Title
Essays on Applied Economics

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Publication Date
2014

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by

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A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy
in
Agricultural and Resource Economics
in the
Graduate Division
of the
University of California, Berkeley

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Spring 2014

Essays on Applied Economics

Abstract

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Doctor of Philosophy in Agricultural and Resource Economics

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This dissertation is comprised of two essays that apply tools from applied microeconomics and empirical methods to study important issues in agriculture, environment and health economics. The unifying topic of the essays is the use of economic reasoning and careful research design to identify causal relationships using observational data.

In the first essay, I investigate the environmental effects due to pesticides for two different genetically modified (GM) seeds: insect resistant (IR) cotton and herbicide tolerant (HT) soybeans. Using an agricultural production model of a profit maximizing competitive farm, I derive predictions that IR trait decreases the amount of insecticides used and HT trait increases the amount of less toxic herbicides. While the environmental impact of pesticides for IR seeds is lower, for the HT seeds the testable predictions are ambiguous: scale and substitution effects can lead to higher or lower environmental impacts. I use a dataset on commercial farms use of pesticides and biotechnology in Brazil to document environmental effects of GM traits. I explore within-farm variation for farmers planting conventional and GM seeds to identify the effect of adoption on the environmental impact of pesticides measured as quantity of active ingredients of chemicals and the Environmental Impact Quotient index. The findings show that the IR trait reduces the environmental impact of insecticides and the HT trait increases environmental impact due to weak substitution among herbicides of different toxicity levels. This is an important result for three reasons. First, it contributes to uncover environmental effects that have been hidden by the qualitative nature of the change mix of herbicides induced by HT trait. Second, environmental policy makers designing policies for biotechnology adoption might consider this new evidence to differentiate among GM traits that produce positive or negative externalities. Finally, the composition of the EIQ index suggests that the environmental impact of pesticides can have multiple dimensions that might involve farmworker health and safety, consumer safety and ecological impacts. Hence, the results on HT soybeans points to additional avenues of work that should be taken to evaluate each of these possible channels since they can also affect other important outcomes such as human capital accumulation.

The second essay studies the behavior of mark-up for antihistaminic medicines, used as a treatment for allergy symptoms caused by seasonal high pollen concentration on air, and test whether it’s consistent with models of dynamic price competition with fluctuating demand. I draw on the empirical tests of the theory of dynamic price competition which examine the

response of observed price-cost margins – retail minus wholesale prices – to expected demand, controlling for current demand. Using a dataset of retail sales, I estimate a reduced form model that captures some of the characteristics of the dynamic price competition with cyclical demand. It consists of a relationship between prices of antihistaminic drugs and measures of pollen concentration on air, taking into account the current level of demand in a given market. Under two basic assumptions – the marginal costs of drugs in each city is the same and level of pollen concentration on air works as a proxy for the expected demand in a given week and prices respond positively to those expectations –, I find evidence that the behavior of the retail margins is consistent with the predictions of models of dynamic price competition under cyclical demand. The essay makes a contribution to understand the dynamics of behavior in oligopolistic markets that might be of interest to academics and practitioners who wants to understand conduct and performance of industrial markets.

To my parents.

CONTENTS

Acknowledgments

Writing these lines has a very special meaning for me: the end of an amazing journey and the start of a new beginning. I'd like to take this opportunity to thank the people and the institutions that made all this possible.

"Come on the amazing journey
And learn all you should know."

I'm grateful to my professors in Berkeley for their guidance and inspiration in the elaboration of the essays that are part of this dissertation. David Zilberman and Sofia Villas-Boas provided superb advice in the elaboration of the essays. Catherine Wolfram also provided great comments and suggestions as external member of dissertation committee.

At different stages of the work I also benefited from comments and suggestions by Jeff Perloff, Jeremy Magruder, Max Auffhammer, Christian Traeger, Denis Nekipelov, Alain de Janvry, José Maria Silveira, Avery Cohn, Marieke Kleemans, Manuel Barron, Kyle Emerick, Sam Heft-Neal and Manuel Barron. Anderson Galvão from Celeres® kindly provided the dataset used in chapter two. Dr. Estella Geraghty from the University of California, Davis kindly provided the data on pollen count and Professor Wolfram Schlenker from the School of International and Public Affairs of the University of Columbia kindly provided data on stores' geographical coordinates for chapter three. None of them should be implied for any remaining errors.

My classmates and colleagues in the ARE department were also an important source of intellectual and emotional support during these past years. I can't express in words how blessed I've been for meeting a group of smart and fun people that gave to me much more than I gave to them. Thanks for everything, guys! You're amazing!

The staff in the ARE department provided invaluable administrative help with professionalism and friendliness, for which I'm greatly indebted. Financial support from CAPES/Fulbright PhD fellowship (grant 2256-08-8) is also greatly acknowledged. The Giannini foundation provided financial support for field work and conference travel and the UC Berkeley Graduate Division provided financial support for conference travel.

Last, but far from least, I'd like to express my gratitude for the love, encouragement and inspiration provided by my family. Even at distance, I carry you in my heart. Geocy, Rosangela and Leandro: I love you.

Chapter 1. Introduction

This dissertation is comprised of two essays that apply tools from applied microeconomics and empirical methods to study important issues in agriculture, environment and health economics. The unifying topic of the essays is the use of economic reasoning and careful research design to identify causal relationships using observational data. Each one contains significant contributions to the field of knowledge which they fit in.

In the first essay, I investigate the environmental effects due to pesticides for two different genetically modified (GM) seeds: insect resistant (IR) cotton and herbicide tolerant (HT) soybeans. Seeds engineered with HT trait are the result of the transfer of part of the genetic code of a soil bacterium, *Agrobacterium tumefaciens*, which allow the plant to metabolize the herbicide glyphosate, which is considered a low toxicity chemical. IR seeds are engineered to produce a natural toxin produced by the soil bacterium *Bacillus thuringiensis* (Bt), which is lethal to a number of bollworms pests but not to mammals.

Using an agricultural production model of a profit maximizing competitive farm, I analyze how the optimal choices of pesticides are changed by the introduction of each GM trait in the plant. I derive two basic predictions: (i) IR trait decreases the amount of insecticides used and (ii) HT trait increases the amount of less toxic herbicides. While the environmental impact of pesticides for IR seeds is lower, for the HT seeds the testable predictions are ambiguous: scale and substitution effects can lead to higher or lower environmental impacts.

To resolve the issue, I conduct an empirical examination of how farmers have changed their choices of pesticides after adopting the GM technology. I use a dataset on commercial farms use of pesticides and biotechnology in Brazil to document environmental effects of GM traits. Exploring within-farm variation for farmers planting conventional and GM seeds, I can identify the effect of adoption on the environmental impact of pesticides measured as quantity of active ingredients of chemicals and the Environmental Impact Quotient index. This measure of environmental impact of pesticides was designed to capture risks associated with both toxicity levels and exposure to chemical pesticides on three components of agricultural systems: farmworker, consumer and ecological. Hence, the EIQ index gives a more complete picture than just the composition of the mix of pesticides used allowing for an adequate weighting of pesticides of different toxicity levels.

The findings show that, as expected, adoption of cotton seeds with IR trait reduces the amount of insecticides used by 24.2% and, consequently, the environmental impact index by 23.4% when compared with fields cultivated with conventional seeds. For soybean seeds with HT traits, however, although farmers use more of less toxic herbicides, I estimate that the net environmental impact is higher than for conventional seeds. I find that adoption of these seeds cause an increase of 44.2% of herbicides use and a corresponding 35.6% increase in the EIQ index when compared with fields cultivated with conventional seeds. Moreover, I estimate that the increase in the use of herbicides of low toxicity levels is twelvefold the decrease in the use of herbicides of high toxicity levels. This result indicates that the main mechanism driving the findings on the EIQ index is the weak substitution among herbicides of different toxicity levels.

This is an important result for three reasons. First, it contributes to uncover environmental effects that have been hidden by the qualitative nature of the change mix of herbicides induced by HT trait. In fact, previous studies on HT soybeans have been found to change the mix of herbicides applied towards less toxic products and to allow the use of no-till cultivation techniques, leading researchers to conclude (tentatively) that they produce environmental benefits. Second, environmental policy makers designing policies for biotechnology adoption might consider this new evidence to differentiate among GM traits that produce positive or negative externalities. Finally, the composition of the EIQ index suggests that the environmental impact of pesticides can have multiple dimensions that might involve farmworker health and safety, consumer safety and ecological impacts. Hence, the results on HT soybeans points to additional avenues of work that should be taken to evaluate each of these possible channels since they can also affect other important outcomes such as human capital accumulation.

The second essay studies the behavior of mark-up for antihistaminic medicines, used as a treatment for allergy symptoms caused by seasonal high pollen concentration on air. The distinguishing characteristic of this allergen is its seasonal pattern of occurrence throughout the year: pollen concentration on air rises in the periods that approach the spring when it achieves its highest level and variation. Hence, the demand for antihistaminic drugs exhibits a cyclical and predictable behavior over the year: it attains peaks during the months of March through May and remains relatively stable over the rest of the year.

I draw on the empirical tests of the theory of dynamic price competition which examine the response of observed price-cost margins – retail minus wholesale prices – to expected demand, controlling for current demand and conclude that the positive relationship between margins and expected demand is consistent with supergame models of tacit collusion. The intuition for this relationship is that, if demand cycle is predictable, in periods of high expected demand, near future expected collusive profits that would be foregone due to the retaliation after a price cut are higher than in periods of low expected future demand. Hence, since near term losses receive more weight in the overall evaluation of collusive vs. non collusive pricing, the sustainable collusive margin will be higher in periods of high expected demand.

Using a dataset of retail sales, I estimate a reduced form model that captures some of the characteristics of the dynamic price competition with cyclical demand. It consists of a relationship between prices of antihistaminic drugs and measures of pollen concentration on air, taking into account the current level of demand in a given market. I explore geographical variation on product prices and pollen concentration to identify the relationship of interest between prices and expected demand. To make the reduced form model compatible with the predictions of the dynamic pricing model we need two assumptions. First, we assume that the marginal costs of drugs in each city is the same and so the different prices in different cities reflect different margins, which is the outcome of interest in the theoretical analysis. This assumption makes sense if the retailer works with a centralized buying unit that serves stores located in different regions and explores economies of scale in purchases, which seems a plausible assumption.

The second key assumption behind the reduced form equation is that the level of pollen concentration on air works as a proxy for the expected demand in a given week and prices respond positively to those expectations, taking into account the current level of demand reflected in the total revenue from antihistaminic drugs in a given week.

The results indicate that the behavior of the retail margins is consistent with the predictions of models of dynamic price competition under cyclical demand. The magnitudes of the coefficients are small but the economic content of the analysis relies on the sign and significance of the coefficients rather than on its magnitudes

Overall, the essay makes a contribution to understand the dynamics of behavior in oligopolistic markets that might be of interest to academics and practitioners who wants to understand conduct and performance of industrial markets.

Chapter 2. Assessing Environmental Impacts of Genetically Modified Seeds in Brazilian Agriculture

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I thank Anderson Galvão from Celeres®, for kindly providing the dataset, and comments from David Zilberman, Sofia Villas Boas, Catherine Wolfram, Max Auffhammer, Christian Traeger, Jeff Perloff, Alain de Janvry, Avery Cohn, Marieke Kleemans, Manuel Barron, Kyle Emerick, Sam Heft-Neal, participants in the ERE seminar and development lunch at UC Berkeley and at the 17th ICABR conference "Innovation and Policy for the Bioeconomy". Financial support from CAPES/Fulbright PhD fellowship (grant 2256-08-8) is greatly acknowledged. All remaining errors are mine.

2.1 Introduction to Chapter

The research agenda on food supply has received increased attention since the global food crisis of 2008. In this context, genetically modified (GM) seeds have been considered one of the major breakthroughs in technological innovation for agricultural systems and have been promoted as an effective tool for control of agricultural pests and food supply expansion. Their relevance can also be measured by the wide spam of controversial issues that have been raised in the related literature since their introduction. Those involve: intellectual property rights over organisms, productivity effects, economic returns, consumer safety, welfare and income distribution, and environmental effects (Qaim, 2009). Potential sources of related economic gains include reduced crop losses, reduced expenditure on pest control, farmworker safety and health conditions, and lower variability of output (Sexton & Zilberman, 2012).

In the environmental front, benefits from adoption of GM seeds have been argued based on findings about pesticide use and agricultural practices induced. Insect resistant (IR) cotton has been found to reduce the use of insecticides and therefore to produce environmental, health and safety gains (Qaim e Zilberman 2003, Qaim e de Janvry 2005, Huang, et al. 2002). Herbicide tolerant (HT) soybeans have been found to change the mix of herbicides applied towards less toxic products and to allow the use of no-till cultivation techniques, leading researchers to conclude (tentatively) that they also produce environmental benefits (Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002; Qaim & Traxler, 2005; Brookes & Barfoot, 2012).

This chapter addresses the environmental impacts, associated with the use of pesticides, resulting from adoption of GM seeds in Brazil. First, I use a model of a profit maximizing competitive farm to show how the interaction of different GM traits (HT and IR) affects the optimal use of pesticides, more specifically herbicides and insecticides. I show that the IR trait works as substitute for insecticides and hence reduces the optimal use of these products. The resulting environmental effect is straightforward: less insecticide usage leads to lower environmental impact. The HT trait, on the other hand, works as a complement to herbicides, specifically to glyphosate[1], and induces an increase in the use of this chemical. The resulting environmental impact is ambiguous and I argue that it depends on the interplay of a substitution effect, between herbicides of different toxicity levels, and a scale effect, of increased use of glyphosate.

In the empirical analysis, I use a unique farm-level dataset that documents adoption of GM seeds and pesticide use between 2009 and 2011 for cotton, maize and soybeans cultivation by commercial farms in Brazil to present the first reduced form models estimates of environmental effects of two different biotechnology traits: IR cotton and HT soybeans. The dataset is disaggregated by fields, within a farm, cultivated with conventional or GM seeds. In other words, for each farm, we have potentially multiple observations related to fields cultivated with conventional or GM seeds. This setup allows me to use within-farm variation for farmers

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[1] The United States Environmental Protection Agency (EPA) considers glyphosate as a pesticide of toxicity level III, in a scale from I (most toxic) to IV (practically nontoxic), requiring products that carry it as active ingredients to obey safety conditions for manipulation such as protective clothing and no re-entrance in treated fields for 4 hours (United States Environmental Protection Agency, 1993). In the classification of environmental impacts, glyphosate is in the 145o position out of 178 active ingredients classified (Kovach, Petzoldt, Degnil, & Tette, 1992).

that plant both conventional and GM seeds to identify the effect of adoption on the environmental impact of pesticides.

The environment impact associated with pesticides is measured as two outcome variables: quantity (kg/ha) of active ingredients of chemicals and the Environmental Impact Quotient (EIQ) index (Kovach, Petzoldt, Degnil, & Tette, 1992). This measure of environmental impact of pesticides was designed to capture risks associated with both toxicity levels and exposure to chemical pesticides on three components of agricultural systems: farmworker, consumer and ecological. Hence, the EIQ index gives a more complete picture than just the composition of the mix of pesticides used allowing for an adequate weighting of pesticides of different toxicity levels. This represents a big advancement over previous studies that only documented increased use of less toxic pesticides for HT soybeans and so cannot capture environmental effects due to substitution and scale effects. Concretely, if the increase in the use of less toxic herbicides is not accompanied by a sufficient decrease in more toxic ones (substitution effect) or if the increase in less toxic is much higher than the decrease in more toxic ones (scale effect), them the new mix of herbicides induced by HT seeds can be more harmful than the one induced by conventional seeds. The EIQ index calculated for field operations allows me to adequately weight pesticides of different toxicity levels and gets around the difficulties of looking only at the mix of pesticides used.

The findings show that, as expected, adoption of cotton seeds with IR trait reduces the amount of insecticides used by 24.2% and, consequently, the environmental impact index by 23.4% when compared with fields cultivated with conventional seeds. For soybean seeds with HT traits, however, although farmers use more of less toxic herbicides, I estimate that the net environmental impact is higher than for conventional seeds. I find that adoption of these seeds cause an increase of 44.2% of herbicides use and a corresponding 35.6% increase in the EIQ index when compared with fields cultivated with conventional seeds. Moreover, I estimate that the increase in the use of herbicides of low toxicity levels is twelvefold the decrease in the use of herbicides of high toxicity levels. This result indicates that the main mechanism driving the findings on the EIQ index is the weak substitution among herbicides of different toxicity levels.

Those results are not inconsistent with the literature on environmental effects of GM seeds. For IR cotton, Qaim & Zilberman (2003), Qaim & de Janvry (2005) and Huan et al. (2005) find significant reductions in average use of insecticides in India, Argentina and China, respectively. For HT soybeans, Fernandez-Cornejo et al. (2002) and Qaim & Traxler (2005) find increases in the use of glyphosate and some reduction in the use of more toxic herbicides, which leads them to conclude for environmental benefits due to the adoption of this type of seed. My results confirm the environmental gains from IR cotton but suggest that the findings on the environmental effects of HT soybeans have been misled by relying solely on the change in the mix of herbicides used.

The rest of the chapter is organized as follows. Section 2 introduces a quick background on biotechnology and its regulation in Brazil. Section 3 describes the theoretical framework that informs the testable hypotheses. Section 4 describes the dataset and presents the empirical strategy. Section 5 shows the results obtained and section 6 concludes.

2. 2 Some Background on Biotechnology and Regulation

Since the mid 1990's, when first-generation GM seeds were commercially introduced, adoption by farmers has grown steadily in industrialized and developing countries as they provide an alternative and more convenient way of reducing pest damage[2] (Figure 1). By 2008, 13.3 million farmers dedicated 8% of total cropland (12.5 million ha) to the cultivation of GM seeds. The leading countries in terms of share of cultivated are in 2009 were the US (50%), Argentina (17%), Brazil (13%), India (6%), Canada (6%) and China (3%) (James, 2008).

The main traits that have been introduced in first generation GM seeds correspond to the herbicide tolerant (HT) and insect resistant (IR) technologies. The focus of this paper relies on HT soybeans and IR cotton.

Soybeans are an annual crop, which means the plant life cycle (seed-flower-seed) last one season only. Weeds are strong competitors with soybean plants for nutrients, water and sunlight. Field infestation can produce yield losses since soybeans are sensitive to moisture and light deficiency, especially in the emergency phase before the plant canopy closes and puts it in advantage against weeds. Weed control techniques have evolved from traditional mechanical methods to herbicides applications introduced in the 1960's (Carpenter & Gianessi, 1999). The first generation of herbicides were known as pre-emergence since they have to applied before planting as weed burn down. Following application, farmers still had to rely on mechanical control until soybean canopy closes and shades competing weeds. Starting in the 1980's, post emergence herbicides were introduced and allowed growers to use chemical control of weeds instead of mechanical tillage over the growing season. This change made possible to increase the planted acreage since herbicide-based weed control is more efficient than mechanical tillage. Post emergence herbicides also make possible to narrow the space between plant rows in the fields which increases yields as a result of a more efficient use of space.

Nevertheless, post emergence herbicides also have drawbacks that limit their application and effectiveness in highly infested areas. These include: potential for crop injury in the form of stunted growth or yellowing/burning leaves, development of herbicide resistant weeds and residual effects on soil that might be deleterious to rotation of crops (Carpenter & Gianessi, 1999).

