliest example of estimating consumer demand to study firm competition. He designs a vertical demand estimation model to analyze the sudden decrease in automobile prices in 1955 and the resulting increase in quantity sold compared to adjacent years in 1954 and 1956. On the buy side, Baldwin, Marshall, and Richard (1997) construct an empirical model to study bidder collusion in the Forest Service timber sale during the 1970's. Ashenfelter and Graddy (2004) discuss the price-fixing scandal from auction houses Sotheby's and Christie's when buyers exploit the auction system to keep the prices artificially low. On the sell side, Borenstein and Shepard (1996) find tacit collusion in the retail gasoline market, because the fluctuation in panel data on sales volume does not correspond with economic theory on inventory behavior or consumer loyalty. Similarly Porter and Zona (1999) detect collusion among suppliers of milk to schools in Ohio when compared against a control group.

This paper considers whether, instead of buyers and sellers organizing and working to-gether, can collusion be a by-product of government regulations? Albek, Mollgaard, and OverGarrd (1997) present a case in which the Danish antitrust authority gather and publish firm specific ready-mixed concrete prices to promote transparency, and find that this official effort resulted in increased prices as firms are able to coordinate using published information. In this study, we explore whether U.S. government policy inadvertently formed an oligopoly in the fresh mushroom market. Our main question is: can laws aimed at reducing market friction from imperfect information actually help farmers better coordinate their quantity supply?[1]

The United States Congress passed the Mushroom Promotion, Research, and Consumer Information Act of 1990 which established the mushroom council – a trade association – to collect and distribute market price and quantity information to all farmers.[2] When the Mushroom Council posts aggregate market price and quantity information, farms are able to adjust their production accordingly. The information serves as the classic focal point in the game theory literature. To study the impact of this law on supplier coordination, ideally we would collect price and quantity information before and after the passage of the law; however, such information was unavailable and impossible to collect at the time of this study. Consequently, we pursue a second-best approach and use current information to infer consumer demand and simulate counterfactuals to examine the effects of the policy.

The mushroom industry is an ideal candidate for this type of study, because, unlike other industries, there is no resale market for used mushrooms. Mushroom farmers can enter and exit with relative ease, so simulating entry and exit is relatively straightforward. Furthermore, the industry is not owned by a few common shareholders that serve to lessen competition, in contrast to for example the U.S. airline industry (Azar, Schmalz, and Tecu, 2017). These factors simplify and reduce the number of variables necessary to control for to perform the analysis. Thus, the mushroom industry presents a relatively sterile opportunity to study the issue of government assisted coordination among firms.

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[1]For more information on the fresh mushroom industry in the U.S., see Appendix B.

[2]For more information on the reason behind the passage of the law and Mushroom Council, see Appendix A.

Due to our data constraints, we apply a random coefficient logit (Berry, Levinsohn, and Pakes (BLP) 1995) to estimate consumer demand. We then create an agent based simulation model to generate the counterfactuals. Our results show that although the policy imposes a focal point for firms, it does not appear to lead to firm collusion or the reduction of consumer welfare. For robustness, we estimate both a logit and a vertical demand estimation model for comparisons, as well as compensating variation as robustness check for our agent based model.[3]

The rest of the article is organized as follows. Section 2 presents the BLP demand estimation model used in the analysis. Section 3 discusses the data, estimation and identifying assumptions. We present the demand estimation results in Section 4. We discuss in detail the agent based model used for analysis and its results in Section 5 and consumer welfare analysis in Section 6. Section 7 concludes.

Demand Estimation Model

BLP's demand estimation method provides us with the necessary inputs to the agent based model for simulation and generating counterfactuals and is ideal for our aggregated data. We follow their method closely.[4]

This model assigns three components to utility. First is the interaction between con- sumers and product characteristics, based on the idea that those consumers who most prefer a specific product are most likely to switch to products with similar product characteristics if their preferred good becomes unavailable or its price increases. This framework helps us

[3]For vertical and logit demand model results see Appendix C and Appendix D.

[4]Nevo's practitioner's guide (Nevo 2000) for more details on implementing the model. Rasmusen's 2008 guide likewise provides a clear discussion on this model. There are also further developments of this method using micro data (Petrin 2002).

remove the independence of irrelevant alternatives (IIA) problem. The products are "close" to each other based on their characteristics and the types of consumers who purchase them. For example, if the price of a minivan increases, consumers who bought minivans previously are more likely switch to a SUV instead of a two-door convertible.

The second component is unobserved product characteristics, which addresses the overfitting issue by taking into account product characteristics known to consumers and firms, but not econometricians. Econometrically, we implement this component through contraction mapping. We run simulation draws on the consumer characteristics and map the draws to the market share of the products, which subsequently allows us to back out the unobserved product characteristics. The last component is the type 1 extreme value independent and identically distributed (iid) error term, which characterizes choice probabilities.

The model following Nevo (2001). The utility for outside goods is,

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + E_{i0t}$$

where the zero subscript denotes the outside option. Since the mean utility of the outside good ξ_0 is unidentified, it is normalized to zero. The coefficient π_0 measures how the taste characteristics vary with observed individual characteristics; σ_0 is a scaling matrix. D_i and v_{i0} denote the individual characteristics that are observed and unobserved, respectively. The utility for the inside goods is specified as[5]

[5]The notation for this model is consistent with the other two demand estimation models in this paper.

$$u_{ijt} = \delta_{jt}(x_j\,, p_{jt}, \xi_j\,, \Delta\xi_{jt}; \theta_1) + u_{ijt}(x_j\,, p_{jt}, v_i, D_i; \theta_2) +$$

$$E_{ijt} \quad \delta_{jt} = x_j\,\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}$$

$$u_{ijt} = [p_{jt}, x_j\,]^{1} \cdot (\Pi D_i + \Sigma v_i)$$

$$\theta_1 = (\alpha, \beta); \theta_2 = (\Pi, \Sigma, \pi_0, \sigma_0)$$

There are essentially four steps involved in our estimation. Initially, we compute market shares based on random draws of consumer characteristics. Secondly, we compute the market shares:

$$s_{jt}(x_t, p_t, \delta_t; \theta_2) = \int_{A_{jt}} dP^*(E)dP^*(v)dP^*(D)$$

$$A_{jt}(x_t, p_t, \delta_t; \theta_2) = \{(D_i, v_i, E_{it}) | u_{ijt} \geq u_{ilt} \forall l = 0, 1, \ldots, J\}$$

We can then compute the vector of δ that equates the market shares computed with the ob-served market shares, completing the second step, or the model's contraction mapping. Next we compute the error term using instrumental variables in two-stage least square regression, and compute the value of the objective function. Finally, we search for the value of θ that minimizes the objective function via GMM.

Data and Estimation

Data

The Mushroom Council provided us with price and quantity data. The data is retail scan data collected by IRI[6] on behalf of Mushroom Council and is aggregated to the regional level at a weekly frequency from January 2013 to August 2016. We use data up to December 2015 to match the availability of our other data sources, and ultimately, our data comprise 156 weeks for 8 regions. Figure 2.1 maps out the geographic regions, included in the data. We exclude Alaska and Hawaii due to the prohibitively high cost of shipping fresh mushrooms to ship to those two states. Data are categorized by type, prep, and variety: type tells us whether the mushroom is organic or not; prep tells us whether the mushroom is sliced or not; varieties are dried mushrooms, white button, cremini, portabella, and specialty. All mushrooms with low sales volumes, such as chanterelles, enoki, oyster, porcini, shiitake, etc. are grouped in the specialty category.

[6]See https://www.iriworldwide.com/en-us/for more detail on how they collected the data.

Figure 2.1
Regions

We present the sample statistics for the main variables just described in Table 2.1, which displays the average price for mushrooms possessing each respective characteristics in each region as well as their market share.

Table 2.1
Sample Statistics

		2016							
		Northeast	Mid South	Southeast	Great Lakes	Plains	South Central	West	California
Average Price ($/lb)	White	3.60	3.71	3.70	3.64	3.69	3.91	3.98	3.93
	Cremini	4.07	4.39	4.31	4.42	4.57	4.77	4.39	5.11
	Portabella	3.85	5.00	5.70	3.45	5.99	5.46	5.84	6.09
	Specialty	6.77	8.74	14.89	12.01	14.79	11.90	12.64	12.95
	Dried	29.08	36.90	4.14	19.00	15.98	31.09	11.72	32.10
	Whole	3.70	3.96	4.11	3.66	4.09	4.30	4.22	4.13
	Sliced	4.18	4.21	4.07	4.25	4.18	4.20	4.33	4.69
	Organic	5.64	5.24	5.93	3.61	6.16	5.96	5.44	5.88
	Conventional	3.82	3.97	4.03	3.97	4.04	4.11	4.15	4.20
Market Share	White	61%	66%	58%	64%	63%	67%	66%	68%
	Cremini	24%	22%	30%	23%	27%	24%	25%	23%
	Portabella	9%	7%	8%	9%	6%	6%	6%	6%
	Specialty	6%	5%	4%	4%	4%	3%	3%	3%
	Dried	0%	0%	0%	0%	0%	0%	0%	0%
	Sliced	36%	39%	53%	39%	47%	44%	39%	39%
	Whole	64%	61%	47%	61%	53%	56%	61%	61%
	Organic	3%	7%	4%	22%	4%	8%	9%	9%
	Conventional	97%	93%	96%	78%	96%	92%	91%	91%

In addition, the hay prices for each region are collected from USDA Agricultural Mar-keting Service; we source monthly utility prices from each state from the U.S. Energy Ad-ministration's online EIA-826 form, and we use population data from U.S. Department of Commerce, Bureau of Economic Analysis.

Market Definition

To avoid serial correlation, we define our analytical market as region-week combination, similar to Nevo (2001). The perishability of fresh produce makes it unlikely that consumers can stock up in the event of a sale. Consequently, consumers typically do not purchase more than one week's worth of fresh produce at a time, assuming fresh produce is reliably available. Furthermore, for simplicity, we ignore weather emergencies that prompt consumers to stock up on food. We implicitly assume that when consumers buy groceries, they have no remaining stocks from previous purchases. If consumers typically have mushrooms leftover, our estimates will be biased, making this an important assumption but also a possible one, as it is unlikely that all consumers always have mushrooms leftover.

Inside and Outside Goods

We define an outside good to avoid estimating market shares that do not incorporate the full set of consumers' substitutes and their relative prices. Our outside good is conceptually based on the USDA recommended serving of vegetables.[7] We define purchases of vegetables other than mushrooms as the outside good, and back out the amount consumed from our data, which shows that on average the U.S. individual consumes a little less than 1 serving of mushrooms per week. We then conservatively assume that the U.S. individual consumes up to about one quarter serving of mushrooms per week and that any amount of the full quarter portion not consumed is the outside good.

Market Share

Thus, based on the outside good assumption, we convert the one quarter serving of mushroom into 0.044 pound of mushroom per week. Multiplying by the population of each region gives us the total market size. We then calculate the total quantity of each variety- type-preparation combination sold in each market. This gives us the inside goods' market shares. Finally, the difference between the total market size and total inside goods' share is the market share for the outside goods.

[7] "Dietary Guidelines for Americans 2015-2020," *USDA*, Eighth Edition, accessed on March 15, 2017. https://health.gov/dietaryguidelines/2015/resources/2015-2020_Dietary_Guidelines.pdf.