Soybean seeds engineered with HT traits were introduced in 1996 under the commercial name Roundup Ready. They're the result of the transfer of part of the genetic code of a soil bacterium, *Agrobacterium tumefaciens*, which allow the plant to metabolize the herbicide glyphosate (Roundup®). In 1998, soybean varieties tolerant to the herbicide glufosinate were introduced under the commercial name Liberty Link. Those herbicides target a large variety of broad-leaf and grass weeds species but cause severe damages to conventional crops when applied after germination (post-emergent weed control). The primary reason given for the rapid diffusion rated of those seeds, notably the Roundup Ready ones, is the simplicity of the glyphosate-based weed control, which allows farmers to concentrate on one herbicide to control a wide range of weeds. In addition, it also proved more convenient for farmers since the timing of application can be extended beyond soybean flowering and the maximum size of weeds that

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[2] Second-generation GM seeds display quality improvements in nutritional contents and third generation are designed for pharmaceutical (vaccines and antibodies) and industrial (enzymes and biodegradable plastics) applications.

are effectively controlled is higher compared with other post emergence herbicides (Carpenter & Gianessi, 1999). Herbicide related cost savings have also been pointed as one of the reasons for adoption, since glyphosate patent expired in the year of 2000, allowing the entry of new suppliers and lowering the price of glyphosate-based herbicides (Qaim, 2009). Hence, from the point of view of farmers, HT soybeans have been shown to be both technically and economically advantageous, which explains the rapid diffusion that they have displayed.

IR seeds[3] are engineered to produce a natural toxin produced by the soil bacterium *Bacillus thuringiensis* (Bt), which is lethal to a number of bollworms pests but not to mammals. IR crops have also been deemed technically and economically efficient for producers. The most straightforward reason is related to savings in insecticides applications (which spams from labor time to savings in machinery use, aerial spraying etc.) targeted to bollworm killing. Specifically, in regions with high insect infestation, typical less developed countries in tropical weather regions, and high rates of insecticide use, the potential for reduction is conversely high (Qaim & Zilberman, 2003). Positive yield effects have also been noted since the Bt toxin compound on the insecticide effect reducing losses due to insect attack (Qaim, 2009). In fact, it has been argued that yield and insecticide reduction effects are closely related: farmers facing high pest pressure and still using low rates of insecticides

Besides, it has also been considered a more efficient tool for managing the risk of pest attack than reactive application of insecticides (Crost & Shankar, 2008) which has been translated in reduced crop insurance premium (Brookes & Barfoot, 2012). Other benefits pointed relate to improve safety conditions for farm workers and shorter growing season (Brookes & Barfoot, 2012).

Crops that have been engineered with the above traits are: cotton, maize, rapeseed and soybean. More recently, some crops have also been engineered with both HT and IR traits and are commonly referred as stacked varieties. The most used technology is HT in soybeans, which corresponded to 53% of GM seeds planted area in 2008 and is grown mostly in US, Argentina and Brazil. The second-most used technology is HT and IR maize, which accounted for 30% of GM seeds planted area in 2008 (James, 2008).

Despite the production benefits, consumers have shown suspicious attitudes regarding the health and environmental safety of products originated from GM seeds and government regulation has ranged from cautionary permission to complete ban. The European Union, for instance, imposed a ban on GM seeds that was lifted in 2008. Also, GM seeds uses have been restricted to animal feed and fiber uses and producers are required to segregate GM crops output throughout the supply chain (Sexton & Zilberman, 2012). Other concerns relate to the undermining of traditional knowledge systems in developing countries and the possibility of monopolization of seed markets by large multinational companies and exploitation of small farmers (Sharma, 2004).

The regulation of GM seeds in Brazil originates in the first Biosafety Law from 1995, which ruled that commercialization of GM seeds is subject to approval by the National Technical Biosafety Commission (CTNBio). After a decision from CTNBio in favor of Monsanto's Roundup Ready seed (a type of HT soybean seed) that waved the company from releasing environmental impact studies was judicially contested in 1998, a period of ban of

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[3] Also referred in the literature as Bt seeds.

commercialization of GM seeds was imposed by the judiciary system, on the grounds that CTNBio's decision violated the principle of precaution espoused by the Brazilian constitution. The judiciary decision, nevertheless, wasn't fully implemented as competitive pressure by farmers from neighbor countries Argentina and Paraguay stimulated the smuggling and illegal adoption of soybean HT seeds by farmers in the southern states that bordered those countries. Also, the executive branch took a mostly favorable stance towards farmers and loosened repression of GM seeds adoption on the grounds that it would impose huge losses on southern producers, responsible for a significant share of soybean production in Brazil. After a series of temporary provisional measures designed to work around the legal ban, a new biosafety law was passed in 2005 that settled the issue in favor of the discretion of CTNBio's power to require environmental impact studies for commercial release of GM seeds (Pelaez, 2009).

In spite of the delay caused by the regulatory issues that took seven years to be resolved, adoption of GM seeds in Brazil spread rapidly and reached a level similar to neighbor country Argentina, which has a longer history of liberal policy towards adoption of GM seeds. Figure 2 illustrates the steady growth in the rates of adoption of GM seeds in cotton, maize and soybean crops. Adoption of HT soybeans increased from 45.2% in 2008 to 91.8 % of planted area. Cotton crops also observed growth in GE seeds adoption rates, ranging from 6.6% of the planted area in 2008 to 29.6% in 2011. It's worth noting the rapid adoption of GM Maize seeds, which were introduced in 2008 and reached an adoption rate of almost 80% of planted area by 2011 (Céleres, 2012). In terms of area, this equivalent to approximately 31.16 million ha of the total planted area with those crops in 2010.[4]

2.3 Theoretical Framework

I present a heuristic model that illustrates the effects of different GM traits on choices of pesticides inputs by a competitive profit maximizing farm. The model allows deriving testable predictions that are going to guide the empirical analysis. Building on previous work (Ameden, Qaim, & Zilberman, 2005) I show that the IR trait works as substitute for insecticides and hence reduce the optimal amount used whereas the HT trait works as complement for herbicides and induce more intense use of those products. The net environmental impact, which is the outcome I am ultimately interested in, will be different for each trait. For the IR trait, the result is unequivocal: less insecticide usage reduces environmental impact. For the HT trait, on the other hand, the environmental impact can't be determined a priori. HT trait makes the plant more resistant to glyphosate, which leads to a more intensive usage of this chemical. The net environmental effect will depend on how strong is the substitution between different types of herbicides.

The set-up of the model uses a damage control framework (Lichtenberg & Zilberman, 1986) that distinguishes between inputs that directly affect production, like labor, land and fertilizers and inputs that indirectly affect output by reducing the damage caused by pests like pesticides, biological control or GM seeds. Total output is given by the interaction between potential output, represented as a conventional production function of direct inputs, and a

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[4] Approximately equivalent to 73% of the State of California.

damage abatement function of indirect inputs that represents the share of output not lost by action of pests. We represent the total output function as:

$$Q = Q_i[1 - D(N_i)], i = 0, 1 \qquad \text{(eq. 1)}$$

where $Q_i$represents potential output, determined by direct inputs, $D(N_i)$ is a damage function that depends on the size of the pest infestation and the subscript i represents conventional or GM seeds respectively. We make the following regularity assumptions on the damage function:

(i) $0 < D(N_i) < 1$ and
(ii) $D' > 0$ and $D'' \geq 0$.

Pest infestation depends on the size of initial population and the fraction that survive the application of chemicals and biotechnology. It is represented by:

$$N_i = Nh(x)B_i\,, \qquad \text{(eq. 2)}$$

Where *N* is the initial population, h(x) is the fraction of survival after application of pesticide quantity x and Bi is a parameter for the biotechnology effect. We also make the following regularity assumptions:

(i) $h' < 0$ and $h'' > 0$,
(ii) $B_0 = 1 \geq B_1$.

Letting p denote the market price for the crop and w the unit cost of application of pesticide, the choice of chemical input (x) for a competitive farm, for each trait *i* = 0, 1, is the result of the following program:

$$max_x\, pQ_i[1 - D(Nh(x)B_i)] - wx. \qquad \text{(eq. 3)}$$

The first order condition for an interior solution is given by:

$$-pQ_iD'Nh'(x_i^*)B_i = w. \qquad \text{(eq. 4)}$$

Equation four represents the solution to the usual profit maximization problem where the left-hand side represents the value of marginal product of the pesticide and the right-hand side its unit cost. The interaction of the effects of different traits will determine the comparative statics of the optimal choice x_i^*.

The IR trait exerts a compound effect with the application of insecticide represented by: $B_0 = 1 > B_1$ and $Q_0 = Q_1$. The effect of adoption is them to reduce (shift down) the value of the marginal product of insecticide and, consequently, the amount of insecticide used. In this sense, the IR trait works as a substitute for insecticides. The left panel of figure 3 illustrates this effect.

The HT trait, on the other hand, allows tolerance to the non-selective herbicide glyphosate[5] which avoids damage to the plant. We interpret this property as an increase in potential output that can be obtained from regular inputs and is represented by: $\mathrm{B}_0 = \mathrm{B}_1$ and $\mathrm{Q}_1 > \mathrm{Q}_0$.[6] This effect increases the value of marginal product of the specific herbicide that the plant becomes tolerant to and the amount of herbicide applied. The right panel of figure 3 depicts this effect graphically.

The environmental impact that follows biotechnology adoption can be differentiated by the type of trait. For the IR trait, the effect is unequivocal: since the amount of insecticides is reduced, environmental impact is reduced with adoption.

For the HT trait the net environmental impact depends on two factors. First, it depends on the degree of substitution between different types of herbicides. Glyphosate is considered a low toxicity chemical. Hence, substitution of more toxic herbicides that are designed for specific weeds for less toxic general purpose herbicides can reduce the environmental impact of chemicals. On the other hand, there is also a scale effect: if the increase in the amount of low toxicity herbicides is much larger than the decrease in high toxicity herbicides, the net effect can be a higher environmental impact due to the use of chemicals. In a nutshell, weak substitution and large scale effect renders the net effect on environmental impact ambiguous.

Economists that studied the issue have focused on the substitution between herbicides to conclude (somewhat tentatively) that there are environmental gains allowed by the use of HT traits (Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002; Qaim & Traxler, 2005). Nevertheless, I argue that weak substitution effect and strong scale effect might undermine this conclusion as I show in the analysis that follows on the next sections.

2.4 Dataset and Empirical Strategy

The dataset originates from a survey conducted by a private firm in Brazil among 1,143 farmers distributed in 10 states for harvest seasons 2008-2011. Information on pesticide use was collected for harvest seasons 2009-2011 and covers 839 farms. The data are disaggregated at the trait level. Hence, each observation correspond to a farm *i*, on year *t*, producing crop *j*, with trait *k*. This separation is possible since the Brazilian agricultural regulation requires segregation of fields cultivated with conventional and GM seeds, as required by the Cartagena Protocol ratified by the Brazilian government in 2004 (Oliveira, Silveira, & Alvim, 2012). The crops covered are cotton maize (summer and winter crops) and soybean. The traits used are conventional (for all crops), HT (soybean) and IR (cotton and maize). For reasons of space, we show results for soybean and cotton crops since these corresponds to the different biotechnology traits analyzed in the theoretical model. [7]

The dataset contains information on physical production and input expenditures separated by type of crop and traits for each farmer. The variables available are:

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[5] More recently, traits that allow resistance to other herbicides like ammonium-glufosinate have been introduced or are on the pipeline (Bidraban, et al., 2009).

[6] I should point here that this is a comparative statics result, i.e., all other factors are held constant. More importantly we're holding constant the variety of the seed in which the GM trait is being inserted.

[7] Results for IR maize are qualitatively very similar to the ones obtained for IR cotton and are available upon request.

1. Production (kg) and planted area (ha) for each field cultivated with different seed trait (conventional and GM);
2. Monetary measures by trait of seed: total and net revenue, gross operating income, expenditures on fuel, pesticides, other chemicals, fertilizers and correctives, direct labor, seeds and planting materials, royalties and fees, outsourced services (planting, defensives application, harvesting and transport), storage and processing, other direct costs,
3. Demographic aspects of farmers8 (sex, age, schooling, years of experience with the crop);
4. Property structure of the farm: whether it's managed by owner or manager,
5. Dose (kg/ha), number of applications and formulation (percentage of active ingredients) of pesticides used (acaricides, formicides, fungicides, insecticides and herbicides).

The environmental impact of pesticides is measured by an index designed by scientists from the Integrated Pest Management program from Cornell University (NY): the Environmental Impact Quotient (EIQ). The EIQ index (Kovach, Petzoldt, Degnil, & Tette, 1992) organizes information on toxicological and environmental impact generated as requirement for registration in the United States Environmental Protection Agency and assesses the environmental impact associated with pesticides by considering three different components of agricultural systems with equal weight: farmworker (picker and applicator), consumers and ecological (terrestrial and aquatic animals). The general principle that guides the index is that the environmental impact for each component is given by the product of the toxicity level of the chemical substance (active ingredient), rated in a scale of one to 5, and the risk of exposure (e.g. half-life of substance on ground and plant surface, leaching potential), ranked in a scale of 1 for low risk, 2 for medium and 3 for high risk of exposure. Figure 4 gives a schematic description of the different components of the index.

The researchers propose an index that weights all those components in a single measure of environmental impact for each active ingredient contained in pesticides.[9] Starting with this measure, a field EIQ for pesticide is obtained in two steps:

1. For each pesticide j, the EIQ is the interaction of the active ingredients' (EIQ_i) and the percentage content in the formulation (% of active ingredient per unit of weight): $EIQ_j = \sum_i \sigma_{ij} \times EIQ_i$, where i represents the active ingredient, j the pesticide and $\sigma_{ij}$is the percentage content of active ingredient i in the formulation of pesticide j. Inactive ingredients are assigned an EIQ value of zero.
2. For each field f, the EIQ is the interaction of the EIQ of each pesticide j (calculated in one) applied to field f (EIQ_{jf}) multiplied by the dose (kg/ha) of pesticide

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[8] Collected only in 2010.

[9] The updated list of pesticides (active ingredients) and their respective indexes can be found at: http://www.nysipm.cornell.edu/publications/eiq/equation.asp#table2 .

required to provide adequate pest control (δ_{jf}) and the number of applications (α_{jf}): $EIQ_f = \sum_j \alpha_{jf} \times \delta_{jf} \times EIQ_{jf}$.

The field EIQ index captures a non-monotonic effect due to scale (dose and number of applications) and substitution effect (mix of active ingredients used). In other words, a pest management strategy that uses less toxic pesticides but in very large amounts can have a higher EIQ than a pest management strategy that uses small amounts of a high toxic pesticide. This represents a clear advantage over comparing variations in quantities of pesticides of different toxicity levels without any proper weighting that takes into account the two aforementioned effects. [10] Since the survey collects information on dose, number of applications and formulation of pesticides used for each seed trait used, we can calculate field EIQ indexes for conventional and GM seeds.

Figures 5 and 6 map the cities where the cotton and soybeans farms where surveyed in the years 2009-2011. They are spread over 8 states which comprise a total area of 3,564.8 thousands Km2, equivalent to 41.8% of the Brazilian territory. Tables one, two and three show the regional distribution of the surveyed farms and descriptive statistics for the surveyed farms that cultivated cotton and soybeans between 2009-2011. [11] It can be seen, for example, that those are on average large operations in terms of total planted area, which also includes other crops, and net revenue. For cotton growers, the average total planted area is 2.521 ha, ranging from 60ha to 28,374 ha. For Soybean growers, the average total planted area is 1,240 ha ranging from 8ha to 13,500 ha. In terms of experience, we notice that famers report an average of 22.4 and 29.4 years for cotton and soybeans respectively. This can be interpreted as a quite high level of accumulated human capital accumulated in the activity. The variable owner indicates whether the farm is managed[12] by the owner of by some other agent (e.g. a manager). This variable documents farms that belong to a business group (eg. some investor that decides to diversify her portfolio) or to an independent farmer. [13] It can be seen that for cotton farms, only two percent are managed by owners, while for soybean we have 25%. In terms of geographical concentration, the region with most observation is the Central-West in both crops. This is not surprising since this is one of the largest geographical regions in terms of agricultural land in Brazil. Finally, in terms of education, it can be seen that the sample corresponds to farmers with quite high schooling level for cotton growers, 68% have at least a college degree, while for soybean growers 48% of them have at least a college degree.

Another interesting statistic is the rates of biotechnology adoption for each crop. For cotton, it can be seen that 43% of the farmers surveyed used some type of GM seed between 2009 and 2011, while 26% reported having used IR seeds. For soybeans, virtually all surveyed farmers used HT seeds in some year between 2009 and 2011. Hence, soybean growers can be divided in groups of partial adopters and complete adopters.

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[10] We should also recognize that the EIQ index is not free of criticism, notably about the simplicity of the linear functional form assumed and the ordinal nature of the toxicity and risk of exposure measures. Other indexes of environmental impact have been proposed in the scientific literature that are more comprehensive and more difficult to apply than the EIQ (Levitan, Merwin, & Kovach, 1995).

[11] The different number of observations corresponds to variables that weren't surveyed every year.

[12] By managed we mean, the person that has decision power on biotechnology use.

[13] It has been documented that soybean production, especially in the Central-West region has taken place predominately in large agricultural enterprises (Weihold, Killick, & Reis, 2013).

As participation in the survey is voluntary, attrition rates are very high; hence, use of panel data techniques cannot be applied to the data. Nevertheless I can use other sources of variation to identify the effect of adoption on the use of pesticides. The level of data disaggregation – fields with conventional and GM traits – allows me to explore within farm variation between fields cultivated with conventional and GM seeds to identify the effect of biotechnology traits on the use of pesticides and corresponding environmental impact. This empirical strategy holds constant all farm-level characteristics that might affect simultaneously the choices of pesticide use and biotechnology adoption such as: management skills, input/output prices, location, weather shocks, etc. Hence, for instance, if soybean farmers that adopt biotechnology have some intrinsic preference for pest management strategies that are more intensive in herbicides than mechanical control (like tillage) the effect of GM traits could be overestimated. Likewise, if cotton farmers that adopt IR traits are more efficient and also use less insecticide in their pest management strategies, the effect of IR trait will be underestimated. The use of within farm variation, i.e., comparing the pesticide use and corresponding environmental impact for farmers that cultivate fields with conventional and fields with GM seeds, gets around these sources of bias on the coefficient that measures the effect of the GM trait.

Two main caveats still need to be addressed. First, there may be systematic differences across fields within the farm that might affect adoption and use of pesticides. This can be particularly important in the case of soybean HT seeds if the presence of weeds is related to soil quality, for example, and if farmers tend to use GM seeds fields with more weed infestation, which would introduce an upward bias in the coefficient of the GM trait. Also, if farmers use no-till farming in fields that are cultivated with HT seeds, the coefficient on HT trait will be upward biased as well since the effect of no-till will be confounded with the effect of HT trait. [14]

To address the issues related to differences in fields I rely on two findings. First, I compare levels of expenditure per hectare on inputs across fields with conventional and GM seeds to look for evidence of soil quality that might drive more intense use of inputs. Specifically I look at expenditures on fertilizers as evidence of systematic differences in soil quality. Tables 4 and 5 show that, for cotton and soybeans crops respectively, the average expenditure on inputs for fields cultivated with conventional and GM seeds are not statistically different. The results for expenditures on fertilizers give some confidence that systematic differences in soil quality are not introducing significant bias in our results. [15] With respect to the use of no-tillage farming, since the survey collects information on the planting system used for each field, I control for the use of conventional versus no-till in the equations for soybean, the crop associated with the use of herbicides. I also estimate the model considering only farmers that don't use different farming systems across fields.

The third possible systematic difference across fields refers to the level of weed infestation in the fields which farmers apply HT seeds. If use of HT seeds is positively correlated with the level of infestation, i.e., knowledge that a field has a high level of weed infestation leads the farmer to use HT seed, so that she can rely on chemical treatment instead of labor demanding

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[14] In no-till cultivation systems, farmers substitute soil tillage for burndown chemical treatment of weeds before planting. Hence, in no-till systems, farmers tend to use more herbicides.

[15] Even if those expenditures don't correspond to pre-treatment observations, we believe that this is the best evidence we can provide on the degree the relative homogeneity of fields cultivated with conventional and GM seeds.

mechanical weeding, we would have an upward bias in our coefficient, since part of the increase in herbicide use would be due to the higher weed infestation and not because of the HT trait.

Unfortunately, I don't have a direct measure of weed infestation in the fields cultivated with HT seeds. Nevertheless, I can address this source of bias by relying on two arguments. First, in order to prevent development of weed resistance to herbicides, farmers have to rotate the fields in which they plant conventional and GM soybeans, as well as soybeans and other crops, most commonly maize. Hence, in a given year, rotation introduces a random component to weed infestation in the fields cultivated with HT soybeans that might alleviate the bias due to weed infestation. Second, as I'm going to show in the results section, there are small or even non-significant differences in the levels of utilization of herbicides of higher toxicity levels across fields cultivated with conventional or HT soybeans, which might be another indication that weed infestation is, on average, similar in both kinds of fields.

The second caveat relates to the sample of farmers chosen to perform the estimation, i.e., farmers that cultivate both conventional and GM seeds. This choice can potentially introduce a selection bias since it only considers adopters. In fact, tables 6 and 7 show that there are significant differences between farmers included and excluded from the regression samples. For cotton farms, the sample is more concentrated in the northeastern region and less in the Central-West. With respect to schooling, we see that farmers in the sample tend to have more of college (not statistically significant) and graduate degrees and less of basic and high school. For soybean farms, we see statistically significant differences for more variables. Specifically, they have larger operations (planted area), spend more on fertilizers, are younger and less experienced, although with in a still high level, more concentrated in the northeastern and southeastern regions and less in the southern region and are also more educated (less concentrated in basic school).

To alleviate this issue I rely on the observation that the farmers in the sample are more educated than the excluded ones. Hence, it's possible to conjecture that the selection bias is in the downward direction. If more educated farmers are also more efficient, them the effect of adoption will be smaller for them than the effect for the whole population. In other words, the results are underestimating the true value of the effect of adopting GM seeds on the outcome variables of interest: pesticides quantities and environmental impact. Another characteristic of the soybean farms is that virtually all farmers are adopters of HT seeds: there's exactly one observation corresponding to a farmer that uses only conventional soybeans. Hence, in the case of soybeans, the distinction between farms included and excluded from the sample refers to complete adopters, excluded, and partial adopters. Hence, the selection problem is also alleviated as unobservable characteristics between these two groups might not be as different as if the excluded farms were comprised of adopters and non-adopters.[16]

The models are estimated for cotton and soybean crops separately. The dependent variables are quantity (kg/ha) of pesticides used (insecticides for cotton and herbicides for soybean) and EIQ index for each field. The traits considered are the most common ones for each crop: IR for cotton and HT for soybean. The estimated equations have the following form:

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[16] A second conjecture might be that, by using only farmers that adopt GM seeds, we are approximating the treatment effect on the treated, that is on farmers that have intrinsic characteristics that make them more likely to adopt GM seeds.

$$y_{itf} = \alpha + \beta trait_f + \gamma_i + \theta_t + \varepsilon_{itf} \ . \quad \text{(eq. 5)}$$

Subscripts i, t and f indicate farmer, year and field (each field cultivated with conventional or GM seed). We include farmers (γ_i) and time dummies (θ_t) that capture farm-specific and year specific effects. Although these variables are orthogonal to the field level effects that we are interested, they provide efficiency gains in the estimation that prove worth keeping them.

2.5 Results

To recap and as derived by the model outlined in section three, for cotton crops (IR trait) we expect a negative coefficient for trait in the equation for quantity of insecticides and for the EIQ index. For the soybean model (HT trait) we expect to find a positive coefficient for trait in the equation for quantity of herbicides but in the EIQ equation, the trait coefficient can go either way. To give a better picture of the intensity of substitution between different types of herbicides, for soybean crop, we estimate separate equations for each type of toxicity class of herbicides. We expect to find positive coefficients for quantities of low toxicity (classes III and IV) and negative (or non-significant) coefficient for quantities of high toxicity (classes I and II) herbicides. The magnitudes of those coefficients might shed light to the process of substitution of herbicides that is induced by the HT trait is soybean crops.

The regression results are consistent with the predictions of the model. For IR cotton, we observe a reduction in the quantity of insecticides and environmental impact. For HT soybean, on the other hand, I find increased quantities (kg/ha) of low toxicity herbicides and no corresponding reduction for high toxicity ones. The net result is an increase in EIQ index of herbicides applied.

Insect Resistant Cotton

Table 8 shows estimates of the effect of adoption of IR trait in cotton crops for quantities (Kg/ha) of active ingredients of insecticides and total pesticides applied, considering all farms in the survey and the restricted sample respectively. The point estimates in the restricted sample are lower (in absolute terms) than the ones in the full sample, which indicates that bias due to uncontrolled unobserved variables is an issue. The coefficient of the IR trait indicates that it allows a reduction of 0.956Kg/ha of active ingredients of insecticides. Table 9 shows the results estimated with farm and year fixed effects, which shows efficiency gains reflected in lower standard errors obtained, and a log-linear specification that estimates the proportional effect of adoption on the dependent variable. The result shows a decrease of 24% in the amount of insecticides[17] used and 9.2% in total quantity of active ingredients.

Table 10 is the counterpart of table 9 for the EIQ index. Consistent with the reduction in quantity of insecticides, the coefficient indicates a reduction of 34.225 EIQ points. To gain some perspective on this magnitude, in comparison with the general classification of active ingredients for insecticides, this is higher than the median EIQ index of 32.07. Also, the Mean EIQ for

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[17] We also estimate similar models per toxicity class (I-IV in decreasing level of toxicity) which indicate reductions in all classes, the most prominent effect being for class III (medium-low level of toxicity) with a proportional decrease of 40%. Those results are available upon request.

insecticides is 145.8 and for all pesticides 304.4. The log-linear specification shows a proportional reduction of 23.4% in the EIQ index for insecticides. Hence, it can be considered a significant reduction in terms of environmental index.

As a robustness check for our results, I perform a falsification test that consists on regressing quantities (Kg/ha) of pesticides that should not be affected by the introduction of IR trait: acaricides, fungicides and herbicides. Table 11 shows the results using all cotton farms and the restricted sample and it can be seen that none of the coefficients are statistically significant.

The results so far are all consistent with the current state of the literature on environmental effects of IR seeds. Studying IR cotton seeds in India, Qaim & Zilberman (2003) found reduction of 1 kg/ha on average use of insecticides (70% compared with the baseline conventional field) while Qaim & de Janvry(2005) found reductions between 1.2kg/ha and 2.6Kg/ha of active ingredients used in Argentina, which represents about 50% reduction in comparison with conventional plots. For China, Huan et al. (2005) found even bigger reductions of about 49kg/ha of average insecticide use (80.5% compared to the average of 60.7 Kg/ha in conventional fields).

Herbicide Tolerant Soybeans

For soybeans, the regression estimates on table 12 show that adoption of HT trait increases the quantities (Kg/ha) of active ingredients of herbicides used. The point estimate for the coefficient of the HT trait effect on the use of herbicides in the restricted sample is bigger than the one in the full sample and indicates that it causes an increase of 0.996Kg/ha of active ingredients of herbicides Table 13 shows the results including year and farmer fixed effects, which provide efficiency gains in the estimation and a log-linear specification that shows a proportionate increase of 44.2% in the quantity of active ingredients of herbicides and 26.2% in total.

Table 14 breaks the effects on herbicides by categories of toxicity level (1 to 4 in decreasing order). Categories 3 and 4 show significant increases of 0.64 and 0.44 kg/ha of active ingredients respectively while categories 1 and 2 show reductions of 0.084 and 0.005 (not statistically significant) respectively. Hence, the increases in less toxic herbicides is twelve fold the reduction in more toxic herbicides. This result reflects two points on the pattern of herbicide use. First, the substitution effect among different toxicity classes is very low, which indicates that this channel of environmental benefits is very limited. Second, the scale effect is not so big as compared to the effect found in other countries. Nevertheless, these results show that farmers are increasing the use less toxic herbicides on top of the more toxic ones, which suggests more environmental impact as a result of adoption of HT seeds.

The environmental effect is shown in Table 15 that reports the results for HT trait coefficient on the EIQ index equation. The weakness of the substitution among herbicides of different toxicity categories is reflected in higher environmental impact as shown by the coefficient that indicates an increase of 13.847 EIQ points. In comparison with the general EIQ classification for herbicides, this is lower than the median value for EIQ index of 19.5. The EIQ for glyphosate is also larger than this result: 15.33. In the sample, the mean EIQ for herbicides is 37.8 and for all pesticides 91.3. The proportional effect on the EIQ index is shows an increase of 35.6% in the EIQ index for herbicides and 16.2% in total. Hence, we can conclude for a relatively modest increase in environmental impact caused by HT soybeans.

I conduct two robustness checks for our results on HT soybeans. First, as with the case of IR cotton, I run a falsification test that consists on regressing quantities (Kg/ha) of pesticides that should not be affected by the introduction of HT trait: fungicides and insecticides. Table 16 shows the results using all soybean farms and the restricted sample and it can be seen that none of the coefficients are statistically significant. Additionally, I estimate the models for quantities and environmental impact controlling for the use of no-tillage cultivation in each field. This cultivation method requires more herbicides since it doesn't use tillage to clean the soil from weed infestation before the planting. Since this variable varies between fields, it might capture an important characteristic that should be controlled for. Tables 17 and 18 show the results for quantity of active ingredients and environmental impact, respectively, that are qualitatively and quantitatively very similar to the ones obtained before.

The results suggest that previous findings on the environmental effects of HT soybeans might have been misled by the qualitative nature of the mix of herbicides. Fernandez-Cornejo et al. (2002) found evidence of reduction in the use of acetamide herbicides and increase in the use of glyphosate in USA. Qaim and Traxler (2005) studying HT seeds in Argentina found a total increase of 107% in the use of herbicides, which are divided in a decreases of 87% and 100% in toxicity classes two and three, respectively, and an increase of 248% in toxicity class four. The authors suggest that this change is basically due to the use of no-till farming by adopters of HT soybeans.

My results are not incompatible with those previous findings. In fact, I also observe a change in the composition of the mix of herbicides used towards less toxic products. This movement is predicted by the theoretical analysis that shows how the HT trait increases the value of marginal product of herbicide (glyphosate) and, therefore, the optimal amount used. On the other hand, I also find very weak substitution among herbicides of different toxicity classes, which suggests that the environmental impact of herbicides in being magnified. The analysis with the EIQ index confirms that this is not only a possibility: even inducing more use of a less toxic herbicide, HT seeds cause higher environmental impact, even when controlling for the use of no-till farming.

2.6 Conclusion

In this essay I analyze the environmental effects related to the use of pesticides arising from adoption of GM seeds in cotton and soybean crops. Cotton crops are genetically engineered to display IR traits that make the plant produce a natural toxin that helps fight certain types of harmful bollworms. Soybeans are modified to display HT trait that make the plant resistant to glyphosate, a general purpose low toxicity herbicide. We use a model of profit maximizing competitive farm to show how the introduction of these traits affects the optimal choices of pesticides. We show that the IR trait works as a substitute for insecticides and reduces the quantity used whereas the HT trait works as a complement for the herbicide glyphosate and so induces more usage of this product.

The environmental effects are also different for each type of trait. The IR trait has unequivocal benefits since it's basically a chemical saving technology. The HT trait, on the other hand, has ambiguous effects: it induces more usage of a less toxic herbicide but I argue that the total effect depends on the substitution among herbicides of different toxicity classes and on the scale of additional usage of glyphosate. Increased environmental impact can arise from a combination of low substitution and high scale effect.

Using within-farm variation across fields treated with conventional and GM seeds, I find that the IR trait reduces the amount of insecticides applied to cotton crops, measured by kg/ha of active ingredients applied to the fields. HT trait, on the other hand, leads to more usage of herbicides. Specifically, I find increased usage of herbicides from lower toxicity classes (3 and 4) and very small reductions in herbicides from higher toxicity classes (1 and 2). This finding evidences a very weak substitution among herbicides which raises the possibility of higher environmental impact.

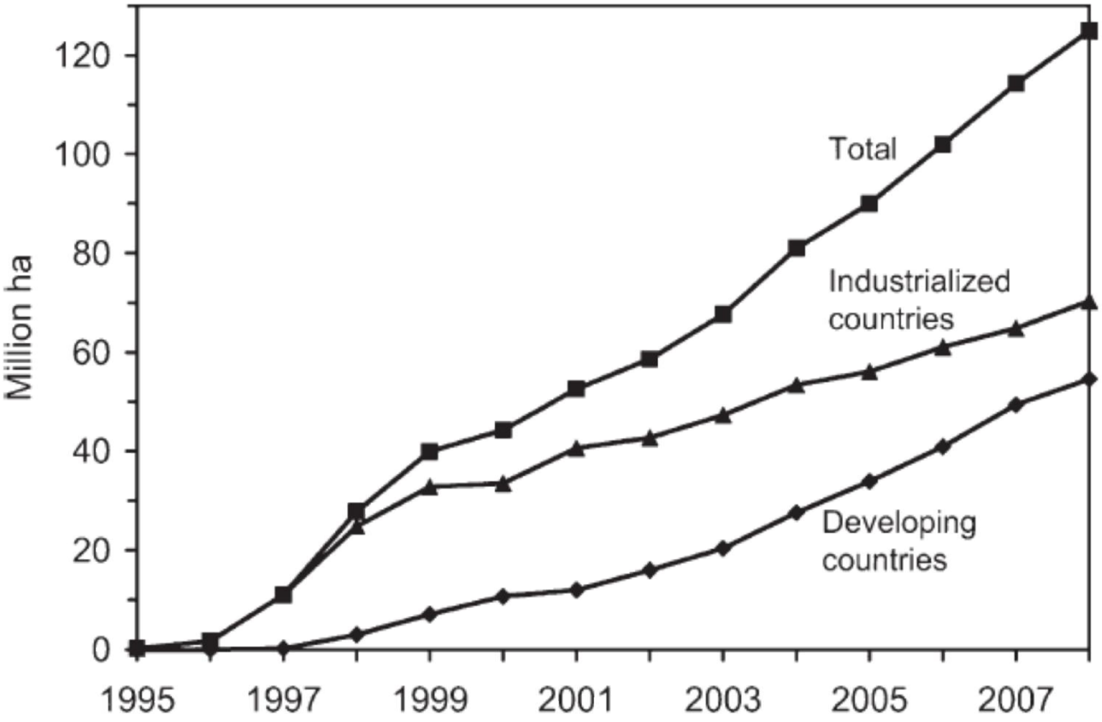
To assess the environmental effect of GM traits due to the use of pesticides, I use a measure developed by integrated pest management scientists that takes into account levels of toxicity of active ingredients, risk of exposure and application in the field (dose and number of applications): the EIQ index. Within-farm analysis shows that IR trait reduces the environmental impact by about 23% in the treated fields compared to fields cultivated with conventional seeds. This is consistent with the previous result on kg/ha of insecticides and confirms the environmental impact saving nature of the IR technology.

The resulting environmental impact for HT trait, on the other hand, is found to be positive. The estimates imply an increase of 35.6% on the impact of herbicides compared to fields cultivated with conventional seeds. This finding confirms that the weak substitution among herbicides makes adoption of HT seeds to increase the environmental impact from pesticide use.

This is an important result for three reasons. First, it contributes to uncover environmental effects that have been hidden by the qualitative nature of the mix of herbicides induced by HT trait. Second, environmental policy makers designing policies for biotechnology adoption might consider this new evidence to differentiate among GM traits that produce positive or negative externalities. Finally, as the composition of the EIQ index suggests, the environmental impact of pesticides can have multiple dimensions that might involve farmworker health and safety, consumer safety and ecological impacts. Hence, the results on HT soybeans points to additional avenues of work that should be taken to evaluate each of these possible channels since they can also affect other important outcomes such as human capital accumulation.

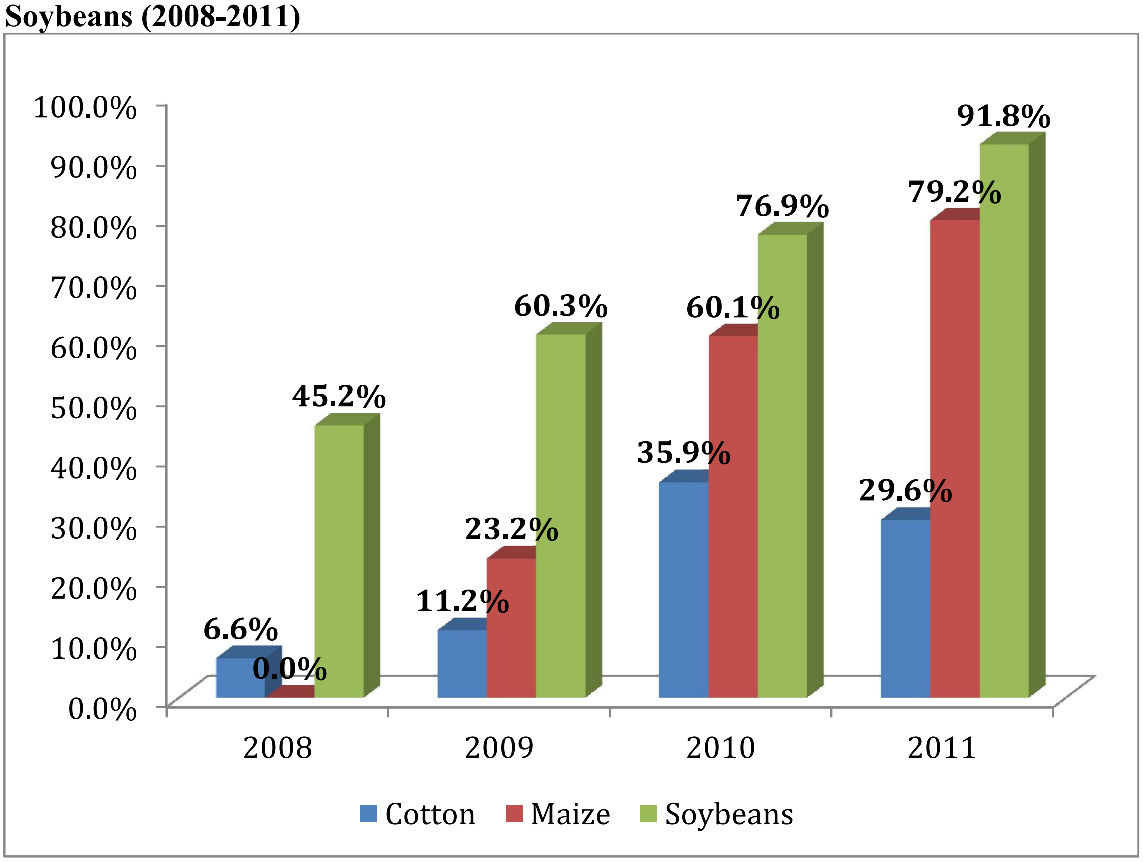
2.7 Tables and Figures

Figure 1: Steady Increase in Global Planted Area Using GM Crops



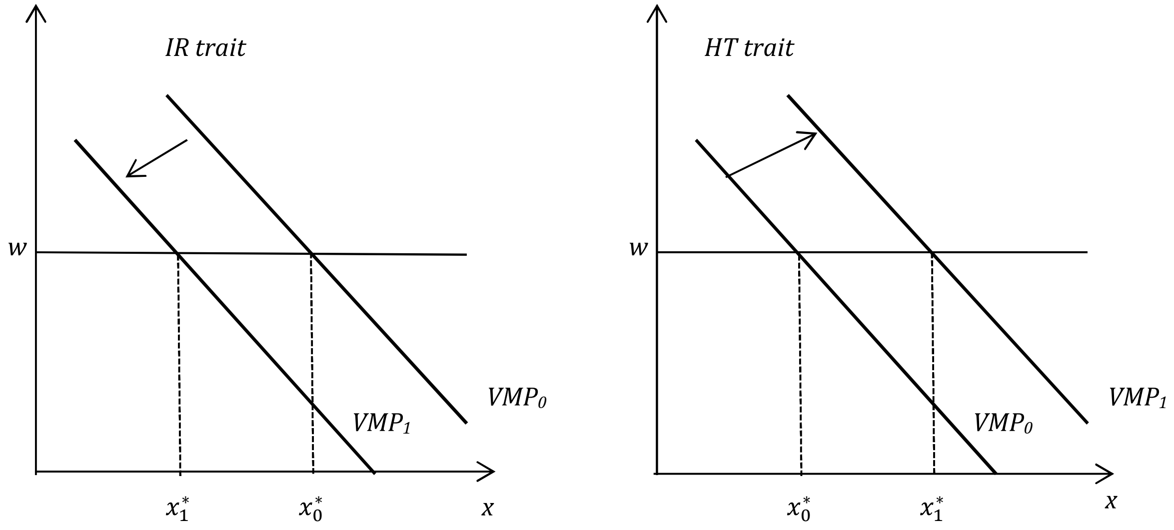
Source: Qaim (2009).