Instruments

BLP used instrumental variables for price (which is endogenous to the demand model), selected because of correlation with specific functions of the observed data from the demand or supply shocks, assuming the unobserved characteristics of supply and demand are mean independent of both observed product characteristics and cost shifters. The authors' basic intuition comes from oligopoly pricing: products with good substitutes tend to have low markups, while those with limited substitutes tend to have higher markups. Moreover, Nash markups respond differently to own and rival products, so BLP can and thereby distinguish the difference between the characteristics of rival and own products to generate instruments for price. However, this style of instrument is impossible for our data, as we cannot distin-guish between farms and there is no heterogeneity of product characteristics for mushrooms produced by different farms. Also, our demand shocks will be correlated across markets and with the error term, rendering BLP's style of instrument unusable for us.

We instead choose to use the Hausman-style instrument (Hausman et al. 1994) as well as two instruments based on marginal costs. First, we model the Hausman instrument following Nevo (2001).

$$p_{jt} = mc_{jt} + f(\xi_{jt}, \ldots) = (mc_j + f_j) + (\Delta mc_{jt} + \Delta f_{jt})$$

As mentioned above, since our data has no variation across mushroom varieties over time, and across regions, the Hausman instrument provides an alternative to using product char-acteristics. Because we assume region-specific valuations are independent across regions and that the prices set by retailers account for demographic variables such as income and unem-ployment within each region, the average prices of the varieties with the same characteristics in other regions produce valid instruments. Then the exogenous variation in prices that are due to differences in marginal costs can be distinguished from endogenous variation that is due to differences in unobserved valuation. In practice, we calculate the average price per pound of mushrooms for all other regions by week and product characteristics.

As a robustness check, we use instrumental variables based on marginal costs, which produce similar estimates. We model a market structure for mushroom composed of three levels: the producers who grow mushrooms, followed by the packers who package the prod-ucts, and finally the retailers who sell groceries to consumers. We believe the variables that effect the cost of growing mushrooms will pass through to the retailers, motivating the use of two instrumental variables for price based on marginal cost at the product level for each region.

First major input for mushroom production is compost, which can be difficult to produce and can compromise the crop's success if the mixture id incorrect. Because hay is often used to manufacture compost, it comprises a prevalent marginal cost for mushroom farmers, and serves as a good instrumental variable for marginal cost. Because much of the U.S. raises alfalfa and other grasses for livestock feed, there is consistent time series data available from USDA. However, since there is no data available for a few of our regions, we assume that prices in the Mid-South reflect those in the Plains region, the Southeast is similar to the South Central region, California is similar to the West region, and that the Great Lakes region is similar to the Northeast region. We acquire data for the Northeast region from a composter in Kennett Square, PA, and as there are only four compost producers in the area, we feel comfortable using it as a proxy for the region.

A second instrument based on marginal cost is the utility prices for each region. We argue that the state-wide utility pricing can proxy for the cost of air conditioning (AC). We explain relevance with the important role of AC in the production process, given the vast amounts of heat generated as the compost cures and the fact that the mycelium, or early-stage fungi, cannot survive temperature above ninety degrees Fahrenheit. Furthermore, mycelium growth breaks down chemicals in the soil, producing additional heat throughout the growing process.

Estimation

Given a moment condition $\psi(\cdot)$, we estimate

$$\theta^{GMM} = arg \min_{\theta} \left(\sum_{i=1}^{n} \psi(s_i, \theta) \right)' \left(\sum_{i=1}^{n} \psi(s_i, \theta) \right)$$

via GMM. Setting $\Gamma = E[\frac{\partial \psi}{\partial \theta'}(x, \theta_0)]$ and $\Delta = E[\psi(x, \theta_0) \cdot \psi(x, \theta_0)']$, we calculate standard errors for the GMM estimates from $(\Gamma' \Delta^{-1} \Gamma)^{-1}$.

When we use the hay and utility IVs, we have an over identified case, so we use Hansen's two step estimator to get the large-sample properties as the just identified case (Hansen 1982) by minimizing

$$Q_c(\theta) = \left(\frac{1}{n} \sum_{i=1}^{n} \psi(x_i; \theta) \right)' C \left(\frac{1}{n} \sum_{i=1}^{n} \psi(x_i; \theta) \right)$$

and using a suitable choice of weighting matrix C. We first estimate θ^{init} by minimizing $Q_c(\theta)$ and choose the identity matrix for C. This gives us a consistent, but not necessarily efficient estimate of θ^{init}. We then recover the optimal weighting matrix according to

$$\sum_{i=1} \psi(x_i, \theta^{init}) \cdot \psi(x_i, \theta^{init})'$$

$$\theta^{2step} = arg \min_{\theta} Q_{\hat{\Delta}^{-1}}(\theta)$$

wherein our covariance matrix takes the same form as in the just identified case.

Given our small sample size, as a robustness measure, we also estimate our BLP model using the continually updating estimator (CUE) and arrive at similar results. This method solves for the optimal weight matrix and θ (Hansen, Heaton, and Yaron 1996).[8]

Because we have already calculated products' market shares, as described above, we can interpret our GMM coefficients as the contribution of product characteristics and price to these market shares.

Demand Estimation Results

Table 2.2 displays the results from OLS as our baseline model.

Table 2.2
OLS with Different IV Strategy

	Constant	type	prep	white	cremini	port	specialty
OLS (Nevo IV):	6.979	0.412	0.168	-6.017	-5.825	-5.340	-3.998
OLS (Hay & Utility IV):	3.988	0.235	0.096	-3.438	-3.329	-3.051	-2.284

[8]In this method, we estimate θ as the solution to

$$\min_{\theta} \left(\frac{1}{n}\sum_{i=1}^{n} \psi(x_i, \theta)\right)' \left(\frac{1}{n}\sum_{i=1}^{n} \psi(x_i, \theta) \cdot \psi(x_i, \theta)'\right)^{-1} \left(\frac{1}{n}\sum_{i=1}^{n} \psi(x_i, \theta)\right).$$

When estimating the vertical and random coefficient logit models, we consider two scenarios. One is when the market is in perfect competition, implying that price equals marginal cost. The other, as monopoly, wherein producers maximize their combined profit instead of individuals. The same data and instruments are applied to all models, only the moment condition differs depending on the competition type. For practicality, we use a Halton sequence for simulation draws on individual characteristics.

As a check on our definition of a market, we use fixed effects for time and location in the logit and vertical model. Due to computational inconsistencies that resulted when time and location fixed effects into contraction mapping, we take the conventional approach of using dummy variables. The results for the time and location dummy variables are mostly insignificant, which confirms our definition of a market.

Results for the model with marginal cost instruments are presented in Table 2.3. The coefficients are similar to those estimated in the vertical model, although the signs on the estimators are reversed, due to the way we wrote the algorithm. The main difference in our random coefficients set up is that we have the coefficient on price while price information is used to calculate for the quality measure in the vertical model. A few of the coefficients on the supply side are not significant where the Hausman instrument is included. The models that include the marginal cost instruments demonstrate upward sloping demand, because the coefficient on price is positive. As we have shown in other model, the model with the Hausmand instrument performs the best.

Table 2.3
Random Coefficient Logit Model with Marginal Cost Instruments

		Hausman IV		Hay & Utility	
	Estimates	Estimate	SE	Estimate	SE
Demand	Const	-11.0456	0.9170	-1.3789	0.4681
	Type	-3.2434	0.0846	-2.2913	0.0453
	Prep	-0.7717	0.0291	-0.5000	0.0218
	White	8.7616	0.5396	3.2002	0.2719
	Cremini	8.6039	0.4842	3.5238	0.2455
	Portabella	6.7382	0.3975	2.6386	0.2037
	Specialty	4.9202	0.2140	2.8688	0.1146
Supply	Const	3.6372	0.0801	3.2176	0.0217
	Type	-2.1387	0.3396	0.0487	0.0180
	Prep	-0.3832	0.0800	0.0188	0.0053
	White	2.8613	0.6727	-1.4788	0.0407
	Cremini	0.4206	0.2959	-1.5111	0.0274
	Portabella	-0.2572	0.1646	-1.3011	0.0245
	Specialty	-0.0846	0.1083	-0.7058	0.0233
	Price	-1.5396	0.2977	1.6353	0.1538
	Quantity	-0.0000	0.0000	-0.0000	0.0000

The results for the estimation under the assumption of perfect collusion are presented below in Table 2.4. When we change the supply side assumption, the demand side coefficients do not change much. None of the coefficients estimated with the Hausman IV are significant, while most of the coefficients estimated with the marginal cost IV are also insignificant. These results suggest that farmers are not able to collude given the government assisted focal point.

Table 2.4
Random Coefficient Logit Model with Perfect Collusion

	Estimates	Nevo IV Estimate	Nevo IV SE	Hay & Utility Estimate	Hay & Utility SE
Demand	Const	-8.7094	0.9170	-4.5404	0.5123
	Type	-3.0986	0.0846	-3.1461	0.0472
	Prep	-0.7349	0.0291	-0.7929	0.0220
	White	7.6630	0.5396	3.7406	0.2984
	Cremini	7.6873	0.4842	4.0861	0.2694
	Portabella	6.1278	0.3975	2.3895	0.2237
	Specialty	4.8538	0.2140	1.0909	0.1263
Supply	Const	20.9336	1.9230	11.5715	0.9373
	Type	-12.0800	7.7696	-0.0109	0.5431
	Prep	-1.7848	1.8005	0.0134	0.1702
	White	13.9480	15.4693	-6.0588	1.4259
	Cremini	-0.4736	6.8552	-4.7550	1.0417
	Portabella	-4.0907	3.8947	-1.8104	0.9671
	Specialty	-0.1039	2.6318	2.7656	0.9558
	Price	-0.6019	0.2977	-0.4338	0.1668
	Quantity	-0.0002	0.0001	0.0000	0.0000

The cross price elasticity η_{jkt} represents the percent change in the market share of product j when price of product k rises in market t and is calculated:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \int \alpha_i s_{ijt}(1 - s_{ijt})\, dP_D^*(D)\, dP_v^*(v), & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} \int \int \alpha_i s_{ijt} s_{ikt}\, dP_D^*(D)\, dP_v^*(v), & \text{otherwise} \end{cases}$$

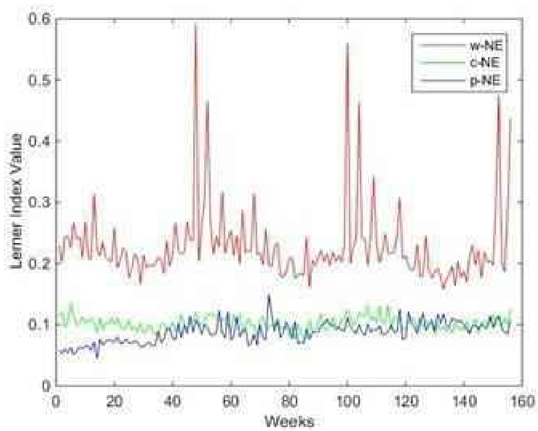
Appendix F shows the result of the elasticity calculation with Hausman IV.

We can then calculate the Lerner index from the own price elasticities:

$$L = \frac{P - MC}{P} = \frac{-1}{\eta_{jjt}}$$

This measure was originally developed to express the degree of monopoly power, which is a function of the price markup over marginal costs. Consequently, the extent to which a firm can take advantage of its monopolistic condition will depend on the demand curve. Traditionally the Lerner index ranges between zero and one, with zero representing perfect competition and one representing absolute market power (Lerner 1934). Figure 2.2 shows the Lerner index in the northeast region. We choose the northeast due to its high concentration of fresh mushroom producers. The plot shows that cremini (in green) and portabella (in blue) varieties are close to zero, signaling that the producers have little market power. On the other hand, white button mushroom (in red) exhibit seasonality in term of producers' market power. During the year, the index value fluctuates between 0.2 and 0.3, implying that producers have little market power. However, during holidays at the end of each year – weeks 52, 104, and 156 – the producers' market power increases threefold, suggesting that the seasonal high demand for white button mushrooms allows the producers to exercise some market power.

Figure 2.2
Lerner Index in Northeast Region



Agent Based Model

The only data available prior to the existence of Mushroom Council are annual survey data collected by National Agricultural Statistics Service (NASS) of United States Depart- ment of Agriculture. The surveys record the number of farms producing fresh mushrooms each year, which is the information of interest to this study. Figure 2.13 demonstrates a dramatic decline in operating farms before the establishment of the Mushroom Council. Un-fortunately, it would be impossible to run a difference-in-difference or regression discontinuity analysis on the impact of the policy change using only annual market price and quantity data. Furthermore, because the data are aggregated and sparse with no breakdown of dif- ferent varieties, preparations, or types – as NASS surveys at the time were focused on the amount of land used and crop yield – we can no longer identify consumer preference. There is no way for us to detect trends in preferences with only the total sale of mushroom per year.

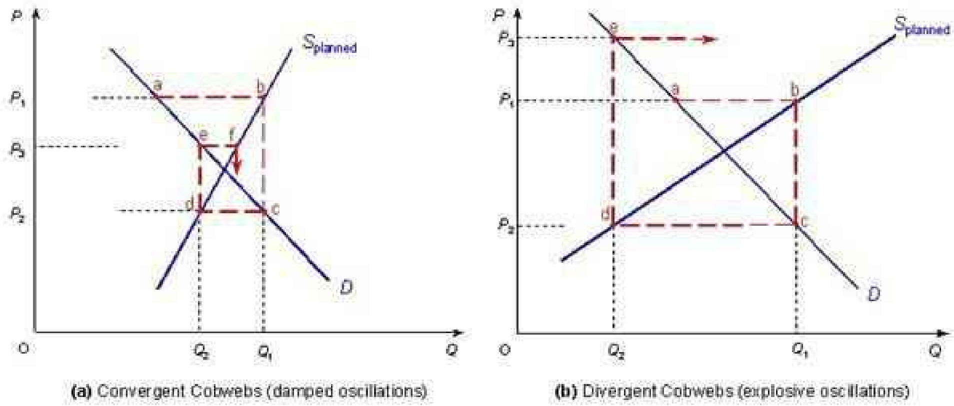
Due to these data constraints, we rather generate counterfactuals in order to evaluate the policy impact on producers' ability to coordinate. The baseline model aims to emulate the features seen in the annual USDA NASS survey. Once our simulations match these features, we create a scenario that removes the access to market information provided by the Mushroom Council from the farmers and model their response. This set up allows the existence of the policy to be the only difference between the baseline simulation and the counterfactual.

We base our simulation on the cobweb model, which is a dynamic model of equilibrium typically used to explain how a market reaches equilibrium. We modify this classic model slightly by adding agents (farmers) who try to meet market demand by adjusting their quantity output. To make the model work, we assume the market is already in equilibrium, which makes sense because the prior demand estimation models from section 2 accounted for the demand and supply shocks. In other words, the results derived from the earlier estimation are in essence in equilibrium. The agent based model is useful in this simulation exercise since we are interested in how individual farms adjust production based on prices can affect the aggregate market. This will give us insights into the impact of a policy that may otherwise be overlooked using a more traditional analysis. We draw from existing literature to form the framework of our simulation. We reference Arifovic (1992), Chang (2015), Rosen, Murphy, and Scheinkman (1994), and Skraba (2006) for cobweb and agent based models.

Cobweb Model

The cobweb model is popular in the agricultural and system dynamics literature, in which farmers often base their current year production on previous year's price. The intuition of the model is as follows: if prices were high in year 1, more product will be planted for year 2, with the expectation that prices will remain high, which may cause an oversupply, resulting in lower prices in year 2. Because of the low prices, less product will be planted in year 3, resulting in higher prices. These model dynamics are based on the adaptive expectations hypothesis, where expectations are based on past behavior. In the mushroom market we study, we observe dynamics across time, even in the absence of external demand or supply shock, due to lags between shocks and production. Thus we observe that supply and demand do not reach equilibrium in the short term. We argue then, that in our analytical context, this process may continue for a number of periods before reaching equilibrium. Figure 2.3 shows when the model converges or diverges overtime.

Figure 2.3
Illustration of Cobweb Model



(http://wps.pearsoned.com.au/wps/media/objects/1634/1673936/case02_6.htm) The number of firms in the industry should remain stable in the convergent case, which

may be difficult for firms to survive in the divergent scenario wherein bankrupted firms may merge with the surviving firms as the industry undergoes a consolidation phase to switch back to the convergent case.

Agent Based Model

One major benefit of the agent based model is that it allows us to include in our analysis particular features of the industry that would otherwise be omitted from other types of structural models such as the three demand estimation models discussed above. We can utilize the industry features to better produce market dynamics in the industry across time. The first feature we learned from talking to mushroom producers is the heterogeneity in farmers' responses to shocks, which we are able to incorporate into the analysis. Although there are three types of production, the most common is known as phase one. This method takes about twenty weeks of preparation before mushrooms sprout. Once the farmer makes a decision to invest in the next plot, the decision cannot be changed for the next twenty weeks, without risking the loss of their upfront investments. We therefore assume a twenty-week moving average. The timing to market is embedded in the farm's decision of how much to produce in the current period. The main difference between baseline and counterfactual model lies in whether farmers have the posted market information to aid their decision making or not.

The second feature we include is the different contract types. Our interviews with pro-ducers revealed that there are two main types of relationship between growers and packers. Some growers prefer long-term relationships rather than spot contracts, and therefore build long-term relationships with a packer by selling exclusively to them. In return, the packer will sell the growers' products to retailers first before buying more inventory sourced from growers with spot contracts. The tradeoff is twofold: growers may not get higher prices during a market shortage, but on the other hand, they also avoid receiving excessively low prices in times of over production. Spot growers tend to treat each transaction as indepen-dent of each other and will sell to the highest bidder each period. This works well in times of shortage, as they receive high prices, but can result in sever losses in times of overproduction. We incorporate the two contract types in the simulation by designating a portion of the farms as long-term contract type and the rest as spot. Randomized data draws prevent the incidence of farmers producing exactly what the market demands. When there is a market surplus, any quantity in excess of market demand will receive increasingly lower prices until the inventory is cleared for the period; during a shortage, the opposite occurs. We use the results from our demand estimation to calculate the price fluctuations. As expected, the prices received by spot farmers are more volatile than the ones with long-term contracts. When assigning prices between market and actual quantity, we allow for randomness in the order that farmers within the two groups are matched to prices for their quantity produced.

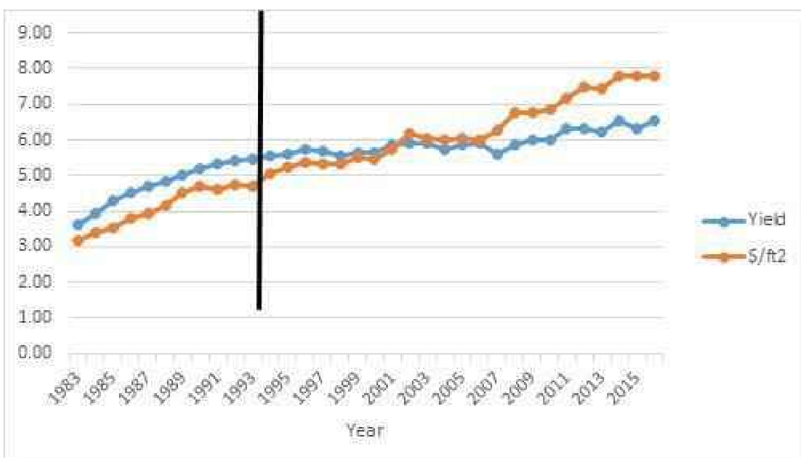
The final real-world feature relates to how farms merge and adjust the size of their operations. In reality, high-performing farms will purchase underperforming farms in an effort to expand their production, as doing so is cheaper and faster than building out their operations organically. Should there be excess capacity, farms will either sell assets to other farms or close down. We simplify this in our simulation and assume that bankrupted farms' capacity is reallocated to surviving farms. We also add a step each period that allows farms to reduce, or sell off, their excess capacity, but we impose a minimum capacity for the industry to maintain in order to prevent the complete disintegration of the industry during the divergent cobweb scenario.

We run the simulation over five hundred periods with one thousand farms, wherein each farm has one-thousand-pound capacity. Each period the farms go through a sequence of six steps. First, they determine what quantity to produce based on the aforementioned timing to market feature. Then the farmers are subjected to a random draw of quantity demanded by consumers in the current period, which allows us as modelers to determine what the market price would be if production exactly meets demand. However, since the quantity produced rarely exactly matches, the prices farms receive will deviate from equilibrium prices. Price deviations cue the entry of the role of contract types, which determine the degree of price deviation. In the fourth step, we determine the farms' profit. The last two steps include allocation and size-adjustment of farms.

USDA-NASS Data

USDA collects data on the mushroom industry annually. As briefly mentioned above, in Figure 2.13 we see that the number of farms increased in the mid-1980s, followed by a sharp decline until the Mushroom Promotion, Research, and Consumer Information Act of 1990 was passed and Mushroom Council was established in 1993. Afterwards, the number of firms stopped declining. In Figure 2.15, we see that the land area used for production fluctuates across time. There is no correlation between the number of farms and the amount of land area used for production, implying that when farms exit the market, their assets are bought out by the surviving farms. In Figure 2.4 we see that farms are able to extract more money per plot of land across time, which is partially due to improvement in yield. The rest of the increase is due to surviving farms earning higher returns for their crops. This could be due to farmers being better able to coordinate which mushroom variety they wish to specialize in as corroborated from the BLP estimation results.