Figure 2: Share of Planted Area with Genetically Modified Seeds for Cotton, Maize and Soybeans (2008-2011)



Source: own elaboration based on Celeres (2012)

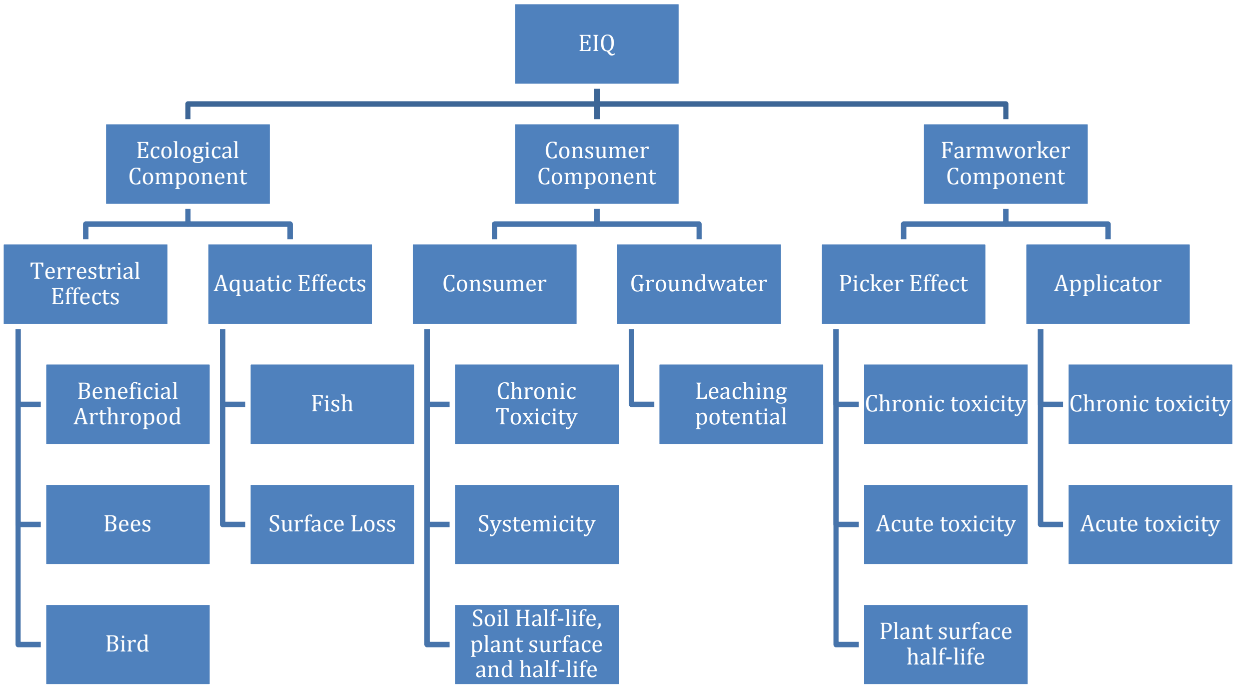
Figure 3: Effect of GM Traits on Pesticide Use



Left panel: IR trait reduces the value of marginal product of insecticides (from VMP0 to VMP1) due to compound effect over insects and so reduces the optimal quantity of insecticides (from x_0^* to x_1^*).

Right panel: HT trait increases the value of marginal product of herbicide (from VMP_0 to VMP_1) due to reduction of harmful side-effects and so increases the optimal quantity of herbicide (from x_0^* to x_1^*).

Figure 4: EIQ Components



EIQ for active ingredient: average of ecological, consumer and farmworker components:

$Ecological = (F \times R) + \left(D \times \frac{S+P}{2} \times 3\right) + (Z \times P \times 3) + (B \times P \times 5)$, F = fish toxicity, R = surface runoff potential, D = bird toxicity, S = soil half-life, P = plant surface half-life, D = bird toxicity, Z = bee toxicity and B = beneficial arthropod toxicity;

$Consumer = C \times \left[\frac{S+P}{2}\right] \times SY + L$, C = chronical toxicity, SY = systemicity (potential of absorption, by plant) L = leaching potential, S = soil half-life and P = plant surface half-life

$Farmworker = C \times [(DT \times 5) + (DT \times P)]$, C = chronical toxicity, P = plant surface half-life and DT = dermal toxicity.

Figure 5: Cities with Cotton Farms Surveyed

Figure 6: Cities with Soybean Farms Surveyed

Table 1: Distribution of Cotton and Soybean Farms by Region

	Cotton		Soybean	
Region	N	pct.	N	pct.
Central-West	145	67.44	124	48.06
Northeast	62	28.84	25	9.69
South	-	-	95	36.82
Southeast	8	3.72	14	5.43
Total	215	100.00	258	100.00

Note: farms are spread over 8 states (figs. 5 and 6) which comprise a total area of 3,564.8 thousands Km^2, equivalent to 41.8% of Brazilian territory.

Table 2: Farm-Level Descriptive Statistics for Cotton Growers

	mean	sd	min	max	count
Planted Area (ha)	2,521.0	3,538.5	60.0	28,374.0	255
Net Rev. (US$/ha)	3,344.1	1,364.9	791.6	7,171.2	255
Gross Margin (US$/ha)	1,495.5	1,112.4	-6.2	4.988.8	255
Costs (US$/ha)	1,848.6	412.0	604.6	2,586.7	255
Pesticides (US$/ha)	588.2	194.9	99.9	1,144.9	255
Fertilizers (US$/ha)	1,007.2	270.7	304.5	1,927.5	255
Central-West	0.67	0.47	0.0	1.0	215
Northeast	0.29	0.45	0.0	1.0	215
South	0.00	0.00	0.0	0.0	215
Southeast	0.04	0.19	0.0	1.0	215
Basic School	0.07	0.26	0.0	1.0	83
High School	0.29	0.46	0.0	1.0	83
College	0.53	0.50	0.0	1.0	83
Graduate Degree	0.11	0.31	0.0	1.0	83
Age	38.08	9.14	23.0	57.0	75
Experience	25.80	14.60	2.0	58.0	75
Owner	0.02	0.15	0.0	1.0	215
Biotech User	0.43	0.50	0.0	1.0	215
IR user	0.26	0.44	0.0	1.0	255

Sample: 2009 – 2011.

Area, revenue, expenditures and IR trait use statistics consider each farm/year as a separate observation since they can change over the years for farms that are surveyed more than once.

Other statistics consider each farm as a separate observation and are not influenced by farms that appear in more than one survey. Age and experience correspond to the maximum value of that variable observed. “Biotech User” shows whether the farmer adopted any type of GM seed over the surveyed years. The value is different than “IR user” since there are other types of GM seeds for cotton.

Table 3 Farm-Level Descriptive Statistics for Soybean Growers

	mean	sd	min	max	count
Planted Area (ha)	1,240.3	1,771.8	8.0	13,500.0	291
Net Rev. (US$/ha)	1,164.8	484.9	334.3	3,711.6	291
Gross Margin (US$/ha)	499.3	352.7	-140.4	2,115.5	291
Costs (US$/ha)	665.6	248.2	283.6	1998.2	291
Pesticides (US$/ha)	135.5	86.8	17.0	630.1	291
Fertilizers (US$/ha)	478.3	190.2	0.0	1,383.4	291
Central-West	0.48	0.50	0.0	1.0	258
Northeast	0.10	0.30	0.0	1.0	258
South	0.37	0.48	0.0	1.0	258
Southeast	0.05	0.23	0.0	1.0	258
Basic School	0.28	0.45	0.0	1.0	120
High School	0.27	0.44	0.0	1.0	120
College	0.38	0.49	0.0	1.0	120
Graduate Degree	0.08	0.28	0.0	1.0	120
Age	43.97	12.41	24.0	74.0	118
Experience	32.46	17.10	5.0	75.0	118
Owner	0.22	0.42	0.0	1.0	258
HT User	1.00	0.06	0.0	1.0	258

Sample: 2009 – 2011.

Area and expenditure statistics consider each farm/year as a separate observation since they can change over the years for farms that are surveyed more than once. Other statistics consider each farm as a separate observation and are not influenced by farms that appear in more than one survey. Age and experience correspond to the maximum value of that variable observed. “HT User” shows whether the farmer adopted HT seeds over the surveyed years. Since HT is the only GM seed for soybean, this table doesn’t display a variable “Biotech User”.

Table 4: Within-Farm Descriptive Statistics: Fields Cultivated with Conventional vs. Fields Cultivated with Insect Resistant Cotton

	CO	IR	Total	Diff.
Area (ha)	1,741.9	1,087.2	1,414.6	654.7
	[2,442.4]	[1,948.8]	[2,224.5]	[1.62]
Yield (Kg/ha)	3,871.8	3,560.2	3,716.0	311.6
	[521.9]	[1,120.3]	[884.2]	[1.95]
Net Rev. (US$/ha)	5,980.2	6,077.3	6,027.5	-97.08
	[2,253.7]	[2,273.0]	[2,253.9]	[-0.23]
Direct Costs (US$/ha)	3,563.3	3,533.3	3,548.7	30.03
	[433.0]	[480.6]	[455.1]	[0.36]
Costs-Seed (US$/ha)	3,461.8	3,349.3	3,407.0	112.5
	[440.1]	[474.8]	[458.8]	[1.33]
Gross Margin (US$/ha)	2,416.9	2,544.0	2,478.8	-127.1
	[2156.2]	[2178.2]	[2158.5]	[-0.32]
Fertilizers (US$/ha)	992.1	981.4	986.9	10.63
	[214.9]	[219.7]	[216.4]	[0.26]
Observations	60	60	120	60

Standard errors (columns CO and IR) and t statistics (column Diff.) in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Cost-Seed: excludes expenditures with seeds and royalties.

Table 5: Within-Farm Descriptive Statistics: Fields Cultivated with Conventional vs. Fields Cultivated with Herbicide Tolerant Soybean

	CO	HT	Total	Diff.
Area (ha)	692.6	706.6	699.6	-14.01
	[992.0]	[773.2]	[886.7]	[-0.10]
Yield (Kg/ha)	3,148.1	3,146.8	3,147.5	1.240
	[512.9]	[603.6]	[558.4]	[0.01]
Net Rev. (US$/ha)	1,865.3	1,850.9	1,858.0	14.42
	[390.8]	[419.2]	[404.2]	[0.23]
Direct Costs (US$/ha)	1,180.3	1,193.3	1,186.8	-12.92
	[241.4]	[247.4]	[243.8]	[-0.34]
Costs-Seed (US$/ha)	1,085.4	1,066.8	1,076.1	18.62
	[243.3]	[249.6]	[245.9]	[0.49]
Gross Margin (US$/ha)	685.0	657.6	671.2	27.34
	[439.7]	[442.3]	[439.9]	[0.40]
Fertilizers (US$/ha)	489.0	488.0	488.5	0.936
	[180.3]	[179.1]	[179.2]	[0.03]
	85	85	170	85

Standard errors (columns CO and HT) and t statistics (column Diff.) in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Cost-Seed: excludes expenditures with seeds and royalties.

Table 6: Differences Between Cotton Farms Included (Sample) and not Included (Non-Sample) in Regression Analysis

	Non-Sample	Sample	Total	Diff.
Total Area (ha)	2,371.5	3,006.6	2,521.0	-635.1
	[3,273.7]	[4,284.0]	[3,538.5]	[-1.06]
Net Rev. (US$/ha)	3,403.3	3,151.7	3,344.1	251.6
	[1,323.3]	[1,487.7]	[1,364.9]	[1.17]
Gross Margin (US$/ha)	1,547.6	1,326.2	1,495.5	221.4
	[1051.1]	[1,286.9]	[1,112.4]	[1.21]
Costs (US$/ha)	1,855.7	1,825.5	1,848.6	30.25
	[429.7]	[350.7]	[412.0]	[0.55]
Pesticides (US$/ha)	592.1	575.5	588.2	16.55
	[205.5]	[156.0]	[194.9]	[0.66]
Fertilizers (US$/ha)	1,001.8	1,024.7	1,007.2	-22.91
	[279.9]	[239.9]	[270.7]	[-0.62]
Age	38.24	34.76	37.28	3.478
	[9.165]	[10.44]	[9.611]	[1.58]
Experience	23.70	19.03	22.41	4.663
	[15.93]	[10.93]	[14.82]	[1.71]
Owner	0.0103	0.0667	0.0235	-0.0564
	[0.101]	[0.252]	[0.152]	[-1.70]
Central-West	**0.749**	**0.317**	**0.647**	**0.432*** **
	[0.435]	**[0.469]**	**[0.479]**	**[6.34]**
Northeast	**0.241**	**0.567**	**0.318**	**-0.326*** **
	[0.429]	**[0.500]**	**[0.466]**	**[-4.56]**
Southeast	**0.0103**	**0.117**	**0.0353**	**-0.106***
	[0.101]	**[0.324]**	**[0.185]**	**[-2.51]**
Basic School	0.0595	0.0313	0.0517	0.0283
	[0.238]	[0.177]	[0.222]	[0.70]
High School	**0.321**	**0.125**	**0.267**	**0.196***
	[0.470]	**[0.336]**	**[0.444]**	**[2.50]**
College	0.571	0.594	0.578	-0.0223
	[0.498]	[0.499]	[0.496]	[-0.22]
Graduate Degree	**0.0476**	**0.250**	**0.103**	**-0.202***
	[0.214]	**[0.440]**	**[0.306]**	**[-2.49]**

Sample: farms that use both conventional and IR seeds and so are included in regression analysis.
Non-Sample: farms that use only one type of seed (conventional or IR) and are not included in regression analysis.
Total: all farms.
Standard errors (columns Non-Sample, Sample and Total) and t statistics (column Diff.) in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Differences Between Soybean Farms Included (Sample) and not Included (Non-Sample) in Regression Analysis

	Non-Sample	Sample	Total	Diff.
Total Area (ha)	**868.2**	**2,142.3**	**1,240.3**	**-1,274.1*****
	[1,201.7]	**[2,480.1]**	**[1,771.8]**	**[-4.52]**
Net Rev. (US$/ha)	1,160.5	1,175.5	1,164.8	-14.99
	[415.2]	[625.2]	[484.9]	[-0.20]
Gross Margin (US$/ha)	**530.1**	**424.5**	**499.3**	**105.6***
	[344.6]	**[362.8]**	**[352.7]**	**[2.29]**
Costs (US$/ha)	**630.4**	**750.9**	**665.6**	**-120.6****
	[192.3]	**[334.8]**	**[248.2]**	**[-3.12]**
Pesticides (US$/ha)	**122.9**	**166.2**	**135.5**	**-43.38****
	[64.33]	**[120.6]**	**[86.76]**	**[-3.14]**
Fertilizers (US$/ha)	**443.8**	**561.9**	**478.3**	**-118.1*****
	[159.7]	**[229.5]**	**[190.2]**	**[-4.33]**
Age	**46.55**	**38.94**	**43.98**	**7.613*****
	[11.06]	**[12.65]**	**[12.13]**	**[3.57]**
Experience	**34.20**	**20.08**	**29.43**	**14.12*****
	[15.53]	**[13.80]**	**[16.35]**	**[5.58]**
Owner	0.248	0.271	0.254	-0.0230
	[0.433]	[0.447]	[0.436]	[-0.40]
Central-West	0.466	0.518	0.481	-0.0516
	[0.500]	[0.503]	[0.501]	[-0.80]
Northeast	**0.0291**	**0.235**	**0.0893**	**-0.206*****
	[0.169]	**[0.427]**	**[0.286]**	**[-4.32]**
South	**0.490**	**0.118**	**0.381**	**0.373*****
	[0.501]	**[0.324]**	**[0.487]**	**[7.52]**
Southeast	**0.0146**	**0.129**	**0.0481**	**-0.115****
	[0.120]	**[0.338]**	**[0.214]**	**[-3.06]**
Basic School	**0.367**	**0.0612**	**0.265**	**0.306*****
	[0.485]	**[0.242]**	**[0.443]**	**[5.11]**
High School	0.235	0.306	0.259	-0.0714
	[0.426]	[0.466]	[0.439]	[-0.90]
College	0.337	0.469	0.381	-0.133
	[0.475]	[0.504]	[0.487]	[-1.53]
Graduate Degree	0.0612	0.163	0.0952	-0.102
	[0.241]	[0.373]	[0.295]	[-1.74]

Sample: farms that use both conventional and HT seeds and so are included in regression analysis.
Non-Sample: farms that use only one type of seed (conventional or HT) and are not included in regression analysis.
Total: all farms.
Standard errors (columns Non-Sample, Sample and Total) and t statistics (column Diff.) in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 OLS Estimates of Effects of IR Trait on Quantity of Insecticides and Total Pesticides
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Insecticides+	(2) Total+	(3) Insecticides	(4) Total
IR trait	-1.279***	-1.790***	-0.956**	-0.980
	[0.264]	[0.485]	[0.362]	[0.568]
Constant	4.914***	12.352***	4.630***	11.551***
	[0.163]	[0.314]	[0.256]	[0.413]
N	312	312	120	120
r2	0.046	0.025	0.056	0.025
F	11.141	145.516	12.215	8.340
Mean of Dep. Var.	4.639	11.967	4.152	11.061

Models (1) and (2) include all cotton farms, models (3) and (4) only farms that use both conventional and IR seeds (within farm variation as source of identification). Models are in linear specification.
+ Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
IR trait affects the quantity (Kg/ha) of insecticides. Total represents the sum of all pesticides used (acaricides, fungicides, herbicides and insecticides). Coefficients are smaller in magnitude in the restricted sample, but not statistically different than the ones in the model with all farms.

Table 9 OLS Estimates of Effects of IR Trait on Quantity of Insecticides and Total Pesticides (Restricted Sample)
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Insecticides+	(2) Total+	(3) Insecticides	(4) Total
IR trait	-0.956***	-0.980***	-0.242***	-0.092***
	[0.155]	[0.252]	[0.037]	[0.024]
Constant	8.721***	19.018***	2.346***	3.025***
	[0.874]	[0.644]	[0.207]	[0.134]
N	120	120	120	120
r2	0.905	0.896	0.913	0.878
F	11.141	145.516	12.215	8.340
Mean of Dep. Var.	4.152	11.061	-	-

Models (1) and (2) are linear specifications, models (3) and (4) are log-linear specifications. All models include farm and year fixed-effects.
Restricted sample: farms that use both conventional and IR seeds (within farm variation as source of identification).
+ Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Farmer and year fixed-effects don't affect coefficients since they are orthogonal to within-farm variables. Log-linear specifications show a reduction of 24% in the quantity of insecticides and 9.2% in total pesticides.

Table 10 OLS Estimates of Environmental Impact of IR Trait (Restricted Sample) Dependent Variable: EIQ

	(1) Insecticides+	(2) Total+	(3) Insecticides+	(4) Total+
IR trait	-34.225***	-36.856***	-0.234***	-0.120***
	[5.525]	[7.482]	[0.035]	[0.026]
Constant	316.085***	557.297***	6.041***	6.455***
	[23.144]	[42.071]	[0.198]	[0.082]
N	120	120	120	120
r2	0.906	0.905	0.918	0.886
F	48.981	11.134	12.972	75.140
Mean of Dep. Var.	145.807	304.489	-	-

Models (1) and (2) are linear specifications, models (3) and (4) are log-linear specifications. All models include farm and year fixed-effects.