Figure 2.4
Farm Efficiency



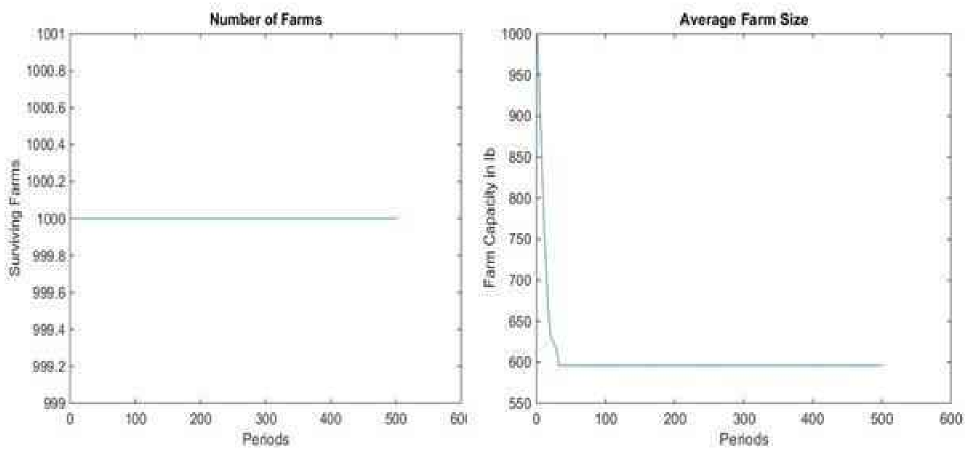
The goal of the following models is to match the dynamics of the USDA-NASS data. We divide our analysis into two time frames based on the creation of Mushroom Council. The vertical line on 1993 demarcates the two regimes. The baseline model is designed to match what happens after Mushroom Council was established. At this time, the number of farms had stabilized and farms can enjoy higher profit. The alternative model is our counterfactual that tries to match the dynamics prior to the establishment of Mushroom

Council, when farms were dying and profits were lower.

Baseline Model

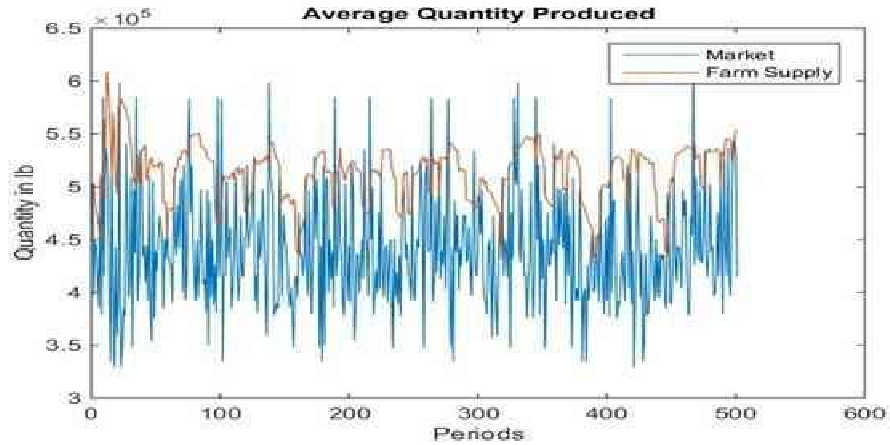
Farms are small enough that they have no pricing power. They take price as given and adjust quantity accordingly. Because mushroom spoil, there is no inventory carried from one period ot the next. In this scenario, all farms survive, and they decrease their excess capacity until it reaches a stable floor as shown in Figure 2.5.

Figure 2.5
Baseline Number of Farms and Average Farm Size



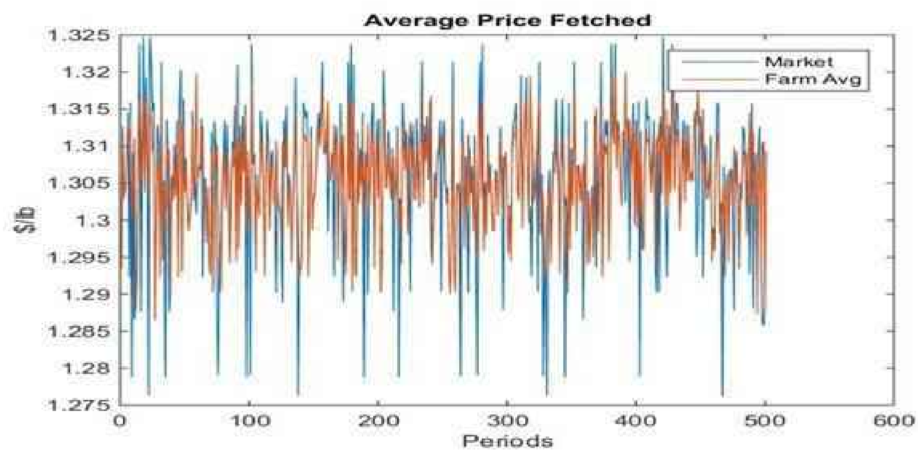
In Figure 2.6 we see that the quantity produced are slightly above the market demand. Farms reduce production during periods when quantity demand is low. Due to the twenty weeks lead time, farms cannot adjust quantity automatically in order to meet demand. The portion of the farms with long-term contracts will tend to produce at a stable level. More of the dynamics come from spot contract farms. The over production will see its counterpart in the price chart.

Figure 2.6
Baseline Quantity Demanded and Produced



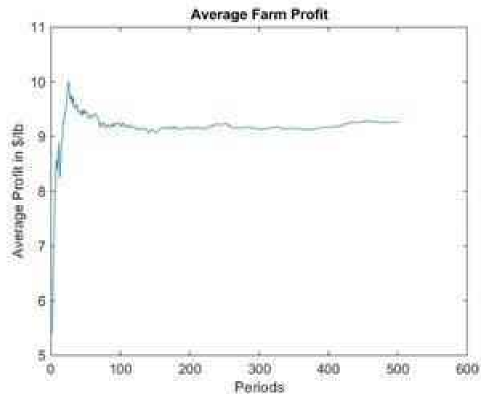
In Figure 2.7 we see that the prices fluctuate to clear production.

Figure 2.7
Baseline Prices



In Figure 2.8 we see that farms' average profits remain stable. The fluctuation from period 1 to 100 is due to the initial condition.

Figure 2.8
Baseline Profit

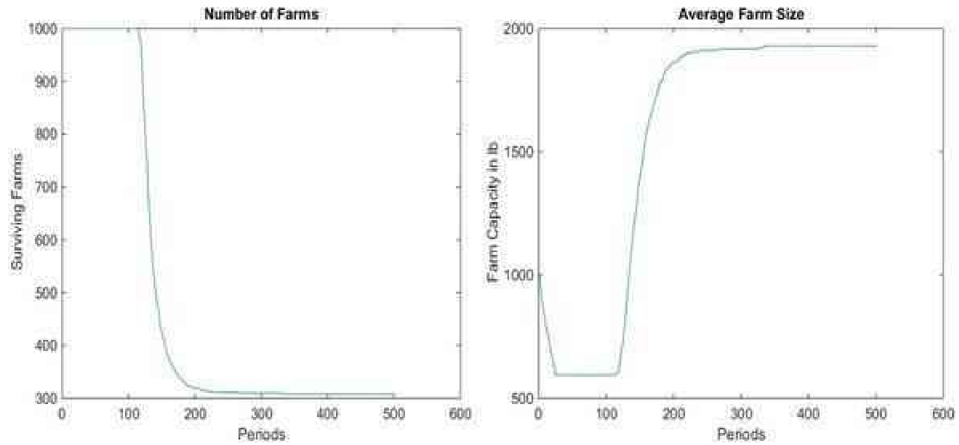


Alternative Model

There was no aggregate market information before the existence of the Mushroom Coun-cil. As such, farms could only rely on their own past sales information to determine what quantity to produce going forward. To simulate this difference, we remove the knowledge of market price and quantity. Similar to the shape of the USDA data, the simulation also shows a decrease in the number of farms over time. Figure 2.9 shows decrease that is more dramatic

than seen in the USDA data, which is attributable to the simulation's running at a much faster pace than real life. The average farm size shows that once farms start dying, they merge and the surviving farms become much larger before eventually stabilizing. This matches the feature we see in Figure 2.15.

Figure 2.9
Alternative Number of Farms and Average Farm Size



In Figure 2.10 we see that without the information focal point, farms have trouble anticipating market demand. There are too many farms, so each one only captures a tiny slice of the market through their sales. As explained in Section 2, there are three levels to this market. There were many small farmers in the 1980's as shown from USDA data. There were few packers who process the fresh mushrooms for retail, and there were many retail- ers. Consequently, the price farmers received resulted a distorted view of the market. The packers adjust the price they offer farmers depending on the quantity demanded by various retailers. During high demand, packers offer incrementally higher prices to purchase enough mushroom to fill their orders from retail; this behavior reverses under low demand. As such, the farmers do not learn about the whole market dynamic until they merge and increase scale.

Figure 2.10
Alternative Quantity Demanded and Produced

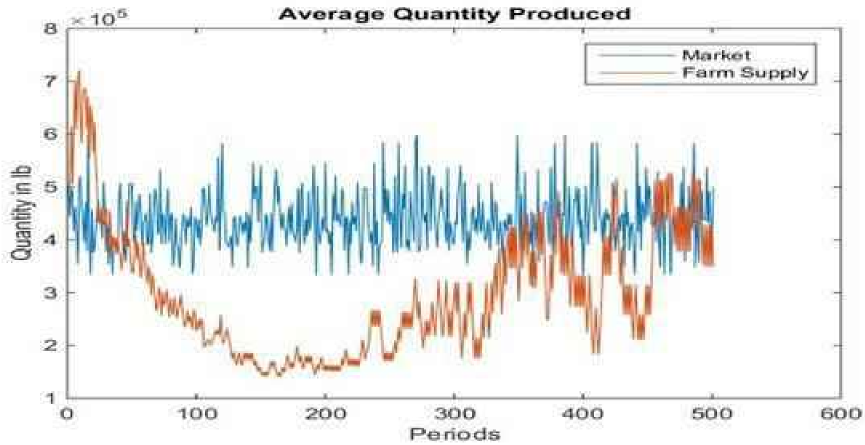
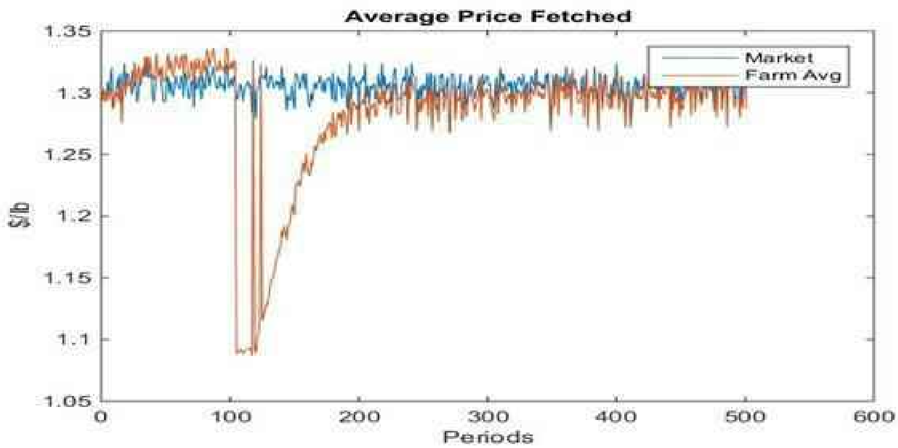


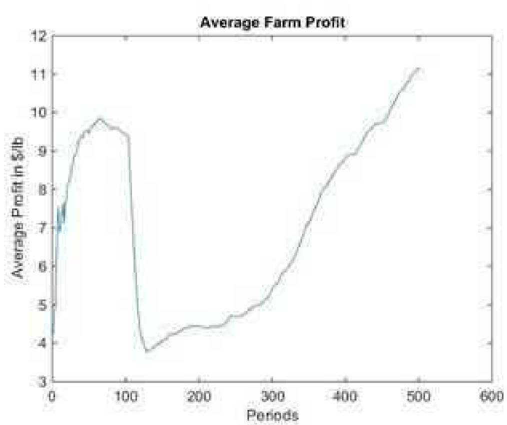
Figure 2.11 shows the drop in price as farms go bankrupt, although prices eventually stabilize as surviving farms increase scale. Only then do their increased sales show them the prevailing market demand and price. We learned from our producer interviews that there had been large scale consolidation in the industry prior to the establishment of the Mushroom Council, which matches what we see in the USDA data from the 1980's. The decreasing number of farms and constant area under production suggest vertical integration among large-scale farms, which absorb packing operations and arrange retail contracts in-house.

Figure 2.11
Alternative Prices



In Figure 2.12 we see that farms' profits drop, but increase at a steady pace after consolidation of failed farms. This matches with the USDA data showing the increase profit over time as the number of farms decrease.

Figure 2.12
Alternative Profit



Consumer Welfare

We use compensating variation (CV) to measure changes in consumer welfare during our simulated market turbulence (Hicks 1945 and Deaton and Muellbauer 1980). We first solve for the utility level achieved at the old income and old prices, based on utility function used in the BLP model. Consumers' initial income comes from the fresh produce purchasing data. We assume that households, consume fresh produce each week subject to a grocery budget and that fresh mushroom is part of their grocery shopping list. The price change is modeled after the dynamics simulated from agent based model.

The CV calculation can be broken down into three steps. First, we use consumers' initial income and old prices to calculate their utility level. Then we use this utility level and new prices to solve for new income. Following Hicks, the difference between the old and new income is the CV, the value of which we report in terms of percentage. During the period when farms were going out of business due to overproduction, the price of the mushrooms decreases by 15 percent, which increases consumer welfare by 15 percent. We do not see prices overshoot above their prior level after the industry is consolidated, so decreases in consumer welfare are only a transitory effect. Once the market stabilizes, consumer welfare returns to its prior level.

Conclusion

In this paper, we study the dynamic impact of a focal point in firm competition as captured by the publication of market prices. Data constraints prompted us to employ agent based modeling to explore the dynamics of firm competition across time. We are able to calculate consumer welfare before and after the establishment of the government assisted focal point.

The evidence supports the conclusion that the U.S. Congress has achieved its objective to "establish a coordinated program of promotion and research" when they passed the law in 1990. Prior to the establishment of Mushroom Council, farms experienced continuous exit due to overcapacity and overproduction, which resulted in low prices and diminished farm profitability, as shown in Figure 2.4. Using demand estimation models, we calculate the input for the agent based model in order to simulate the dynamics exhibited in the USDA data.

Unsurprisingly, consumers benefited during the overproduction when prices were low. The long term impact of farm exit is the consolidation of the industry, resulting in fewer farms in the industry today, which are more vertically integrated than before. We conclude that the focal point created by the policy change that helps stabilize the industry, while allowing small scale farmers to enter the market and be competitive. It does not aid the large-scale farms, since they already have the scope to observe market level information due to their size, regardless of the government's assistance. Finally, as shown in Figure 2.2, producers have little market power except on holidays when the demand for white button mushroom is high.

Appendix A: Mushroom Council

In the 1980s, mushroom farmers began expanding their operations in response to a period of price stability. The expansion in output eventually overshot actual market demand and farmers were left with perishable inventory. The mushroom prices fell and many farmers were put out of business. Each farmer had little to no information about overall production in the industry. This in part allowed the overproduction to occur because without information about market price and demand at the consumer level, farmers were unable to see the surplus and the resulting falling price.

There are three levels in the fresh mushroom supply chain: farmers, packers, and retailers. Farmers grow the mushroom and sell to packers. There are many mushroom farmers of varying sizes located in different regions across the country. Packers process and package the products before distributing them to retailers.[9] Mushrooms have a short shelf life, so packers tend to locate near the farmers. There are far fewer packers than farmers. Consumers buy fresh mushrooms from the retailers.

In this market structure, the small growers are not aware of market demand or retail prices. Rather, they have a distorted view of the market. Their source of information are the prices they received from packers. If they experience stable prices, they tend to expand their operations and produce more, as they did in the 1980s. Due to a lack of insight into overall market conditions, the farmers expanded their capacities and overproduced beyond market demand. As a result, many farms went out of business, as can be seen in Figure 2.13. Figure 2.14 shows the number of farms for all produce with comparable size to mushroom farms. The farm debt crisis of the 1980's impacted all produce. The mushroom industry

[9]Mushrooms are also sold by packers to restaurant suppliers or directly to restaurants. We foc us on the supply channel that ends with fresh mushrooms in consumers' hands as our interest ultimately lies in the impact of a policy on consumer welfare.

[10]Data from USDA NASS annual survey.

was arguably hit the hardest, with a decline of 32.4% from 1987 to 1989 compared to a decline of 6.2% for all small farms, pointing to the importance of this lack of market information.

Figure 2.13
Number of Mushroom Farms

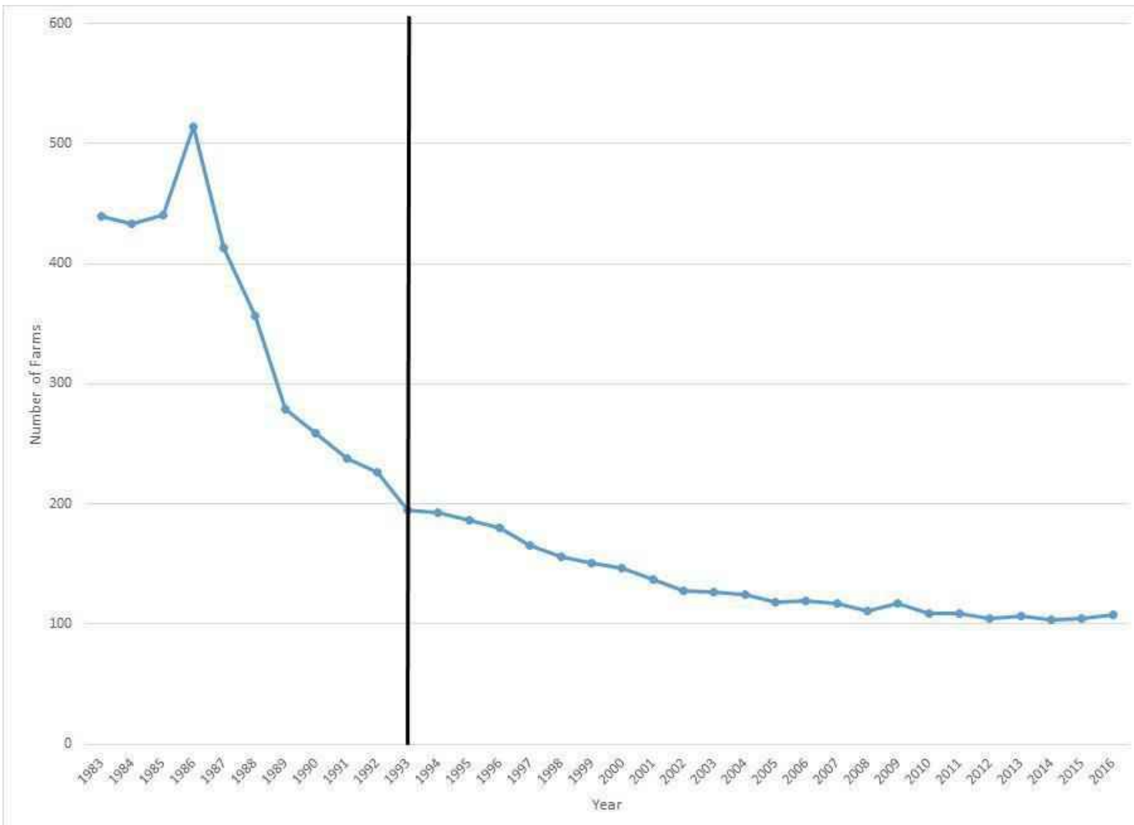
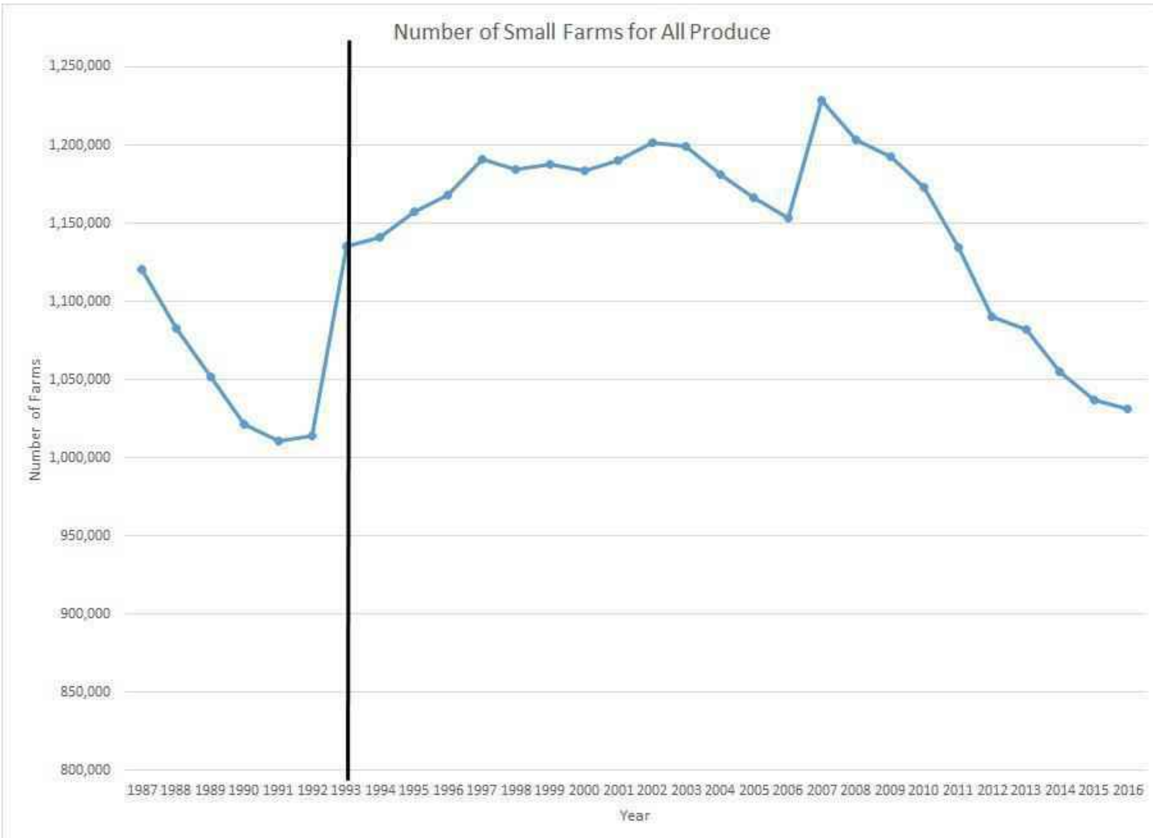


Figure 2.14
Number of Small Farms in the U.S. (for all produce)