Restricted sample: farms that use both conventional and IR seeds (within farm variation as source of identification).

+ Robust standard errors in brackets.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Consistent with the reduction in quantity of insecticides, the coefficient indicates a reduction of 34.225 EIQ points. In comparison with the general classification of active ingredients for insecticides, this is higher than the median EIQ index of 32.07. The log-linear specification shows a proportional reduction of 23.4% in the EIQ index.

Table 11 Robustness Check: OLS Estimates of Effect of IR Trait on Other Pesticides. Dependent Variable: Active Ingredients (Kg/ha).

	(1) Acaricides	(2) Fungicides	(3) Herbicides	(4) Acaricides	(5) Fungicides	(6) Herbicides
IR trait	0.003	-0.063	-0.346	-0.011	0.007	-0.056
	[0.049]	[0.091]	[0.366]	[0.027]	[0.032]	[0.191]
Constant	0.428***	0.956***	4.933***	0.544***	1.283***	7.723***
	[0.023]	[0.042]	[0.170]	[0.152]	[0.181]	[1.075]
N	312	312	312	120	120	120
r2	0.000	0.002	0.003	0.906	0.950	0.840
F	0.003	0.481	0.894	11.185	22.264	6.123
Mean of Dep. Var.	0.429	0.942	4.858	0.455	0.869	4.608

Models (1)-(3) include all farms and models (4)-(6) only restricted sample (farms that use conventional and IR seeds) with farm and year fixed-effects. All models are linear specifications.

+ Robust standard errors in brackets.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Falsification test shows that other pesticides are not affected by IR trait.

Table 12 OLS Estimates of Effects of HT Trait on Quantity of Herbicides and Total Pesticides
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Herbicides+	(2) Total+	(3) Herbicides+	(4) Total+
HT Trait	0.762***	0.546***	0.996***	0.995***
	[0.099]	[0.150]	[0.138]	[0.202]
Constant	1.741***	3.284***	1.769***	3.315***
	[0.075]	[0.121]	[0.074]	[0.122]
N	376	376	170	170
r2	0.091	0.025	0.236	0.126
F	59.114	13.192	51.766	24.194
Mean of Dep. Var.	2.326	3.703	2.267	3.813

Models (1) and (2) include all soybean farms, models (3) and (4) only farms that use both conventional and HT seeds (within farm variation as source of identification). Models are in linear specification.
+ Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
HT trait affects the quantity (Kg/ha) of herbicides. Total represents the sum of all pesticides used (fungicides and insecticides).

Table 13 OLS Estimates of Effects of HT Trait on Quantity of Herbicides and Total Pesticides (Restricted Sample)
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Herbicides+	(2) Total+	(3) Herbicides	(4) Total
HT Trait	0.996***	0.995***	0.442***	0.262***
	[0.089]	[0.096]	[0.056]	[0.027]
Constant	4.518***	5.930***	2.206***	1.848***
	[0.880]	[0.814]	[0.486]	[0.214]
N	170	170	170	170
r2	0.836	0.899	0.755	0.888
F	90.919	249.438	3.278	144.793
Mean of Dep. Var.	2.267	3.813	-	-

Models (1) and (2) are linear specifications, models (3) and (4) are log-linear specifications. All models include farm and year fixed-effects.
Restricted sample: farms that use both conventional and HT seeds (within farm variation as source of identification).
+ Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Farmer and year fixed-effects don't affect coefficients since they are orthogonal to within-farm variables. Log-linear specifications show as increase of 44.2% in the quantity of herbicides and 26.3% in total pesticides.

Table 14 OLS Estimates of Effects of HT Trait on Quantity of Herbicides per Toxicity Level (Restricted Sample)
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Herbicides 1	(2) Herbicides 2	(3) Herbicides 3	(4) Herbicides 4
HT Trait	-0.084***	-0.005	0.635***	0.438***
	[0.021]	[0.054]	[0.098]	[0.090]
Constant	0.444***	0.053	2.103***	-0.499
	[0.046]	[0.344]	[0.466]	[0.523]
N	168	168	168	168
r2	0.887	0.777	0.855	0.845
F	508.764	404.682	20.309	12.929
Mean of Dep. Var.	0.200	0.219	1.124	0.706

Restricted sample: farms that use both conventional and HT seeds (within farm variation as source of identification).

Robust standard errors in brackets.

* p < 0.05, ** p < 0.01, *** p < 0.001

Toxicity levels 1 - 4 in decreasing order (from more to less toxic). Herbicides based on Glyphosate are considered of lower toxicity level. Increases in less toxic herbicides (levels 3 and 4) are twelvefold the decreases in more toxic ones (levels 1 and 2).

Table 15 OLS Estimates of Environmental Impact of HT Trait (Restricted Sample)
Dependent Variable: EIQ

	(1) Herbicides	(2) Total	(3) Herbicides	(4) Total
HT Trait	13.847***	14.329***	0.356***	0.162***
	[1.639]	[2.054]	[0.049]	[0.023]
Constant	75.205***	140.924***	4.987***	4.925***
	[13.188]	[12.379]	[0.472]	[0.136]
N	170	170	170	170
r2	0.836	0.936	0.790	0.933
F	634.267	1378.593	142.869	556.876
Mean of Dep. Var.	37.875	91.337	-	-

Models (1) and (2) are linear specifications, models (3) and (4) are log-linear specifications. All models include farm and year fixed-effects.

Restricted sample: farms that use both conventional and HT seeds (within farm variation as source of identification).

Robust standard errors in brackets.

* p < 0.05, ** p < 0.01, *** p < 0.001

Weakness of the substitution among herbicides of different toxicity categories is reflected in higher environmental impact as shown by the coefficient that indicates an increase of 13.847 EIQ points. Log-linear specifications show an increase of 35.6% in the EIQ index for herbicides and 16.2% in total. In comparison with the general EIQ classification for herbicides, this is lower than the median value for EIQ index of 19.5. The EIQ for glyphosate is also larger than this result: 15.33. Result can be interpreted as reflecting the weakness of substitution between high and low toxicity herbicides shown in table 14.

Table 16 Robustness Check: OLS Estimates of Effect of HT Trait on Other Pesticides
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Fungicides	(2) Insecticides	(3) Fungicides	(4) Insecticides
HT Trait	-0.047	-0.131*	0.021*	-0.007
	[0.047]	[0.066]	[0.009]	[0.020]
Constant	0.445***	0.841***	0.913***	-0.017
	[0.042]	[0.058]	[0.045]	[0.178]
N	376	376	170	170
r2	0.003	0.011	0.989	0.970
F	0.975	3.955	1228.421	20622.927
Mean of Dep. Var.	0.409	0.740	0.454	0.840

Models (1)-(2) include all farms and models (3)-(4) only restricted sample (farms that use conventional and HT seeds) with farm and year fixed-effects. All models are linear specifications.
Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Falsification test shows that other pesticides are not affected by HT trait.

Table 17 Robustness Check: OLS Estimates of Effects of HT Trait on Quantity of Herbicides and Total Pesticides and Controlling for No-Tillage Cultivation (Restricted Sample)
Dependent Variable: Active Ingredients (Kg/ha)

	(1) Herbicides	(2) Total	(3) Herbicides	(4) Total
HT Trait	0.983***	0.983***	0.892***	0.876***
	[0.089]	[0.096]	[0.089]	[0.095]
No Tillage	0.180	2.443***		
	[0.469]	[0.469]		
Constant	2.272***	3.095***	1.038***	4.069***
	[0.328]	[0.392]	[0.096]	[0.091]
N	168	168	154	154
r2	0.833	0.899	0.829	0.887
F	248.083	363.742	864.663	4047.737
Mean of Dep. Var.	2.248	3.8	2.180	3.626

Restricted Sample: farms that use conventional and HT soybeans (within-farm variation as source of identification). All models use linear specifications and farm and year fixed-effects.
Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Models (1) and (2) control for the use of no-tillage techniques that require more herbicides than conventional planting. Models (3) and (4) consider only farmers that use conventional planting.

Table 18 Robustness Check: OLS Estimates of Environmental Impact of HT Trait Controlling for No-Tillage Cultivation (Restricted Sample)
Dependent Variable: EIQ

	(1) Herbicides	(2) Total	(3) Herbicides	(4) Total
HT Trait	13.457***	13.944***	12.151***	11.951***
	[1.613]	[2.043]	[1.667]	[2.047]
No Tillage	3.160	69.325***		
	[6.713]	[6.513]		
Constant	36.751***	68.413***	16.518***	112.068***
	[5.635]	[9.850]	[0.999]	[1.119]
N	168	168	154	154
r2	0.828	0.937	0.814	0.928
F	355.885	1213.411	308.650	1698.950
Mean of Dep. Var.	37.280	90.935	36.006	85.974

Restricted Sample: farms that use conventional and HT soybeans (within-farm variation as source of identification). All models use linear specifications and farm and year fixed-effects.

Robust standard errors in brackets.

$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Models (1) and (2) control for the use of no-tillage techniques that require more herbicides than conventional planting. Models (3) and (4) consider only farmers that use conventional planting.

Chapter 3.

Dynamic Price Competition in Allergy Pharmaceutical Markets

I'd like to thank comments from Sofia Villas-Boas, Jeff Perloff, Jeremy Magruder, Catherine Wolfram, Kyle Emerick and Manuel Barron. Dr. Estella Geraghty kindly provided the data on pollen count and Professor Wolfram Schlenker kindly provided data on stores' geographical coordinates. Financial support from CAPES/Fulbright PhD fellowship (grant 2256-08-8) is greatly acknowledged. All remaining errors are mine.

3.1 Introduction to Chapter

Be it for the evolution of its market structure or for the market conduct of its participants, the pharmaceutical industry has been under debate among academic economists and policymakers. In the US for example, the health care debate has raised proposals for price controls over pharmaceuticals (Ellison, Cockburn, Griliches, & Hausman, 1997). More recently, pharmaceutical industry has been under the scrutiny of antitrust authorities in cases involving the use of patents as an instrument for entry deterrence of generic competition (Morse, 2003). Overseas, recent consolidation movements of large multinational companies also raised questions on how price-cost margins are determined in pharmaceutical markets (Saleh, 2010).

In the empirical industrial organization literature, the methodological foundations of the studies of individual industries with market power were developed during the 80's and have been summarized by other authors (Bresnahan, 1989). Since then, a wave of studies has concentrated their attention in identifying price conduct in individual industries, as opposed to the old tradition of inter-industrial studies in the industrial organization literature.

In this essay I study the behavior of the pattern of mark-ups in the antihistaminic pharmaceuticals market. Antihistaminic drugs are used as treatment for symptoms of allergies, such as, runny nose. These allergies can be caused by the hypersensitivity response of the body to some external agent. Pollen released by plants during the periods close to the spring season is one of the prominent examples of causal agents of allergies. The distinguishing characteristic of this allergen is its seasonal pattern of occurrence throughout the year: pollen concentration on air rises in the periods that approach the spring when it achieves its highest level and variation. Hence, the demand for antihistaminic drugs exhibits a cyclical and predictable behavior over the year: it attains peaks during the months of March through May and remains relatively stable over the rest of the year.

I draw on the empirical tests of the theory of dynamic price competition (Borenstein & Shepard, 1996) which examine the response of observed price-cost margins – retail minus wholesale prices – to expected demand, controlling for current demand, and conclude that the positive relationship between margins and expected demand is consistent with supergame models of tacit collusion. [1] The intuition for this relationship is that, if demand cycle is predictable, in periods of high expected demand, near future expected collusive profits that would be foregone due to the retaliation after a price cut are higher than in periods of low expected future demand. Hence, since near term losses receive more weight in the overall evaluation of collusive vs. non collusive pricing, the sustainable collusive margin will be higher in periods of high expected demand.

In the empirical part, I estimate a reduced form model that captures some of the characteristics of the dynamic price competition model outlined above. It consists of a relationship between prices of antihistaminic drugs and measures of current and one week lagged[2] pollen concentration on air, taking into account the current level of demand in a given market. I explore geographical variation on product prices and pollen concentration to identify

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[1] The term tacit collusion refers to the situation where market participants set high margins as a result of non-cooperative repeated interaction.

[2] I also use lagged pollen concentration since it might be reasonable that retail prices don't adjust instantly to perceptions of pollen concentration.

the relationship of interest between prices and expected demand. To make the reduced form model compatible with the predictions of the dynamic pricing model I need two assumptions. First, I assume that the marginal costs of drugs in each city is the same and so the different prices in different cities reflect different margins, which is the outcome of interest in the theoretical analysis. This assumption makes sense if the retailer works with a centralized buying unit that serves stores located in different regions and explores economies of scale in purchases, which seems a plausible assumption.

The second key assumption behind the reduced form equation is that the level of pollen concentration on air works as a proxy for the expected demand in a given week and prices respond positively to those expectations, taking into account the current level of demand reflected in the total revenue from antihistaminic drugs in a given week.

My results show that profit margins respond positively to expected demand in cities with high levels and variation of pollen concentration. The magnitudes of the coefficients are small but the economic content of the analysis relies on the sign and significance of the coefficients rather than on its magnitudes (Nevo & Whinston, 2010). Different specifications using different distances to pollen count stations, separating the drugs by categories and using lagged pollen concentration show similar results: coefficients are positive, statistically significant and relatively stable to inclusion of fixed effects and time trends.

The essay relates to a rich empirical literature on conduct in pharmaceutical markets. Entry deterrence, for example, has been studied in the context of patent expiration, (Ellison & Ellison, 2011) and generic entry (Scott-Morton, 2000). Pricing strategies have been studied in the context of impending regulatory intervention as a response to foreseen losses by incumbent firms (Ellison & Wolfram, 2006).

The remainder of the chapter is organized as follows. After this introduction, section 2 presents the main theories of dynamic pricing in industrial organization. In particular, two models are presented: the Rothemberg-Saloner model of price wars during moments of unexpected peak demand and the Haltiwanger-Harrington model of deterministic cyclical demand. Section 3 discusses the empirical strategy and presents the econometric models. Section 4 describes the data used and section 5 presents the main results. In section 6 I provide some concluding comments.

3.2 Dynamic Price-Competition Models

The literature that develops dynamic models of price competition makes use of the tools and concepts of repeated game theory. By acknowledging that firms in real world interact repeatedly with each other, it's possible to develop models that challenge the conclusions of models of static competition. In the more extreme case, the Bertrand model of static price competition, i.e., when identical firms producing homogeneous products compete in a single period static game with price as the main decision variable, the resulting pricing equilibrium is identical to perfect competition: if the number of firms in the market is greater than one, they price at marginal cost and make no profits.[3]

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[3] For a review of the Bertrand model and other models of static price competition see (Tirole, 1988).

When firms interact repeatedly for an indefinite number of periods (formally and infinite number of periods), a richer set of equilibria is possible. When making their pricing decisions, firms now have to compare the discounted value of profits obtained by cooperating (charging a price above marginal cost) versus the short-run profits from undercutting their rivals' prices and the losses derived from future retaliation in the form of a price war.

In the most simple model of repeated price competition (Tirole, 1988), two identical firms produce a homogeneous product and choose their prices independently at each time period t. One (subgame-perfect) equilibrium for this game is the static Bertrand equilibrium repeated infinitely: each firm prices at marginal cost in each period, regardless the history of the game. On the other hand, for a sufficient high discount factor of future profits, i.e. if firms are patient enough to wait for future profits, a strategy in the form "charge the monopoly price ($\mathrm{p_m}$) in the beginning and stick with that price in period t if both firms have charged it or charge marginal cost otherwise" can be sustained as an equilibrium of the game. This is known as a "trigger strategy", since a deviation from the monopoly (or collusive) price triggers a (infinite) period of retaliation.[4]

A distinguishing feature of the trigger strategy equilibrium described above is that price wars never occur in the equilibrium path. In fact, if both firms play trigger strategies in equilibrium, no one has incentive to deviate from $\mathrm{p^m}$. This result is known in the literature as tacit collusion, in the sense that the collusive result ($\mathrm{p^m}$) is enforced by a non-cooperative (tacit) mechanism.

One assumption of the repeated game model is that demand is stable over time. If demand is stochastic in the sense that it can be either high or low in each period t, price wars can be observed in the equilibrium path depending on the nature of the distribution of demand shocks. On one hand, if demand shocks are independent and identically distributed over time and, at each period; both firms know the state of demand before they choose their prices, it can be shown that, for some range of the discount parameter, collusion ($\mathrm{p_i} = \mathrm{p_m}$) can be sustained in the low state of demand while in the high state, firms charge below the monopoly price. In other words, the profit margins are adjusted in response to unanticipated changes in demand and, hence, margins will be lower in periods of high demand. Prices, on the other hand, can be either higher or lower in periods of high demand than in periods of low demand (Rothenberg & Saloner, 1986). The interpretation of the Rotemberg-Saloner analysis is as follows. In periods of unexpected high demand, firms have a high incentive to undercut the rivals' prices and capture a large share of a big demand. The retaliation will come in the future where the level of demand is uncertain and independent from the current level. So, the expected value of the losses from retaliation, given by the present discounted value of the difference between the expected profits under collusion and the expected profits under retaliation, is constant. Hence, in periods of high demand, collusion is sustained by reducing the profit margins, i.e., by reducing the gains to deviation. In the present context, this means $p_i < p_m$ for the high demand.

The Rotenberg-Saloner result of "price wars during boons" is sensitive to the nature of demand shocks. On the other hand, considering a context of serially correlated demand cycle, as

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[4] In fact, other strategies involving limited periods of punishment and return to cooperation can also be sustained as equilibrium for sufficient high discount factors. Also, the monopoly price is not the unique price equilibrium: any p in the interval $[c, p^m]$ (where c is the firm's marginal cost) can be shown to be an equilibrium in the repeated game. For a discussion of these multiple equilibria see (Tirole, 1988).

opposed to independent shocks, price wars (lower margins) will happen during the downward phase of the demand cycle (Haltiwanger & Harrington Jr., 1991; Kandori, 1991). Figure one is illustrative of the mechanism behind this kind of model.

Consider two periods t_1 and t_2 when the demand is at the same level Q^*. In period t_1, demand is in the upward phase of the cycle. Since the demand level is the same, the short-run gain from undercutting the rivals is the same in both periods. In period t_1, since demand is increasing, the firm will be retaliated in a high demand period and so will forego high levels of collusive profits in the near future. On the other hand, in period t_2, demand is decreasing, and so, the retaliation after the price cut will take place in a lower demand level. Hence, near future expected collusive profits that will be foregone are lower than those in period t_1. Since earlier profits receive more weight in the discounted sum of future profit stream, the expected total loss is higher in period t_1 than in period t_2. Hence, in the logic of repeated games, the sustainable collusive margin will be higher in t_1, i.e., higher margins occur in periods of strong demand.

The discussion suggests that the models of dynamic pricing with cyclical demand have distinctive predictions on the behavior of margins, namely: that they will respond to anticipated changes in demand and, controlling for current demand, margins will be higher in periods of expected rising demand (Borenstein & Shepard, 1996). These predictions are distinct from other pricing models and will guide the specification of the empirical model described below.

3.3 Data Description and Graphical Analysis

The data set used for the analysis consists of transaction level sales of over-the-counter antihistaminic pharmaceuticals sold in 268 stores of a retail supermarket chain in 156 cities in the States of California, Nevada and Hawaii, between 2003 and 2006. The stores are identified and geocoded by latitude and longitude[5] and are also located by five digit zip codes. The dataset contains information on: quantity sold, transaction net revenue (which allows us to calculate transaction-level prices), product identification (Universal Product Code – UPC), date of transaction, store identification. Antihistaminic drugs are divided in four categories that are used in the analysis: adult, pediatric, general eye care and nasal. For each different product (UPC), the individual level data on quantities and net revenues were aggregated by store and week. The average price for each product in each store/week is calculated as the ratio of the net revenue to the quantity sold.

The data set on pollen concentration comes from the National Allergy Bureau of the American Academy of Allergy, Asthma and Immunology. [6] It consists on (approximately) daily pollen counts per cubic meter of air on eleven stations in the States of California and Nevada between 2004 and 2006 and contains the address of each counting station, which allows to find the geographic coordinates (latitude and longitude) of each one. With geographic coordinates of stores and pollen count stations, I can associate each store with the closest pollen count station in the two data sets. In the models below, I use stores that have the closest pollen count station at

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[5] Professor Wolfram Schlenker, from the School of International and Public Affairs of the University of Columbia, kindly provided the information about geographic coordinates of the stores.

[6] Access to the dataset was provided by Dr. Estella M. Geraghty, from the University of California, Davis.

distances of at most 5, 10, 15 and 20 Km.[7] Table 1 shows the average distance for stores located in the cities indicated in the rows and the location of the closest pollen count station for the stores selected.

After selecting the stores for the analysis, I need to find which ones are subject to high levels of pollen concentration (treated stores) and low levels of pollen concentration (control stores). This is necessary in order to explore differential levels of pollen concentration across locations that might create a seasonal and somewhat predictable level of demand for antihistaminic drugs. In the empirical analysis, I take the concentration of pollen on air as the main driver of expected demand.

The cities with pollen count stations that have stores located at no more than 20 Km are Pleasanton (CA), Roseville (CA), San Jose (CA) and Sparks (NV). Table 2 shows descriptive statistics for pollen count during the period 2003-2006 for the aforementioned cities. San Jose is the one with higher mean level of weekly pollen count and Pleasanton is the one with higher coefficient of variation of weekly pollen count. Figure 2 illustrates this by showing the levels and dispersion (two standard errors around the mean) for the four cities. Based on these statistics, I define San Jose and Pleasanton as the pollen count stations with high levels of pollen concentration and Roseville and Sparks as pollen count stations with low levels of pollen concentration. Hence, looking back at table 1, the stores located in cities with closest pollen count stations in Pleasanton and San Jose are the ones considered of high pollen concentration (treatment group) and the stores located in cities with closest pollen count stations in Roseville and Sparks are considered of low pollen concentration (control group).

In order to check for the comparability of the two groups of stores, I look at socioeconomic indicators from the 2010 census for the minimum geographic area compatible with each store's location: the 5 digits zip code. The results of this comparisons are on table 3, where it can be seen that treated stores are different relative to control ones with respect to some attributes: median income (higher) and median house value (higher). These systematic differences suggest that there are potential omitted variables specific to each five digit zip code that can be possibly correlated with the treatment. Hence, the empirical models should incorporate location fixed effects in order to control for these potential biases. Another important piece of information on table 3 refers to the average distance to the closest pollen count station in the two groups, which is a proxy of the quality of the pollen concentration measure that I use. The comparison shows that the average distance to the closest pollen count station is not statistically different across treated and control groups which indicates that the quality of pollen measure is not affected by unobservables related to the location of pollen count stations.

Figures 3 to 6 show the seasonal pattern of monthly pollen count variation (monthly average and two standard errors) for the four cities. It can be seem a pronounced pattern in which the months close to spring (March, April and May) display higher levels and bigger variation in pollen concentration. Also, the patterns are somewhat different across cities, as reflected by the descriptive statistics on table 2. I use these geographical and temporal variations to identify the relationship between margins and expected demand.

Figure 7 compares the movements in average daily quantities sold for antihistaminic medicines and other medicines not related to allergy treatment. For the antihistamines it can be

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[7] The distances between stores and the closest pollen count stations vary between 1.22 and 3,955 Km.

seen that the movements in average daily quantity sold exhibits a seasonal pattern where the peaks occur in the months of April and May and valleys right after on the months of June and July. The non-allergy related medicines, on the other hand, have demand not driven by the level of pollen concentration on air and hence exhibit a different pattern of seasonality than the antihistamines.

Figure 8 shows the evolution of average monthly prices for antihistamines and non-allergy medicines. It can be seen that the price for antihistamines also exhibits a less prominent but somewhat seasonal pattern as does demand. This pattern can be understood as a consequence of the seasonal evolution of pollen concentration on air throughout the year. For the non-allergy medicines, which are not affected by the level of pollen concentration on air, it's seen that the prices exhibit a different pattern too. As explained in the introduction, antihistamines are used as treatment of allergies symptoms caused by hypersensitivity response to allergens exposure like pollen released by plants during the spring season. Hence, it's not surprising that we observe the seasonal pattern of increasing purchases/ quantity sold during spring months (March, May and June).

3.4 Empirical Strategy

The empirical strategy of the paper consists of estimating a reduced form model that captures some of the characteristics of the dynamic price competition model outlined above. It consists of a relationship between prices of antihistaminic drugs and measures of pollen concentration on air, taking into account the current level of demand in a given market. Under some assumptions, this relationship reflects the prediction of the dynamic pricing model with cyclical demand on the behavior of margins, namely: that they will respond to anticipated changes in demand and, controlling for current demand, margins will be higher in periods of expected rising demand (Borenstein & Shepard, 1996). The specification used consists of the following:

$$p_{ijt} = \alpha_i + \gamma_j + \theta_m + \beta_1 pollen_{jt} + \beta_2 pollen_{jt} \times Pleasanton + \beta_3 pollen_{jt} \times San\,Jose + \beta_4 Pleasanton + \beta_5 San\,Jose + \beta_6 Revenue_{jt} + \varepsilon_{ijt}, \qquad \text{(eq. 1)}$$

where p_{ijt} is the price of product *i*, at store *j* on week *t*, $Revenue_{jt}$ is the total revenue of allergy drugs at store *j* on week *t*, $pollen_{jt}$ is the pollen count for the nearest pollen count station for store *j* and week *t*, *Pleasanton* and *San Jose* are dummy variables for the two cities selected as treated. The interactions of city dummies and pollen variable identify the differential effect of pollen concentration for the cities in the treated group, i.e., the ones that have high levels and variation of pollen concentration.

Prices and Pollen are transformed to log form, so that the coefficients can be interpreted as (approximate) elasticities. The model is estimated for all allergy drugs together and by separate categories: Adult, Pediatric, General Eye Care and Nasal. To check the robustness of our estimates as well as the quality of the pollen count measure – pollen count in the nearest station – we estimate models using stores that have nearest counting stations at different distances, namely: 5 km, 10 km, 15 km and 20 km.

To make the reduced form equation compatible with the predictions of the dynamic pricing model we need two assumptions. First, we assume that the marginal costs of drugs in each city is the same and so the different prices in different cities reflect different margins, which is the outcome of interest in the theoretical analysis. This assumption makes sense if the retailer works with a centralized buying unit that serves stores located in different regions and explores economies of scale in purchases, which seems a plausible assumption. The product fixed effects (α_i) play the important role of capturing common shocks to products across stores that I relate to the assumption of common costs for different stores. Hence, the inclusion of product fixed effects allows identifying the other coefficients as effects on margins, rather than on prices, as predicted by the theoretical analysis.

The second key assumption behind the reduced form equation is that the level of pollen concentration on air works as a proxy for the expected demand in a given week and prices respond positively to those expectations, taking into account the current level of demand reflected in the total revenue from antihistaminic drugs in a given week. Hence, to be consistent with the theoretical model, I expect a positive value of the coefficient on the interaction between the pollen variable and the city dummies that identify the treated group as an indication that expected demand has a positive sign on the margin. With respect to magnitudes of the coefficients, it has been pointed out that the economic content of the effect of expected demand on the behavior of margins is not on the magnitude of that impact but in the indication that it gives about whether the firms price consistently with the tacit collusive dynamic model (Borenstein & Shepard, 1996; Nevo & Whinston, 2010). Hence, when interpreting the results, we should focus on statistical significance and signs of coefficients rather than on magnitudes.

3.5 Results

Tables 4 to 8 present the results of the reduced form models for all allergy drugs and the four categories: Adult, Pediatric, General Eye Care and Nasal. The models are estimated using stores that have pollen count stations at distances of at most 5 km. [8]

Recapping the discussion in sections two and four, we want to test the predictions that the price-cost margins will respond to anticipated changes in demand and, controlling for current demand, margins will be higher in periods of expected rising demand. Assuming that marginal costs are the same for different stores, in a given week, price differences across stores are going to reflect different margins. I also assume that the levels of pollen concentration on air are a proxy for expected demand and that stores close to the pollen count stations of Pleasanton and San Jose are subject to high levels and variation of pollen concentration throughout the year (treatment). Hence, the coefficients of interest are the ones associated with the interactions $\text{Pollen} \times \text{Pleasanton}$ and $\text{Pollen} \times \text{San Jose}$ in equation 1. The theoretical analysis predicts that those coefficients should be positive and statistically significant.

The model for all allergy drugs shows that the coefficients of interest are consistent with the hypothesized predictions. The first column coefficients are not statistically significant, but, as additional controls are added – product, store and quadratic trend – they become more precise and significant. The magnitudes also change when controls are added and are relatively stable for

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[8] Results for other distances (10 km, 15 km and 20 km) are qualitatively similar and are provided in appendix.

different specifications. I interpret the change in significance and magnitude after the inclusion of product fixed effects in the following way. Those fixed effects control for product (UPC) specific shocks that are common across different stores, as the assumption of common costs. Hence, they allow us to interpret the remaining variation as variations in margins, and de effect of pollen variation, which we associate with expected demand, can them be interpreted as the effect on margins, as predicted by the theoretical analysis.

The magnitudes of the coefficients are small, indicating that prices respond 0.4% to a 1 percent increase in pollen concentration (column 4 in table 4). This is hardly surprising given that pollen concentration is a somewhat crude proxy for expected demand. Nevertheless, as has been pointed out, the economic content of the effect of expected demand on the behavior of margins is not on the magnitude of that impact but in the indication that it gives about whether the firms price consistently with the tacit collusive dynamic model. Hence, I take the statistical significance and the sign of the coefficients of interest as supporting the prediction of the theoretical analysis.

The remaining categories also display similar patterns for the coefficients of interest that can be summarized in the following bullets:

- Coefficients are not statistically significant for basic model (column 1);
- Coefficients are positive, statistically significant and magnitudes are relatively stable for models with additional controls: product and store fixed effects and quadratic trend;

Besides those basic specifications in equation 1, I also estimated models using the pollen count for the week before the price observed. This alternative specification reflects the fact that retail prices are not adjusted instantly, and so might respond to pollen variation with some delay. Formally, the alternative model is given by:

$$p_{ijt} = \alpha_i + \gamma_j + \theta_m + \beta_1 pollen_{jt-1} + \beta_2 pollen_{jt-1} \times Pleasanton + \beta_3 pollen_{jt-1} \times San\,Jose + \beta_4 Pleasanton + \beta_5 San\,Jose + \beta_6 Revenue_{jt} + \varepsilon_{ijt}. \qquad \text{(eq. 2)}$$

The results are given in tables 9 – 13 and are all compatible with the ones obtained so far. The model for all allergy drugs, for example, exhibits similar patterns of statistical significance of coefficients: coefficients not significant for the basic model (column 1 of table 9) and positive and significant for the other models (except for the interaction between pollen and San Jose in column 3). I note that the magnitudes are somewhat bigger, indicating that the lagged pollen measures do a better job in explaining the behavior of product margins.

For the separate categories – adult, pediatric, general eye care and nasal – the same conclusions from the bullets are valid. When estimating the models with pollen count stations with higher distances, the results remain stable. I take this as an indication of robustness of our estimates and of the conclusions of the empirical exercise.

3.6 Conclusion

In this essay I look for evidence that the model of dynamic price competition with cyclical demand can describe the behavior of margins in the retail market for antihistaminic medicines. The results obtained are quite strong. The reduced form model that relates the difference in margins on a treated city (with high variation on pollen concentration on air) and a control city (with low variation on pollen concentration on air) suggests that profit margins respond positively to expected demand in the cities with high levels and variation of pollen concentration on air, controlling for the current level of demand, as predicted by the theoretical model.

On the other hand, the analysis contains some caveats that should not be overlooked. Besides the disclosed assumptions to make the reduced form model compatible with the predictions of theoretical analysis - the marginal costs of drugs in each city is the same and level of pollen concentration on air works as a proxy for the expected demand in a given week and prices respond positively to those expectations – the structure of the market which I analyze is somewhat different than the original oligopoly model. The Pharmaceutical retail sector, which corresponds to the level of analysis that I develop, is closer to a competitive sector with many small local players than to the tight oligopoly model that is supposed in the abstract game theoretical model. Hence our findings can be considered more of an approximation nature than describing the real behavior of market participants.

Another caveat to the results that might be pointed relates to the small magnitudes of the coefficients obtained. Although very small, we rely on the observation that the economic content of the effect of expected demand on the behavior of margins is not on the magnitude of that impact but in the indication that it gives about whether the firms price consistently with the tacit collusive dynamic model (Borenstein & Shepard, 1996; Nevo & Whinston, 2010). Also, the robustness of the results can be attested by the additional estimates presented in the appendix that corroborate the basic specifications.

Overall, the essay makes a contribution to understand the dynamics of behavior in oligopolistic markets that might be of interest to academics and practitioners who wants to understand conduct and performance of industrial markets.

3.7 Tables and Figures

Figure 7: Dynamics of Margins with Cyclical Demand

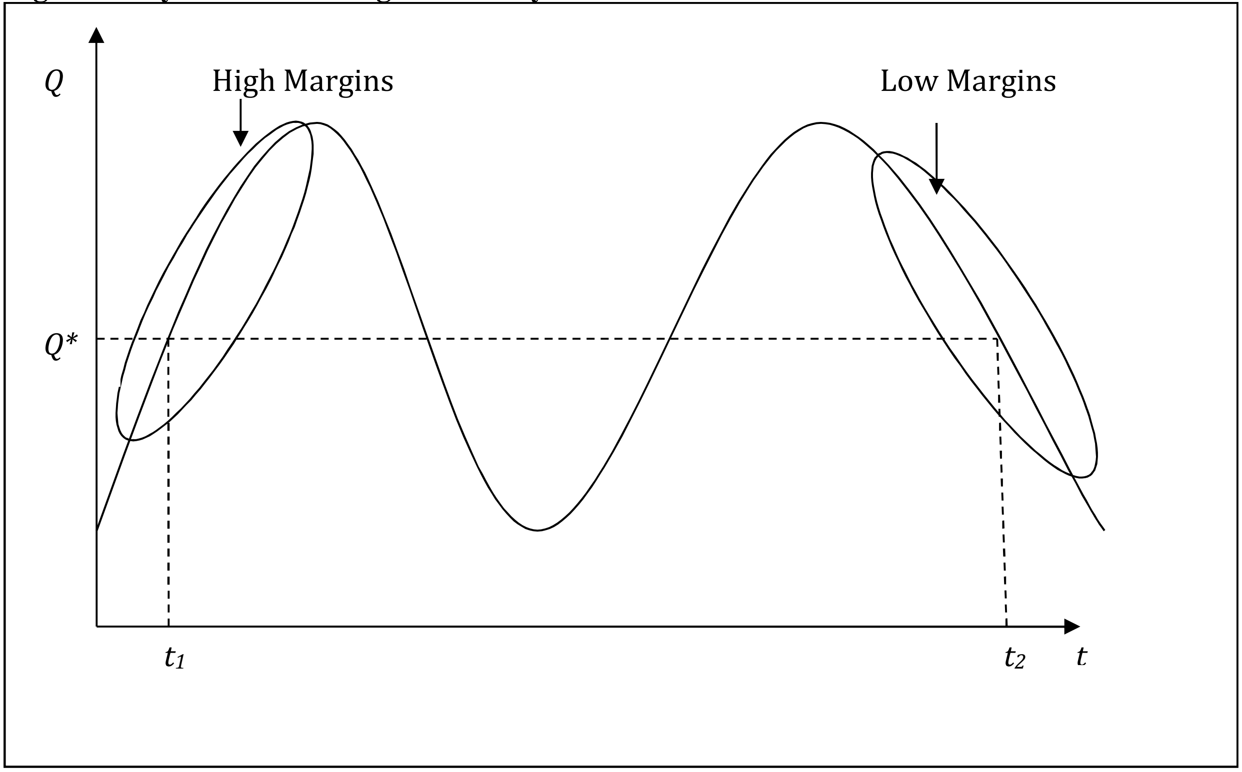

Figure 8

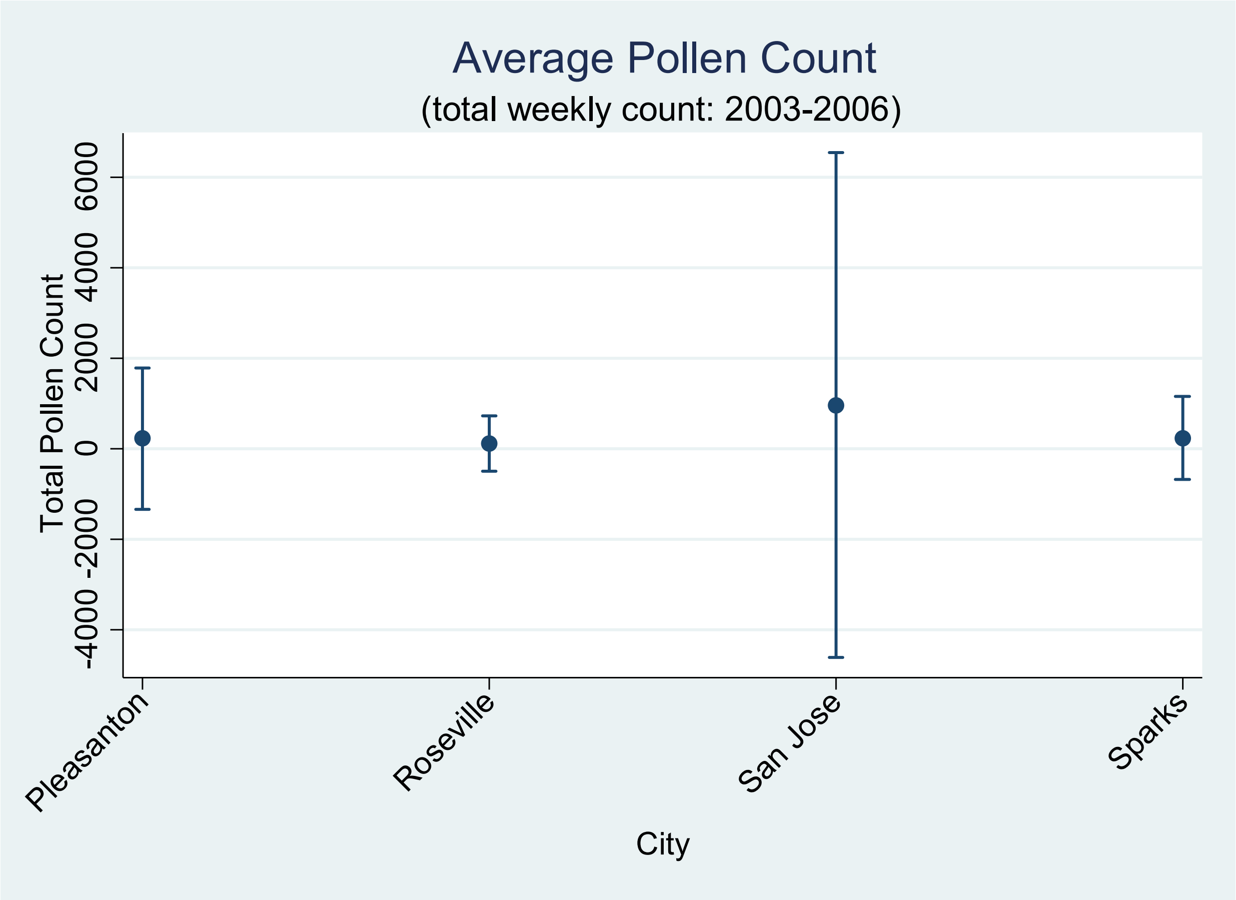
Average Pollen Count
(total weekly count: 2003-2006)
Total Pollen Count
6000
4000
2000
0
-2000
-4000
Pleasanton
Roseville
San Jose
Sparks
City