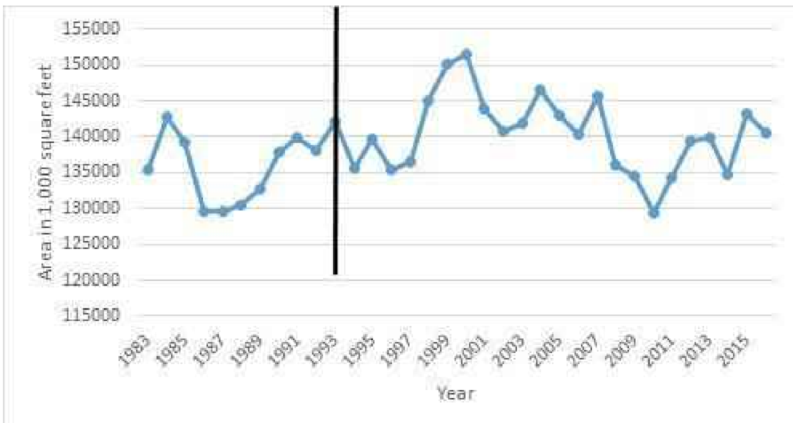
In response, The Mushroom Promotion, Research & Consumer Information Act was signed into law on November 28, 1990. Congress explained the purpose of the bill by saying, "the production of mushrooms plays a significant role in the Nation's economy in that mush-rooms are produced by hundreds of mushroom producers, distributed through thousands of wholesale and retail outlets, and consumed by millions of people throughout the United States and foreign countries" (Mushroom Promotion, Research, and Consumer Information Act of 1990). As such Congress declared it to be of public interest to establish a coordi- nated program of promotion and research. As part of the act, the Mushroom Promotion, Research, and Consumer Information Order lead to the creation of the Mushroom Council on January 8, 1993. The black line in Figure 2.13 demarcates when the trade association was established.

Aggregate market price and quantity data are collected and distributed to mushroom farmers by Mushroom Council. This aids small scale farmers who would otherwise have no access to market information to help them determine quantity output. There are other benefits to small farmers as well. Mushroom Council operates as the research and promotion program to maintain and expand the existing markets and uses. It is administered under USDA’s Agricultural Marketing Service and composed of industry representatives nominated by their peers and appointed by the Secretary of Agriculture. The Council is funded by fresh mushrooms produced in or imported into the 50 states, Puerto Rico, and the District of Columbia. Due to the shelf life of fresh mushroom, it is unlikely to see imports from across the Atlantic or Pacific Ocean. Most of the imports are from Canada’s Ontario state. Producers and importers with volume of over 500,000 pounds of mushrooms annually pay a fee of 0.0055 cents per pound. The handlers collect the fee from producers and remits it to the Council. Assessment on imported mushrooms are collected by the U.S. Department of Homeland Security’s Customs and Border Protection. For calendar year 2016, the Council received about $4.5 million in assessments on domestic producers and $625,000 on importers (AMS 2017).

At first glance, it seems that the law may have slowed the exodus of farmers and eventually stabilized the number of firms in the industry. However, this does not necessarily mean the policy had an overall positive effect. It signaled that the farmers exiting were the most inefficient; perhaps the remaining farmers would have enjoyed returns to scale as they began serving larger portions of the market. Figure 2.15 shows the area used for mushroom cultivation. The time series is more of a reflection of the health of the U.S. economy rather than the number of surviving farms. This shows that the survivors were able to gain scale.

A referendum in 1998 to decide on the continuation of the Mushroom Council was approved by 80% of the voters who represent 70% of all the producers and importers. This indicates that the trade association provides value to the farmers.

Figure 2.15
Land Area Used for Production



Appendix B: Mushroom Industry

Most Americans do not have the habit of picking mushroom out in the wild for consumption. Consumers generally purchase them from grocery stores. The fresh mushroom market in the U.S. is dominated by white button mushroom variety. In August 2016, white button encompassed 64% of the market. Brown cremini at 24% had the second largest market share. Brown portabella at 8% had the third largest market share. The rest of the 4% market are made up of specialty mushrooms such as chanterelles, enoki, oyster, porcini, and shiitake.

All mushrooms are grown indoor in houses with multiple levels of beds that contain compost for the mushrooms to grow. The production occurs year round. Due to the large amounts of heat generated during the growing process, air conditioning is necessary even in the winter. Should the temperature of the soil reach beyond 90 degrees Fahrenheit, the mycelium growing in the soil will die off and no mushroom will be produced.

There are three main phases of mushroom production, henceforth denoted as phase one, two and three. Depending on the technology and the age of the mushroom houses, producers may choose to start the growing process in any one of the three phases. Phase one takes the longest as the growers will take raw compost and cure it before combining it with nutrients and spores. Phase one takes about twenty weeks from the beginning of the process to the harvesting of mushrooms. The main ingredients for the compost are hay, straw, and waste from chickens or horses. Other ingredients may be used should there be a temporary shortage. A large amount of oxygen is required for the ingredients to decompose. The best period to make compost is when the temperature is low and the air is dense. Phase two begins after the compost is cured and involves combining the compost with nutrients and spores. Choosing to begin in phase two shortens the process as producers will purchase compost that have been cured from the composter. Phase three begins after the cured compost has been combined with nutrients and spore. A small number of producers focus only on phase three production. As a composter will have already mixed in the nutrients and spores into the compost, by the time producers receive the compost, mycelium will have already taken root. Once the mixture is transported into beds and layered with peat moss, the mushrooms will be ready to grow. One important note on the varieties. Even though consumers distinguish between creminis and portabellas, they are of the same species. To grow a portabella, you simply wait a few more days for the creminis to grow to a larger size. Once the mushrooms are harvested, they are sent to a packer to be packaged. Some of the mushrooms are sliced before packaging. The overall market for sliced and whole mushrooms are quite similar. Overall, there were 118 million pounds of mushroom sold as sliced and 167 million pounds sold as whole as of August 2016. The packers provide the service of slicing and packing mushrooms before they are shipped to retailers. In general mushroom stay fresh for about two weeks once it is on the retailer's shelf. Some packers may also grow specialty mushrooms themselves as they have trouble sourcing it from growers in the region. For example one packer one of the authors visited grows shiitake. The growing process is similar, but the compost used is completely different. The main ingredient is sawdust. The compost is shaped like a bread and sits on racks to allow for shiitake to emerge from all sides.

Over half of the fresh mushrooms consumed in the U.S. are produced in the Kennett Square, Pennsylvania area. There are between 60 and 80 producers congregated in the region. The producers in Kennett Square focus on producing white button, cremini, and portabella varieties. There are four composters who produce the type of compost necessary to grow these mushrooms.

The margins for mushrooms are relatively thin. Based on the account of one farm, on average six bad crops can send a producer into receivership. This is a real concern for farmers because mushrooms can contract many different diseases. Due to the proximity of the beds within a house, diseases can spread rapidly, especially in the summer when flies like to gather around compost. Producers prefer to use water infused with chlorine, not unlike the water from a faucet, to lower the risks of bacterial diseases. However, organic mushrooms are grown without chemicals. Thus, the risks for growing organic mushrooms can be substantial compared to conventional mushrooms. The size of the organic market is times smaller than the conventional market. In August 2016, organic accounted for 23 million pounds of mushrooms sold in the U.S. while conventional accounted for 263 million pounds.

Appendix C: Vertical Demand Estimation Model

The vertical model we use follows closely with Bresnahan's study on auto market's competition and collusion (Bresnahan 1987). We follow his set up as much as possible while expand some areas to better explain the model. The notations in this paper are standard- ized across all three models to be coherent. His idea was to assume that marginal costs do not vary. This allowed him investigate whether the relationship between pricing and demand elasticities changed in a manner consistent with a shift from collusion to oligopolistic pricing. This model works well for us since we know from talking with mushroom farmers that their marginal costs are consistent across time.

The main intuition of this model is as follows. Consumers agree on the relative quality of the products. They can be ranked in a linear fashion in terms of quality. The difference lies in consumers' willingness to pay for quality. Utility in this model has the form:

$$u_{ijt} = \underline{u}_{t} - \alpha_i p_{jt} + \delta_{jt}$$
$$i = 1, \ldots, I_t, \quad j = 1, \ldots, J_t \quad t = 1, \ldots, T,$$

where u is the utility consumer i derived from product j in market t. The goal is to solve for the range of α that purchase each good given a distribution. We order the products by increase in price p_{jt}. Such that if the products in the sample all have non-zero share, the ordering should be increasing in quality δ_{jt}, otherwise nobody would buy the product. We normalize the outside good u_t to zero. We proceed by calculating product market shares as a function of the parameters, then we find the parameters that maximize the probability of observing the shares in the data.

We make the assumption that consumer taste α_i is distributed exponentially with parameter λ. We let $F(\cdot)$ be the exponential CDF with parameter λ. The shares are determined from the distribution of consumer tastes. The generalized form for δ is

$$\delta_j = \delta_{j-1} + \frac{(p_j - p_{j-1})}{-\lambda} \ln \sum_{k=0}^{j-1} S_k$$

This allows us to solve for all the δ_j in terms of shares after ordering by price. On a side note, we do not know the consumer taste. In the estimation part, the betas require the deltas, and the deltas depend on lambda. We form a grid for the choice of lambda to estimate the demand system. We iterate through the lambda until we find one that best minimizes the objective function. All the identification is done using only the shares. We reduced the dimensionality by projecting product quality down onto characteristics so that, $\delta_j = \sum_k \beta_k X_{kj}$ where $k < j$.

Due to the simplicity of this product market, we avoid four issues that arises with the vertical model. One is there may be too many characteristics that are relevant. With J products, there are J^2 parameters to estimate to get the cross-price effects. This is not an issue for mushrooms. There are only a limited number of characteristics. The second is that there may be characteristics that are relevant, but not observed by the econometrician. For example, a consumer may choose to purchase a handbag based on it being a perceived status symbol instead of whether or not it is water proof. Mushrooms do not have this issue. Consumers do not eat portabellas to show off. Farms do not put their name on the packaging, so there are no brands. We observe whether the mushroom is organic or not, so this characteristic is not hidden. With mushrooms, what you see is what you get. The third has to do with the introduction of new goods. For example, consumers may delay buying a phone because they know a new model will be released soon. This is also not a problem since there were no new mushrooms introduced to the market in our data set.

The final issue is the simultaneity of price and perceived quality. For example, the Maserati car brand may invoke a sense of prestige, Italian craftsmanship, and perhaps even the image of driving through the hills of picturesque Italian Riviera on a sunny afternoon for a shot of espresso. In reality, the Maserati Ghibli, a seventy thousand dollar car, is made with the same components as a Chrysler 300, a thirty thousand dollar. The engine of the Ghibli, commonly acknowledged by enthusiasts as the soul of the sports car, starts life at a cast engine block manufactured in a Chrysler plant in Indiana USA. When it comes to engineered products, it is common for consumers to confuse price with quality. The vertical model depends on the separation of product quality and willingness to pay. In this example, the higher the price of the product, the higher the perceived quality and therefore more willingness to pay. This may be the case for truffles, where the quality can be difficult to judge for the general public. However, truffles are not in our analysis because you cannot farm truffles. They can only be found in the wild. This issue is not relevant fresh mushroom market.

The advantage of this model is its ease of implementation. Bresnahan studied competitive and collusive pricing. This model will serve as a baseline for comparing with our logit demand models. There are, however, some disadvantages to this model. We will go through each and discuss whether it is an issue for our application or not. First, this model relies on function

form for identification and the error term is deterministic given the functional form for $F(\cdot)$ and is not probabilistic. We choose product characteristics to maximize the log-likelihood by

counting the individuals choosing the good as part of the market share. We have to make a decision of whether the outside good is the highest value or lowest value alternative. In our application, we choose the outside good to be the lowest-value alternative. Per U.S. surgeon general's recommendations, mushrooms do not need to be part of our diet in order to have a healthy balance. As such we only eat fresh mushrooms because we want to.

Second the cross-price elasticities only exist with respect to neighboring goods. This leads to a highly constrained substitution matrix. This is not an issue for us as we will show later with the results from the logit model. The results do not vary much when we explicitly group by different varieties of mushrooms.

Vertical Model Derivation

Consumer i will choose 0, the outside good, iff $0 > \delta_1 - \alpha_i p_1 \Longrightarrow \alpha_i > \frac{\delta_1}{p_1}$. Since $Pr\left(\alpha_i > \frac{\delta_1}{p_1}\right) = 1 - F\left(\frac{\delta_1}{p_1}\right)$, we would expect a proportion $S_0 = 1 - F\left(\frac{\delta_1}{p_1}\right)$ of the households to purchase the outside good or not purchase mushroom. A consumer i will choose 1, the lowest priced mushroom, iff $0 > \delta_1 - \alpha_i p_1$ and $\delta_2 - \alpha_i p_2 < \delta_1 - \alpha_i p_1 \Longrightarrow \frac{\delta_2 - \delta_1}{p_2 - p_1} < \alpha_i < \frac{\delta_1}{p_1}$, since $Pr\left(\frac{\delta_2 - \delta_1}{p_2 - p_1} < \alpha_i < \frac{\delta_1}{p_1}\right) = F\left(\frac{\delta_1}{p_1}\right) - F\left(\frac{\delta_2 - \delta_1}{p_2 - p_1}\right)$, we would expect a proportion $S_1 = F\left(\frac{\delta_1}{p_1}\right) - F\left(\frac{\delta_2 - \delta_1}{p_2 - p_1}\right)$ of households to purchae the lowest prices mushroom. In general, $S_j = F\left(\frac{\delta_j - \delta_{j-1}}{p_j - p_{j-1}}\right) - F\left(\frac{\delta_{j+1} - \delta_j}{p_{j+1} - p_j}\right)$, up untile the highest priced mushroom, which would have a proportion of $S_J = F\left(\frac{\delta_j - \delta_{j-1}}{p_j - p_{j-1}}\right)$

We can determine δ_j by starting at the outside good and iterating through each product, Since we know the market size, we can use it to account for the share of the outside good. This helps us solve for the first delta, $S_0 = 1 - F\left(\frac{\delta_1}{p_1}\right) = e^{-\lambda\left(\frac{\delta_1}{p_1}\right)}$ or $\delta_1 = \frac{p_1}{-\lambda} ln(S_0)$. Then we iterate forward to solve for δ_2 using the share of the first product, $S_1 = F\left(\frac{\delta_1}{p_1}\right) - F\left(\frac{\delta_2 - \delta_1}{p_2 - p_1}\right) = e^{-\lambda\left(\frac{\delta_2 - \delta_1}{p_2 - p_1}\right)} - e^{-\lambda\left(\frac{\delta_1}{p_1}\right)}$. From there we can get $\delta_2 = \delta_1 + \frac{p_2 - p_1}{-\lambda} ln(S_1 + S_0)$. A generalized form for delta would be

$$\delta_j = \delta_{j-1} + \frac{p_j - p_{j-1}}{-\lambda} ln\left(\sum_{k=0}^{j-1} S_k\right)$$

Vertical Model Estimation Result

For the vertical model, we make two different supply side assumptions. One is the marginal cost pricing for firms operating in perfect competition. The other is the perfect collusion or join profit maximization for firms working together to act as a monopoly without combining their operations to achieve cost reduction. We examine which assumption fits the data better. In return, we will begin to get a sense of whether or not there is even any collusive behavior in the market at all.

In the case of marginal cost pricing, the supply side equation is specified as

$$p_j = x_j y + \eta q_j + \omega_j$$

and the moment condition for GMM is,

$$E[Z(p - xy - \eta q)] = 0$$

The variable p_j stands for price of product j. The variable x_j stands for all the product characteristics and γ is the estimator matrix. The variable q_j stands for quantity of product j and η is the estimator. The variable ω_j is the error.

Results of the vertical demand estimation are presented in Table 2.5. Consumers are willing to pay more for organic and sliced mushrooms, while producers require hire prices for producing organic and sliced mushrooms. In terms of the variety of mushroom, the baseline variety is dried mushroom. It seems that dried mushrooms are much more expensive compared to other varieties since the density of the mushroom are much higher when dried.

The relative magnitudes show consumers' preference among the different varieties relative to dried mushrooms. They prefer white and cremini by similar amounts. They prefer portabella more and specialty the most. By comparing the different instruments we can see that in general Nevo IV generates estimators that are about twice in magnitude as the hay and utility IV. This could be due to our assumption about the market structure. Although the hay and utility IV accounts for the marginal cost at the producer level, it does not account for the packers and retailers. On the supply side hay and utility IV shows a negative estimator for sliced mushroom. This is counter to what we expected. Slicing mushrooms adds a cost to the process, so suppliers should then require a higher price to supply these mushrooms.

Table 2.5
Vertical Model with Marginal Cost Pricing

		Nevo IV		Hay & Utility	
		Estimate	SE	Estimate	SE
Demand	Const	7.146	0.125	3.916	0.061
	Type	0.435	0.018	0.234	0.010
	Prep	0.135	0.010	0.113	0.006
	White	-6.179	0.125	-3.373	0.062
	Cremini	-5.990	0.125	-3.269	0.062
	Portabella	-5.508	0.125	-2.985	0.062
	Specialty	-4.169	0.126	-2.219	0.063
Supply	Const	3.012	0.033	3.144	0.021
	Type	0.728	0.147	0.194	0.014
	Prep	0.168	0.034	-0.030	0.004
	White	-2.731	0.297	-1.760	0.033
	Cremini	-2.045	0.137	-1.592	0.024
	Portabella	-1.571	0.082	-1.327	0.023
	Specialty	-0.863	0.059	-0.677	0.022
	Eta	6.16E-06	1.97E-06	-1.80E-07	1.67E-07

In the case of joint profit maximization. We have multiple product firms working together to maximize profits similar to how a monopoly would act. The firm solves the following.

$$\max_{\{p_j\}_{j \in J_f}} \Pi = \sum_{j \in J_f} (p_j - mc_j) \cdot s_j(p_j) \cdot M$$

where J_f is the set of products produced by firm f . This is uniquely maximized for each ( ) product r by setting FOC $\frac{\partial \pi_f}{\partial p_j}$ to zero.

$$s_r(p) + \sum_{j} (p_j - mc_j) \frac{\partial s_r(p)}{\partial p_j} = 0$$

The resulting markups is as follows,

$$\Delta_{jr} = \begin{cases} -\frac{\partial s_r}{\partial p_j}, & \text{if } r \text{ and } j \text{ are are produced by the same firm} \\ 0, & \text{otherwise} \end{cases}$$

From there, the first order condition can be written as

$$s - \Delta[p - mc] = 0$$

The pricing equation becomes

$$p = mc + \Delta^{-1} s$$

Results of the estimation are presented in Table 2.6. The demand side results for the perfect collusion case are mostly the same as the marginal cost pricing assumption. The main difference is on the supply side. It seems that once producers collude, they can get out of each other's way and specialize in different types of mushrooms. Some mushroom framers currently specialize while others switch between varieties depending on the market condition. The coefficient for organic and white mushroom is insignificant using Nevo IV. The coefficient for preparation is insignificant for the alternative IV. This is evidence that farmers may not be colluding. They are unable to corner the white mushroom with the largest market share among all the varieties. They also are unable to have discipline in restraining the quantity of organic mushrooms sold to market. This hurts their bottom line because the organics are relabeled as conventional at a lower price if they do not sell. The estimation results show that they may be unable to time their inventory better for the sliced mushrooms. The sliced mushroom spoil faster, so if they flood the market the mushrooms will go bad before they are sold. Altogether, it seems for mushroom with low market share, farmers are better off as they get out of each other's way. This could be the result of posting market information to help farmer coordinate better on which mushroom to grow.

Table 2.6
Vertical Model with Perfect Collusion

		Nevo IV		Hay & Utility	
		Estimate	SE	Estimate	SE
Demand	Const	6.812	0.125	3.732	0.061
	Type	0.386	0.018	0.250	0.010
	Prep	0.177	0.010	0.083	0.006
	White	-5.842	0.125	-3.185	0.061
	Cremini	-5.650	0.125	-3.076	0.061
	Portabella	-5.165	0.125	-2.800	0.061
	Specialty	-3.813	0.126	-2.038	0.062
Supply	Const	30.702	1.447	28.909	0.558
	Type	2.813	6.766	2.563	0.666
	Prep	1.844	0.601	0.065	0.230
	White	-31.486	11.372	-27.310	1.434
	Cremini	-27.714	7.055	-25.360	0.768
	Portabella	-25.880	2.773	-22.515	0.604
	Specialty	-19.812	1.805	-17.081	0.587
	Eta	3.62E-05	7.86E-05	1.38E-05	6.26E-06

Appendix D: Logit Demand Estimation Model

Consumers choose the bundle of characteristics of a product to maximize their utility. A logit model can account for horizontal differentiation rather than solely focusing on vertical qualities. Our model follows closely with (Berry 1994) and we reference (Goldberg 1995) for her empirical techniques. We briefly explain logit and nested-logit model follow by our reasons for only using the basic logit model.

In discrete choice specification, the utility of consumer i for product j in market t is given by

$$u_{ijt} = x_j \overline{\beta}_i - \alpha p_{jt} + \xi_{jt} + E_{ijt}$$

Where the consumer specific taste parameters are $\tilde{\beta}_i$ and E_{ijt}. The parameter α is the consumer's elasticity. The ξ_{jt} term is the mean of consumers' valuations of an unobserved product characteristic such as prestige. In the logit model, we assume that $\tilde{\beta}_i = \beta$ and E_{ijt} is identically and independently distributed across products and consumers with the extreme value distribution function $exp(-exp(-E))$. The market share of product j is given by the logit formula.

$$s_j(\delta) = \frac{e^{\delta_j}}{\sum_{k=0}^{n} e^{\delta_k}}$$

Once we normalize the mean utility of the outside good to zero,

$$ln(s_j) - ln(s_0) = x_j\beta - \alpha p_j + \xi_j$$

The logit model allows us to use instrumental variables regression of differences in log market shares on (x_j, p_j).