Figure 9

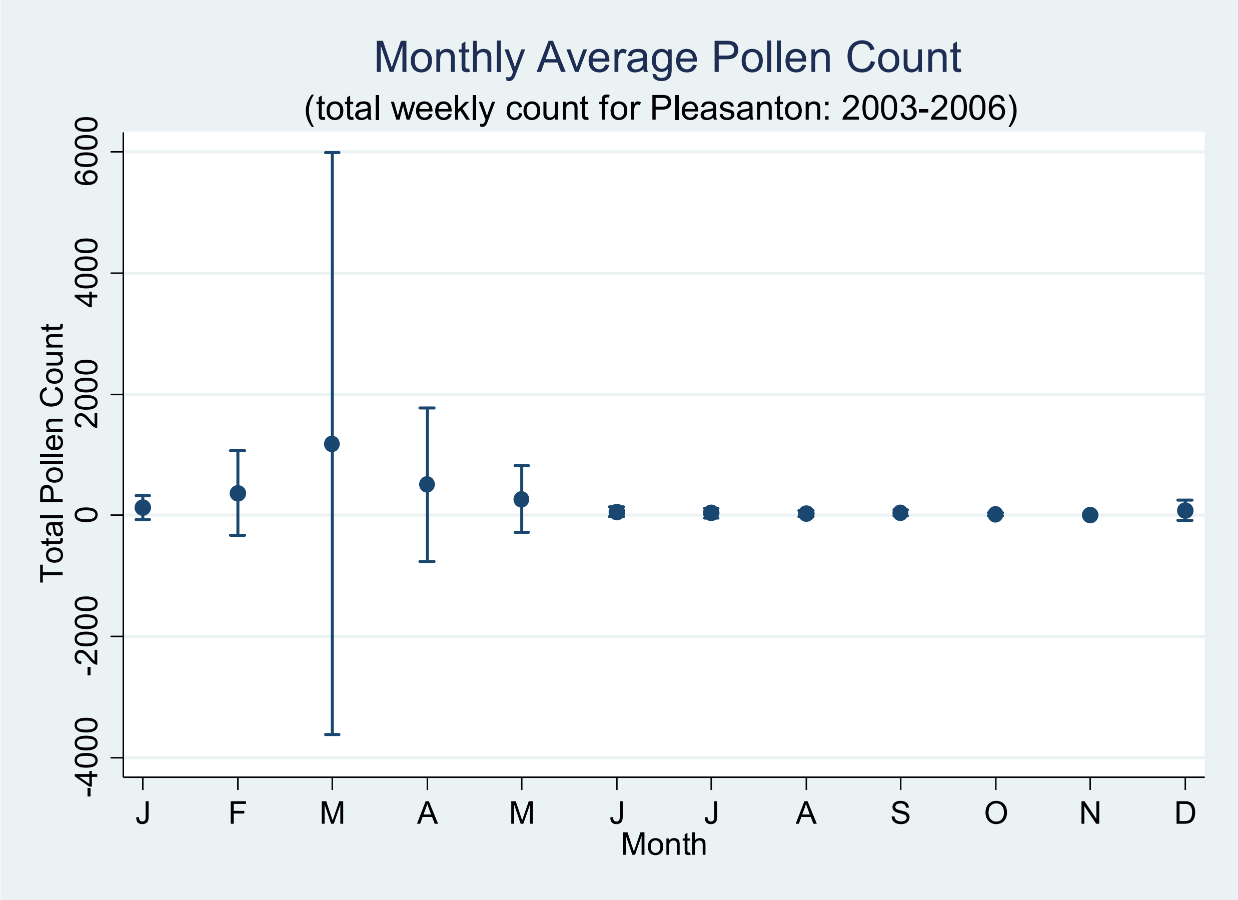
Monthly Average Pollen Count
(total weekly count for Pleasanton: 2003-2006)
Total Pollen Count
6000
4000
2000
0
-2000
-4000
J
F
M
A
M
J
J
A
S
O
N
D
Month

Figure 10

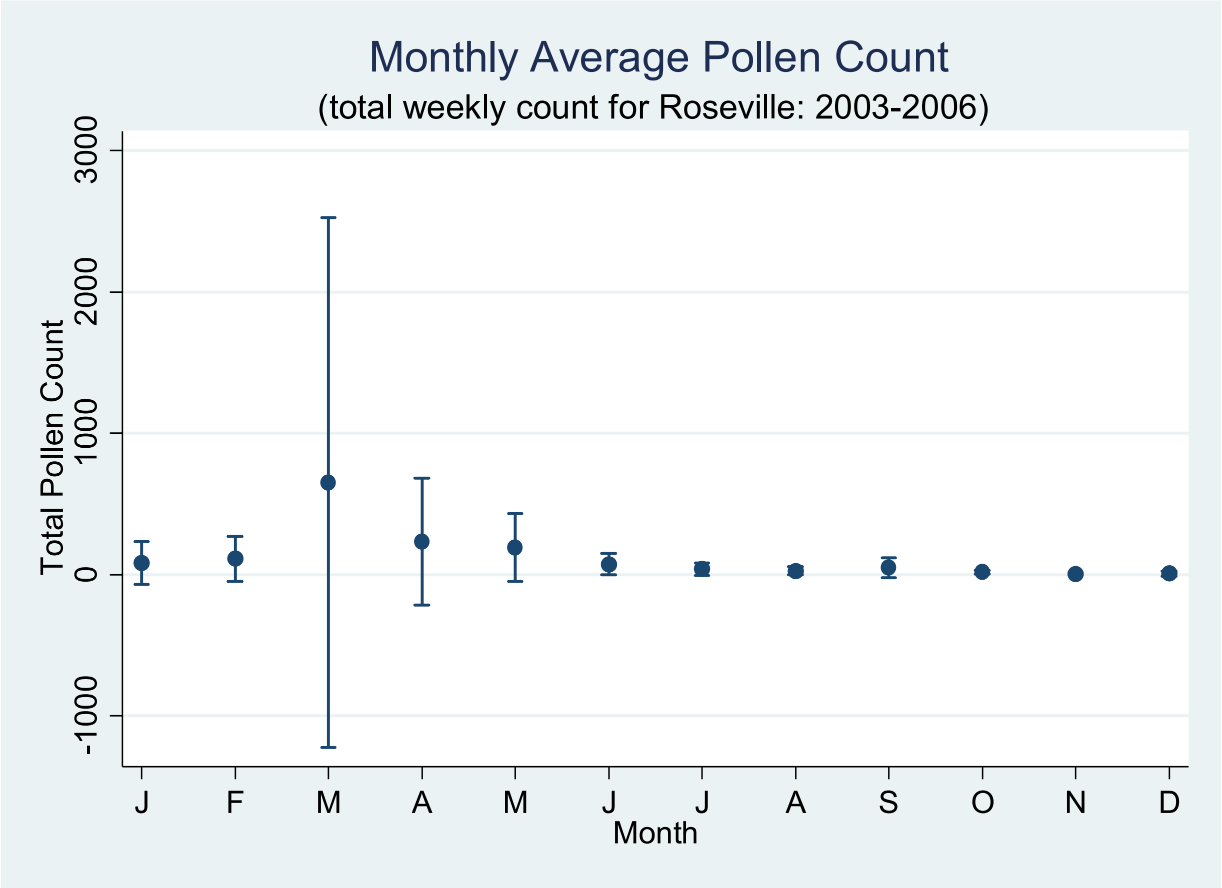
Monthly Average Pollen Count
(total weekly count for Roseville: 2003-2006)
Total Pollen Count
3000
2000
1000
0
-1000
J
F
M
A
M
J
J
A
S
O
N
D
Month

Figure 11

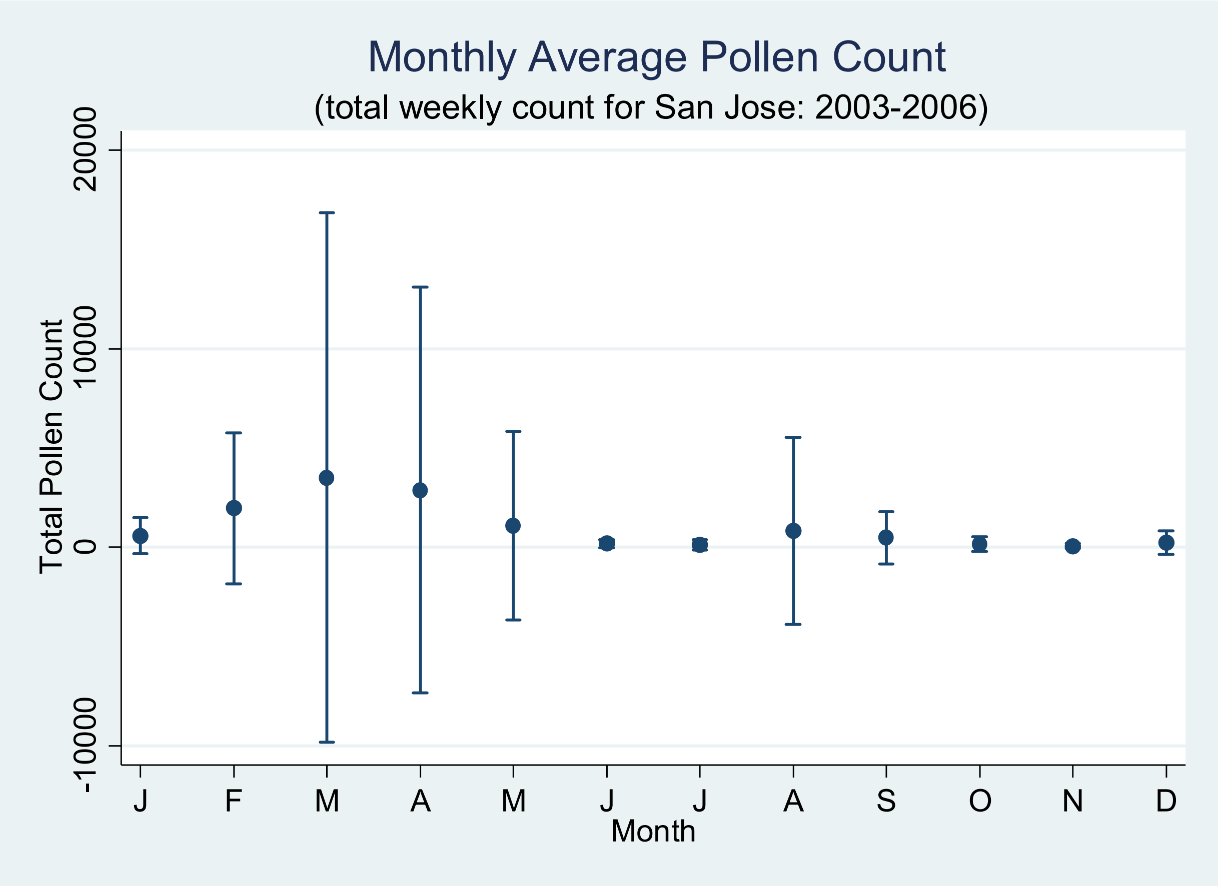
Monthly Average Pollen Count
(total weekly count for San Jose: 2003-2006)
Total Pollen Count
20000
10000
0
-10000
J
F
M
A
M
J
J
A
S
O
N
D
Month

Figure 12

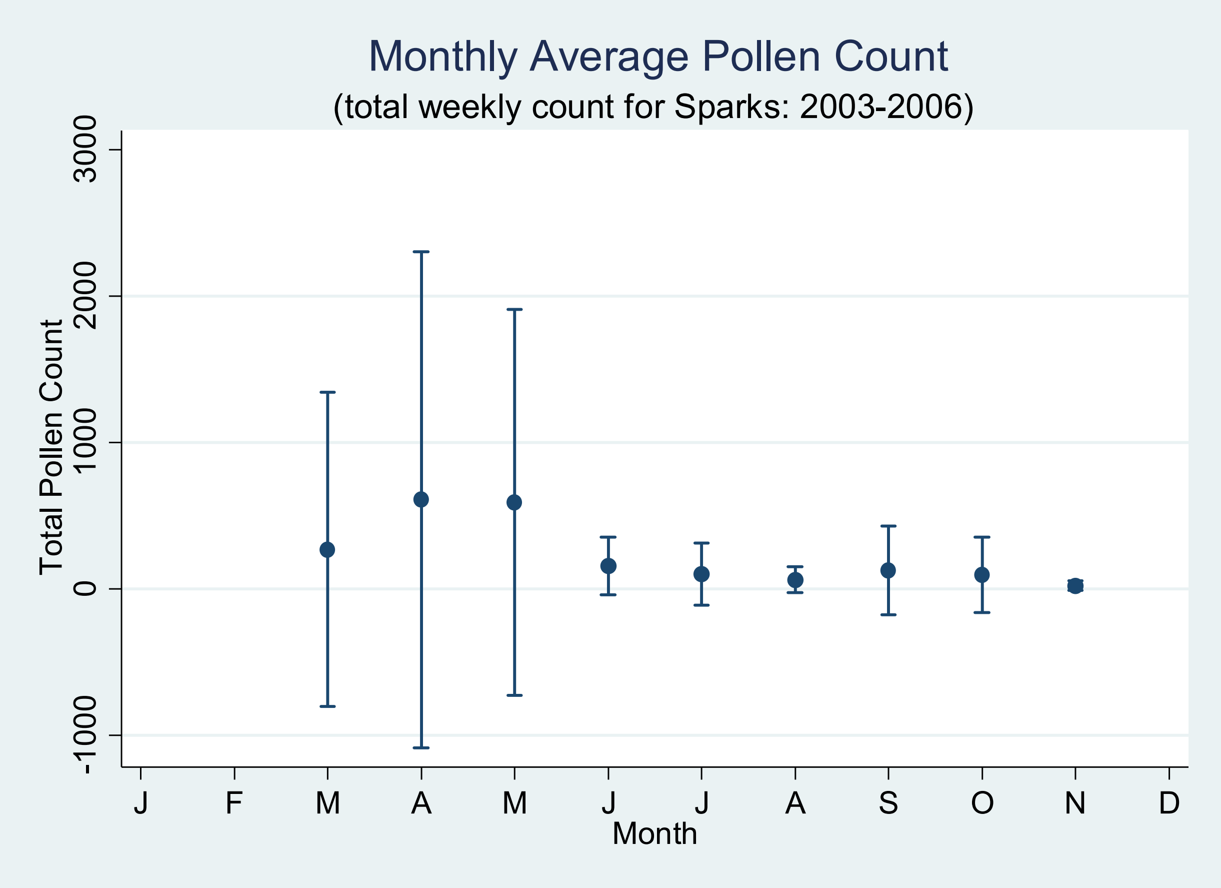
Monthly Average Pollen Count
(total weekly count for Sparks: 2003-2006)
Total Pollen Count
-1000
0
1000
2000
3000
J
F
M
A
M
J
J
A
S
O
N
D
Month

Figure 13: Average Daily Sales

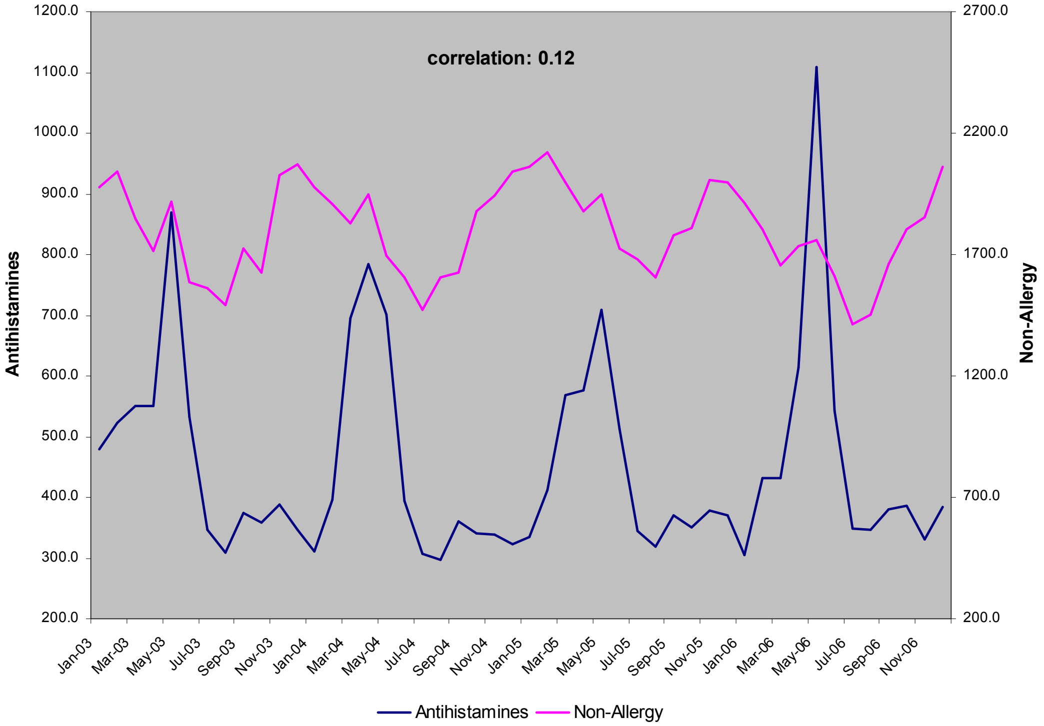

Figure 14: Average Monthly Price

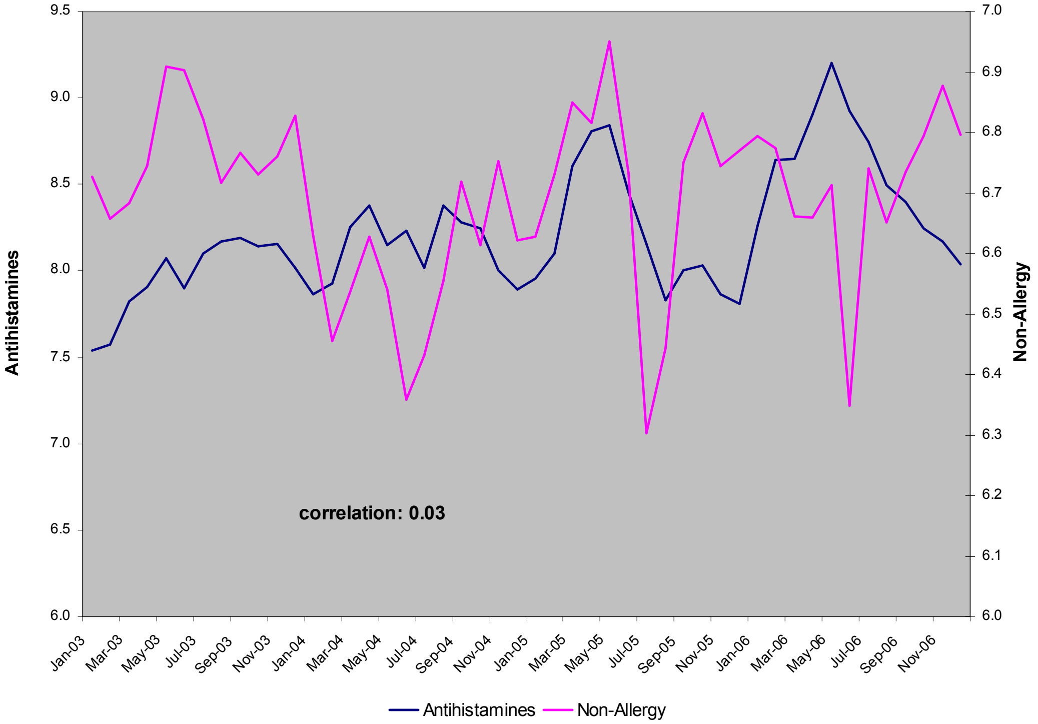

Table 19: Average Distance (Km) Between Stores (rows) and Pollen Count Stations (columns)

Stores	State	Pleasanton	Roseville	San Jose	Sparks
Alamo	CA	6.81	-	-	-
Benicia	CA	18.77	-	-	-
Campbell	CA	-	-	3.36	-
Carmichael	CA	-	14.70	-	-
Citrus Heights	CA	-	9.50	-	-
Clayton	CA	9.05	-	-	-
Concord	CA	6.99	-	-	-
Danville	CA	16.29	-	-	-
Fair Oaks	CA	-	11.34	-	-
Folson	CA	-	15.62	-	-
Fremont	CA	-	-	18.20	-
Lafayete	CA	7.20	-	-	-
Lincoln	CA	-	14.23	-	-
Los Altos	CA	-	-	15.95	-
Los Gatos	CA	-	-	7.56	-
Martinez	CA	8.91	-	-	-
Moraga	CA	11.53	-	-	-
Mountain View	CA	-	-	14.95	-
Oakland	CA	18.82	-	-	-
Orinda	CA	13.46	-	-	-
Pleasant Hill	CA	4.97	-	-	-
Rancho Cordova	CA	-	18.78	-	-
Rocklin	CA	-	4.69	-	-
Roseville	CA	-	3.86	-	-
Sacramento	CA	-	10.43	-	-
San Jose	CA	-	-	6.87	-
San Ramon	CA	-	-	10.80	-
Saratoga	CA	-	-	7.39	-
Santa Clara	CA	-	-	4.66	-
Sunnyvalle	CA	-	-	8.67	-
W Pittsburg	CA	14.54	-	-	-
Walnut Creek	CA	2.51	-	-	-
Reno	NV	-	-	-	8.84
Sparks	NV	-	-	-	4.44

Entry X_{ij}shows the average distance between stores located in row i and the nearest pollen count stations located in column j, e.g.: for the stores located in Alamo (CA) the average distance to the closest pollen count station located in Pleasanton (CA) is 6.81 km.