The utility for nested-logit is slightly different. It includes an extra variable, ζ_{ig}, that is common to all products in group g and has a distribution function that depends on σ, with $0 \leq \sigma < 1$.

$$u_{ijt} = \delta_{jt} + \zeta_{ig} + (1 - \sigma)E_{ijt}$$
$$\delta_{jt} = x_j \beta - \alpha p_{jt} + \xi j$$

The market share of product j can be calculated as a fraction of the total group share multiplied by the probability of choosing one of the group g products.

$$s_j(\delta, \sigma) = \frac{e^{\frac{\delta_j}{1-\sigma}}}{D_g^{\sigma} \sum_g D_g^{(1-\sigma)}}, \quad D_g \equiv \sum_{j \in F_g} e^{\frac{\delta_j}{1-\sigma}}$$

The set of products in group g is denoted as F_g. The estimates of β, α, and δ can be obtained from a linear instrumental variables regression of differences in log market shares on product characteristics, prices, and the log of the within group share.

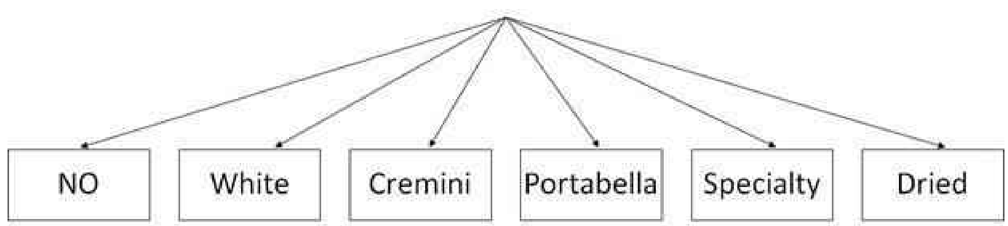
$$ln(s_j) - ln(s_0) = x_j \beta - \alpha p_j + \sigma ln(s_{j/g}) + E_j$$

The estimation can be done by backward induction with maximum likelihood (Goldberg

1995).

Nested-logit can improve upon a basic logit model in two ways. The first is that the substitution matrix for logit is solely a function of shares and not the relative proximity of products in characteristic space. The second is the independence of irrelevant alternatives (IIA) problem. This problem is made famous by McFadden's (1981). An example to illustrate the problem: commuting choices are "bicycle", "red bus", and "blue bus". One expects tastes for red and blue bus to be positively correlated. However, in a logit model, removing the "blue bus" choice induces blue bus riders to split between "bicycle" and "red bus" according to their relative market shares, instead of according to their obvious preference for riding a bus over a bicycle. Thanks to the simplicity of the mushroom products, we avoid the IIA problem because we do not have a complicated hierarchy of product characteristics like the automotive industry. Our "nest" is flat as shown below in Figure 2.16. We also do not have issues with the substitution pattern. If white button mushrooms are unavailable, consumer would evaluate the rest of the varieties. They would either pick a different mushroom varieties or not buy mushrooms at all.

Figure 2.16
Logit Model



Logit Model Estimation Result

The simplicity of the logit model allows us to compute the results quickly. As shown in Table 2.7, after controlling for price and preparation, consumers demand organic mushrooms. Consumers also prefer sliced mushrooms in general, likely because it saves their meal preparation time. The results are similar to the vertical model.

Table 2.7
Logit Model Estimation Result

		Const	Type	Prep	Price
Nevo IV	Coef:	5.973	1.435	0.468	5.227
	SE:	0.133	0.029	0.023	0.075
Hay / Utility IV	Coef:	1.858	1.214	0.790	3.128
	SE:	0.337	0.027	0.033	0.171

The coefficient on price is positive due to how we set up the algorithm to calculate it in Matlab. We are not actually getting an upward slopping demand curve. The coefficients on type and preparation are in the correct direction, but the magnitudes are higher than the vertical model. This could be due to the fact that we explicitly model the mushroom varieties. The results using Nevo IV continue to have higher coefficient values than the alternative IV strategy. Consistent with our previous findings.

The cross price elasticity η_{jkt} is the percent change in the market share of product j when price of product k goes up in market t. It can be calculated as follows.

$$\eta_{jkt} \equiv \frac{\%\Delta s_{jt}}{\%\Delta p_{kt}} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\alpha p_{jt}(1 - s_{jt}), & \text{if } j = k \\ \alpha p_{kt} s_{kt}, & \text{otherwise} \end{cases}$$

Appendix E shows the result of the elasticity calculation with Nevo IV.

Appendix E: Logit Model Elasticities

Below shows the elasticity of different mushroom varieties by region using Nevo IV. There are no variation in cross-price elasticity due to the model assumptions. The equation for elasticity is included for reference.

$$\eta_{jkt} \equiv \frac{\%\Delta s_{jt}}{\%\Delta p_{kt}} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\alpha p_{jt}(1 - s_{jt}), & \text{if } j = k \\ \alpha p_{kt} s_{kt}, & \text{otherwise} \end{cases}$$

Elasticity for dried mushroom is large due to its density. Consumers get more mushroom per pound when it is dried. Dried mushroom also tends to be higher value varieties. Not every region has dried mushroom data.

Table 2.8
Northeast – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-8.085	2.783	0.935	0.969	0.029
2	Cremini	9.808	-19.001	0.935	0.969	0.029
3	Portabella	9.808	2.783	-20.849	0.969	0.029
4	Specialty	9.808	2.783	0.935	-25.674	0.029
5	Dried	9.808	2.783	0.935	0.969	-273.269

Table 2.9
Mid-South – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-13.460	1.805	0.506	0.532	0.012
2	Cremini	5.774	-21.488	0.506	0.532	0.012
3	Portabella	5.774	1.805	-26.084	0.532	0.012
4	Specialty	5.774	1.805	0.506	-40.514	0.012
5	Dried	5.774	1.805	0.506	0.532	-217.273

Table 2.10
Southeast – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-14.349	2.414	0.644	0.364	0.000
2	Cremini	5.208	-19.368	0.644	0.364	0.000
3	Portabella	5.208	2.414	-29.845	0.364	0.000
4	Specialty	5.208	2.414	0.644	-79.425	0.000
5	Dried	5.208	2.414	0.644	0.364	-21.680

Table 2.11
Great Lakes – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-12.695	2.106	0.703	0.376	0.014
2	Cremini	6.542	-21.287	0.703	0.376	0.014
3	Portabella	6.542	2.106	-22.857	0.376	0.014
4	Specialty	6.542	2.106	0.703	-61.249	0.014
5	Dried	6.542	2.106	0.703	0.376	-189.796

Table 2.
Plains – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-13.523	2.771	0.544	0.475	NaN
2	Cremini	6.904	-21.969	0.544	0.475	NaN
3	Portabella	6.904	2.771	-30.033	0.475	NaN
4	Specialty	6.904	2.771	0.544	-72.310	NaN
5	Dried	6.904	2.771	0.544	0.475	NaN

Table 2.13
South Central – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-16.025	1.606	0.396	0.230	0.002
2	Cremini	4.671	-23.844	0.396	0.230	0.002
3	Portabella	4.671	1.606	-27.700	0.230	0.002
4	Specialty	4.671	1.606	0.396	-64.679	0.002
5	Dried	4.671	1.606	0.396	0.230	-185.543

Table 2.14
West – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-12.647	2.915	0.592	0.484	0.012
2	Cremini	8.437	-20.333	0.592	0.484	0.012
3	Portabella	8.437	2.915	-32.822	0.484	0.012
4	Specialty	8.437	2.915	0.592	-72.108	0.012
5	Dried	8.437	2.915	0.592	0.484	-60.369

Table 2.15
California – Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-13.867	2.241	0.541	0.370	0.001
2	Cremini	6.981	-25.283	0.541	0.370	0.001
3	Portabella	6.981	2.241	-31.899	0.370	0.001
4	Specialty	6.981	2.241	0.541	-73.517	0.001
5	Dried	6.981	2.241	0.541	0.370	-201.746

Appendix F: Random Coefficient Logit Model Elasticities

Below shows the elasticity of different mushroom varieties by region using Nevo IV. The random coefficient logit model allows for flexible cross-price elasticity. The equation for elasticity is included for reference.

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt}(1 - s_{ijt}) \, d\hat{P}^*_D(D) \, d\hat{P}^*_v(v), & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} \int \alpha_i s_{ijt} s_{ikt} \, d\hat{P}^*_D(D) \, d\hat{P}^*_v(v), & \text{otherwise} \end{cases}$$

Elasticity for dried mushroom is large due to its density. Consumers get more mushroom per pound when it is dried. Dried mushroom also tends to be higher value varieties. Not every region has dried mushroom data.

Table 2.16
Northeast – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-2.282	1.409	0.476	0.715	0.456
2	Cremini	4.966	-7.929	0.656	0.984	0.628
3	Portabella	5.000	1.952	-9.276	0.991	0.632
4	Specialty	7.237	2.826	0.955	-16.155	0.915
5	Dried	156.672	61.173	20.683	31.044	-3886.327

Table 2.17
Mid-South – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-4.704	2.132	0.717	1.407	0.246
2	Cremini	6.817	-12.883	0.930	1.827	0.319
3	Portabella	8.172	3.316	-20.299	2.189	0.382
4	Specialty	15.274	6.198	2.084	-57.689	0.714
5	Dried	114.659	46.531	15.645	30.721	-2449.861

Table 2.18
Southeast – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-5.392	2.587	1.109	2.272	0.000
2	Cremini	5.582	-10.163	1.280	2.623	0.000
3	Portabella	8.966	4.797	-27.506	4.213	0.001
4	Specialty	32.482	17.378	7.451	-265.028	0.002
5	Dried	5.534	2.961	1.269	2.600	-12.976

Table 2.19
Great Lakes – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-4.122	2.156	0.723	1.525	0.224
2	Cremini	6.697	-11.926	0.957	2.019	0.297
3	Portabella	6.733	2.869	-14.001	2.030	0.298
4	Specialty	26.503	11.293	3.788	-146.089	1.174
5	Dried	102.567	43.706	14.660	30.920	-1832.066

Table 2.20
Plains – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-4.432	2.693	0.731	2.237	NaN
2	Cremini	6.710	-11.681	0.972	2.973	NaN
3	Portabella	9.269	4.946	-24.716	4.107	NaN
4	Specialty	32.480	17.331	4.704	-202.959	NaN
5	Dried	NaN	NaN	NaN	NaN	NaN

Table 2.21
South Central – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-6.749	2.880	0.812	1.397	0.044
2	Cremini	8.378	-17.362	1.058	1.820	0.058
3	Portabella	9.574	4.288	-25.429	2.079	0.066
4	Specialty	28.351	12.698	3.580	-176.065	0.196
5	Dried	96.429	43.190	12.176	20.943	-1771.026

Table 2.22
West – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-3.771	2.149	0.782	2.036	0.039
2	Cremini	6.220	-9.222	0.920	2.395	0.046
3	Portabella	11.151	4.532	-28.625	4.293	0.082
4	Specialty	35.488	14.422	5.248	-195.656	0.261
5	Dried	27.448	11.155	4.059	10.566	-134.461

Table 2.23
California – Random Coefficient Logit Elasticities

#	Variety	White	Cremini	Portabella	Specialty	Dried
1	White	-4.521	2.761	0.859	1.881	0.020
2	Cremini	8.602	-16.168	1.288	2.822	0.030
3	Portabella	11.072	5.332	-29.155	3.633	0.038
4	Specialty	35.532	17.112	5.321	-213.560	0.123
5	Dried	119.033	57.324	17.826	39.053	-2059.686

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