Table 20: Descriptive Statistics for Total Pollen Count (2003 – 2006)

	Mean	sd	cv	min	max	N
Pleasanton	230.5	781.9	3.393	0	9,144	166
Roseville	119.8	306.7	2.560	0	3,409	178
San Jose	965.9	2,791.1	2.890	0	29,906	317
Sparks	242.0	455.8	1.884	5	3,184	126
Total	503.5	1860.3	3.695	0	29,906	787

Descriptive statistics for total weekly pollen count (pollen/m3).

Table 21: Mean Comparison Between Treated (high) and Control (low) Zip Codes

	High	Low	Total	Diff.
Population	33,070.5	32,823.9	33,007.8	246.5
	[14708.4]	[14376.7]	[14501.4]	[0.06]
Median Income	**81,512.9**	**55,386.9**	**74,870.7**	**26,126.0*** **
	[26761.3]	**[13359.0]**	**[26564.6]**	**[4.92]**
HH Size	2.687	2.621	2.670	0.0666
	[0.455]	[0.176]	[0.403]	[0.81]
Median House Value	**457,716.0**	**172,246.7**	**385,139.0**	**285,469.3*** **
	[202516.2]	**[37747.8]**	**[215563.1]**	**[8.91]**
Percentage of 65 plus	0.120	0.113	0.118	0.00728
	[0.0701]	[0.0447]	[0.0643]	[0.47]
Stores	1.341	1.200	1.305	0.141
	[0.680]	[0.414]	[0.623]	[0.95]
Revenue Allergy	105,273.1	80,271.3	98,916.7	25,001.8
	[66110.9]	[41508.6]	[61455.3]	[1.71]
Distance to Pollen Station	9.654	9.229	9.546	0.425
	[5.297]	[4.945]	[5.171]	[0.28]
CA	1	0.800	0.949	0.200
	[0]	[0.414]	[0.222]	[1.87]
NV	0	0.200	0.0508	-0.200
	[0]	[0.414]	[0.222]	[-1.87]

Socioeconomic indicators form the 2010 census for the zip code where each store is located. Systematic differences indicate that location specific fixed effects are necessary.
Standard errors and t statistics in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(5)
Total Pollen	0.0005	-0.0030***	-0.0040***	-0.0063***
	[0.0018]	[0.0003]	[0.0004]	[0.0003]
Total Pollen x Pleasanton	0.0009	0.0055***	0.0044***	0.0040***
	[0.0025]	[0.0005]	[0.0005]	[0.0004]
Total Pollen x San Jose	0.0000	0.0036***	0.0009*	0.0041***
	[0.0021]	[0.0004]	[0.0004]	[0.0004]
Pleasanton	0.0201	0.0071**	2.0618***	2.0407***
	[0.0110]	[0.0022]	[0.0067]	[0.0095]
San Jose	0.0257**	0.0018		
	[0.0098]	[0.0020]		
Revenuejt	0.0803***	0.0042***	0.0153***	0.0050***
	[0.0023]	[0.0005]	[0.0008]	[0.0007]
N	99,209	99,209	99,209	99,209
r2	0.014	0.958	0.959	0.967
F	229.234	.	.	124246.810
ll	-61999.814	95066.687	95520.133	106308.656

Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 23: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0051*	-0.0019***	-0.0032***	-0.0053***
	[0.0025]	[0.0005]	[0.0005]	[0.0004]
Total Pollen x Pleasanton	0.0024	0.0039***	0.0028***	0.0023***
	[0.0035]	[0.0006]	[0.0006]	[0.0005]
Total Pollen x San Jose	0.0048	0.0033***	0.0005	0.0041***
	[0.0029]	[0.0005]	[0.0006]	[0.0005]
Pleasanton	0.0152	0.0154***	2.0515***	2.0163***
	[0.0155]	[0.0029]	[0.0086]	[0.0113]
San Jose	0.0053	0.0013	2.0584***	2.0028***
	[0.0140]	[0.0027]	[0.0086]	[0.0114]
Revenuejt	0.0928***	0.0055***	0.0185***	0.0072***
	[0.0031]	[0.0006]	[0.0010]	[0.0009]
N	65497	65497	65497	65497
r2	0.015	0.962	0.963	0.971
F	158.102	155624.801	94998.892	151047.529
ll	-47627.222	59283.659	59632.280	67730.496

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 24: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0016	-0.0050***	-0.0056***	-0.0080***
	[0.0020]	[0.0006]	[0.0007]	[0.0006]
Total Pollen x Pleasanton	0.0023	0.0071***	0.0061***	0.0061***
	[0.0029]	[0.0008]	[0.0008]	[0.0007]
Total Pollen x San Jose	-0.0008	0.0033***	0.0004	0.0032***
	[0.0024]	[0.0007]	[0.0008]	[0.0007]
Pleasanton	-0.0126	-0.0157***	0.0210***	0.0006
	[0.0124]	[0.0037]	[0.0060]	[0.0053]
San Jose	0.0171	-0.0011	0.0604***	0.0253***
	[0.0111]	[0.0034]	[0.0058]	[0.0052]
Revenuejt	0.0283***	0.0026**	0.0120***	0.0003
	[0.0028]	[0.0009]	[0.0015]	[0.0013]
N	25219	25219	25219	25219
r2	0.006	0.902	0.903	0.920
F	25.493	.	.	.
ll	-3179.616	26069.184	26185.915	28523.510

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 25: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0187**	-0.0064***	-0.0056***	-0.0078***
	[0.0058]	[0.0013]	[0.0014]	[0.0015]
Total Pollen x Pleasanton	0.0113	0.0111***	0.0103***	0.0096***
	[0.0076]	[0.0015]	[0.0016]	[0.0016]
Total Pollen x San Jose	0.0193**	0.0083***	0.0061***	0.0069***
	[0.0066]	[0.0014]	[0.0015]	[0.0015]
Pleasanton	0.0313	0.0263***		0.0512***
	[0.0337]	[0.0065]		[0.0102]
San Jose	-0.0160	0.0377***		
	[0.0304]	[0.0060]		
Revenuejt	0.0546***	-0.0007	0.0006	-0.0003
	[0.0064]	[0.0012]	[0.0022]	[0.0020]
N	5185	5185	5185	5185
r2	0.021	0.962	0.962	0.968
F	18.058	10238.477	4133.093	6243.284
ll	-1084.282	7345.794	7372.030	7773.618

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 26: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0281***	0.0027*	0.0030*	0.0007
	[0.0068]	[0.0011]	[0.0012]	[0.0011]
Total Pollen x Pleasanton	-0.0075	-0.0006	-0.0006	-0.0029
	[0.0102]	[0.0018]	[0.0018]	[0.0016]
Total Pollen x San Jose	-0.0344***	-0.0014	-0.0014	-0.0017
	[0.0080]	[0.0013]	[0.0013]	[0.0012]
Pleasanton	0.1939***	0.0603***		
	[0.0498]	[0.0086]		
San Jose	0.2000***	0.0117	-0.0648***	-0.0752***
	[0.0400]	[0.0066]	[0.0107]	[0.0091]
Revenuejt	0.0123	-0.0043*	-0.0077*	-0.0032
	[0.0088]	[0.0019]	[0.0030]	[0.0026]
N	3308	3308	3308	3308
r2	0.043	0.952	0.952	0.965
F	26.750	7969.445	3386.266	4868.453
ll	-926.781	4013.185	4033.671	4524.934

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 27: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0020	-0.0033***	-0.0048***	-0.0070***
	[0.0019]	[0.0004]	[0.0004]	[0.0004]
Total Pollen (-1) x Pleasanton	0.0008	0.0063***	0.0054***	0.0036***
	[0.0027]	[0.0005]	[0.0005]	[0.0005]
Total Pollen (-1) x San Jose	-0.0030	0.0023***	-0.0004	0.0035***
	[0.0023]	[0.0004]	[0.0005]	[0.0004]
Pleasanton	0.0168	0.0025		
	[0.0118]	[0.0024]		
San Jose	0.0394***	0.0080***	2.0623***	2.0164***
	[0.0111]	[0.0022]	[0.0080]	[0.0090]
Revenuejt	0.0804***	0.0055***	0.0195***	0.0088***
	[0.0025]	[0.0005]	[0.0008]	[0.0007]
N	88945	88945	88945	88945
r2	0.014	0.959	0.959	0.967
F	205.436	.	.	851772.373
ll	-55895.100	85300.842	85792.060	95241.675

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 28: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0042	-0.0020***	-0.0039***	-0.0060***
	[0.0027]	[0.0005]	[0.0005]	[0.0005]
Total Pollen (-1) x Pleasanton	0.0029	0.0053***	0.0043***	0.0022***
	[0.0037]	[0.0007]	[0.0007]	[0.0006]
Total Pollen (-1) x San Jose	0.0028	0.0019**	-0.0010	0.0035***
	[0.0032]	[0.0006]	[0.0006]	[0.0005]
Pleasanton	0.0110	0.0088**	2.0279***	1.9988***
	[0.0167]	[0.0032]	[0.0097]	[0.0109]
San Jose	0.0143	0.0072*		
	[0.0156]	[0.0030]		
Revenuejt	0.0933***	0.0069***	0.0225***	0.0111***
	[0.0034]	[0.0007]	[0.0011]	[0.0009]
N	58912	58912	58912	58912
r2	0.015	0.963	0.963	0.971
F	142.166	.	.	.
ll	-42991.752	53532.098	53899.565	60947.877

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 29: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0022	-0.0054***	-0.0068***	-0.0090***
	[0.0022]	[0.0007]	[0.0007]	[0.0007]
Total Pollen (-1) x Pleasanton	0.0018	0.0067***	0.0058***	0.0048***
	[0.0031]	[0.0009]	[0.0009]	[0.0008]
Total Pollen (-1) x San Jose	-0.0037	0.0019*	-0.0012	0.0025**
	[0.0027]	[0.0008]	[0.0009]	[0.0008]
Pleasanton	-0.0150	-0.0151***	0.0300***	0.0126*
	[0.0132]	[0.0039]	[0.0062]	[0.0055]
San Jose	0.0283*	0.0071	0.0368***	0.0246***
	[0.0126]	[0.0039]	[0.0057]	[0.0050]
Revenuejt	0.0277***	0.0040***	0.0175***	0.0051***
	[0.0030]	[0.0009]	[0.0016]	[0.0014]
N	22463	22463	22463	22463
r2	0.006	0.902	0.903	0.920
F	21.856	39091.083	21551.947	40504.447
ll	-2904.450	23147.127	23289.055	25367.233

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 30: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0179**	-0.0067***	-0.0063***	-0.0085***
	[0.0062]	[0.0013]	[0.0014]	[0.0015]
Total Pollen (-1) x Pleasanton	0.0125	0.0129***	0.0120***	0.0101***
	[0.0081]	[0.0016]	[0.0016]	[0.0017]
Total Pollen (-1) x San Jose	0.0189**	0.0083***	0.0065***	0.0076***
	[0.0071]	[0.0015]	[0.0016]	[0.0016]
Pleasanton	0.0234	0.0174*		
	[0.0365]	[0.0070]		
San Jose	-0.0160	0.0392***	0.0255*	0.0138
	[0.0339]	[0.0067]	[0.0105]	[0.0085]
Revenuejt	0.0550***	0.0006	0.0036	0.0021
	[0.0069]	[0.0013]	[0.0024]	[0.0022]
N	4638	4638	4638	4638
r2	0.021	0.963	0.963	0.968
F	15.841	9334.086	3766.229	5645.475
ll	-989.823	6580.373	6601.232	6944.242

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table 31: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0350***	0.0030*	0.0032*	0.0011
	[0.0072]	[0.0012]	[0.0014]	[0.0012]
Total Pollen (-1) x Pleasanton	-0.0180	-0.0017	-0.0018	-0.0045*
	[0.0108]	[0.0019]	[0.0019]	[0.0017]
Total Pollen (-1) x San Jose	-0.0390***	-0.0027	-0.0023	-0.0027*
	[0.0087]	[0.0015]	[0.0015]	[0.0013]
Pleasanton	0.2243***	0.0666***		
	[0.0532]	[0.0091]		
San Jose	0.2077***	0.0200**	-0.0648***	-0.0794***
	[0.0449]	[0.0074]	[0.0117]	[0.0103]
Revenuejt	0.0081	-0.0026	-0.0056	-0.0033
	[0.0093]	[0.0021]	[0.0034]	[0.0029]
N	2932	2932	2932	2932
r2	0.038	0.949	0.950	0.963
F	20.857	7001.268	3011.759	4480.223
ll	-832.820	3477.304	3496.238	3937.946

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=5 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

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Appendix. Additional Regressions with Pollen Stations at Bigger Distances (>5 Km)

In this appendix, I provide the results for additional regressions estimated with stores that have the closer pollen count stations at distances of at most: 10 Km, 15 Km and 20 Km. Presumably, this pollen measure is of worse quality than the one used in the models presented in tables 4 – 13. Nevertheless they can be considered a robustness check for the results of the regressions I equation 1 and 2. The regressions show similar estimates in terms of signs and significance levels, which gives us confidence on the robustness of our results.

Table A 1: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0042**	-0.0041***	-0.0053***	-0.0053***
	[0.0013]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x Pleasanton	-0.0023	0.0062***	0.0051***	0.0036***
	[0.0017]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x San Jose	-0.0017	0.0043***	0.0016***	0.0033***
	[0.0015]	[0.0003]	[0.0003]	[0.0003]
Pleasanton	0.0266***	0.0044**	-0.0431	-0.0365
	[0.0075]	[0.0015]	[.]	[256.9280]
San Jose	0.0275***	0.0038*	-0.0479	-0.0421
	[0.0072]	[0.0015]	[.]	[258.3592]
Revenuejt	0.0730***	0.0064***	0.0184***	0.0036***
	[0.0015]	[0.0003]	[0.0005]	[0.0004]
N	231270	231270	231270	231270
r2	0.013	0.958	0.959	0.967
F	501.491	.	.	.
ll	-1.460e+05	219832.824	221082.104	245954.183

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 2: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0045***	-0.0038***	-0.0051***	-0.0061***
	[0.0011]	[0.0002]	[0.0002]	[0.0002]
Total Pollen x Pleasanton	-0.0022	0.0060***	0.0053***	0.0043***
	[0.0015]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x San Jose	-0.0018	0.0041***	0.0017***	0.0041***
	[0.0013]	[0.0003]	[0.0003]	[0.0002]
Pleasanton	0.0293***	0.0035**		
	[0.0064]	[0.0013]		
San Jose	0.0306***	0.0026*	1.9384***	1.9077***
	[0.0059]	[0.0012]	[0.0054]	[0.0078]
Revenuejt	0.0737***	0.0063***	0.0168***	0.0041***
	[0.0013]	[0.0003]	[0.0004]	[0.0004]
N	314245	314245	314245	314245
r2	0.013	0.959	0.959	0.967
F	705.693	267774.916	172632.363	302343.526
ll	-1.980e+05	300061.078	301580.854	335434.211

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 3: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0043***	-0.0034***	-0.0047***	-0.0061***
	[0.0010]	[0.0002]	[0.0002]	[0.0002]
Total Pollen x Pleasanton	-0.0032*	0.0053***	0.0048***	0.0041***
	[0.0013]	[0.0003]	[0.0003]	[0.0002]
Total Pollen x San Jose	-0.0018	0.0037***	0.0013***	0.0041***
	[0.0012]	[0.0002]	[0.0002]	[0.0002]
Pleasanton	0.0314***	0.0044***	1.9417***	1.9133***
	[0.0057]	[0.0012]	[0.0052]	[0.0073]
San Jose	0.0341***	0.0033**	1.9374***	1.9051***
	[0.0055]	[0.0012]	[0.0052]	[0.0073]
Revenuejt	0.0757***	0.0071***	0.0174***	0.0045***
	[0.0012]	[0.0002]	[0.0004]	[0.0004]
N	367131	367131	367131	367131
r2	0.014	0.958	0.958	0.967
F	864.800	314779.380	.	330467.710
ll	-2.297e+05	349364.930	351179.209	391461.989

Robust standard errors in brackets.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All variables in log form.

(2): UPC Fixed Effects

(3): UPC and store fixed effects

(4): UPC and store fixed effects and quadratic trend

Prices are deflated by cpi.

Total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.

Treatment: stores which have closest pollen count in Pleasanton and San Jose.

Total revenue of allergy drugs in store j and week t.

Table A 4: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(5)
Total Pollen	-0.0016	-0.0032***	-0.0048***	-0.0043***
	[0.0019]	[0.0004]	[0.0004]	[0.0003]
Total Pollen x Pleasanton	-0.0009	0.0053***	0.0040***	0.0023***
	[0.0024]	[0.0004]	[0.0004]	[0.0004]
Total Pollen x San Jose	0.0033	0.0041***	0.0013**	0.0032***
	[0.0021]	[0.0004]	[0.0004]	[0.0004]
Pleasanton	0.0275**	0.0092***	0.0097	0.0135
	[0.0105]	[0.0020]	[.]	[51.1036]
San Jose	0.0136	0.0034	-0.0036	-0.0027
	[0.0101]	[0.0020]	[.]	[49.7345]
Revenuejt	0.0837***	0.0078***	0.0223***	0.0059***
	[0.0020]	[0.0004]	[0.0007]	[0.0006]
N	152328	152328	152328	152328
r2	0.013	0.962	0.962	0.970
F	333.255	222565.907	.	.
ll	-1.118e+05	135714.905	136668.962	154792.364

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 5: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0010	-0.0030***	-0.0047***	-0.0052***
	[0.0016]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x Pleasanton	-0.0010	0.0052***	0.0044***	0.0032***
	[0.0020]	[0.0004]	[0.0004]	[0.0003]
Total Pollen x San Jose	0.0026	0.0039***	0.0015***	0.0041***
	[0.0018]	[0.0003]	[0.0003]	[0.0003]
Pleasanton	0.0309***	0.0073***	0.0020	0.0155
	[0.0090]	[0.0017]	[.]	[52.5785]
San Jose	0.0198*	0.0015	-0.0089	-0.0013
	[0.0084]	[0.0017]	[.]	[55.1743]
Revenuejt	0.0831***	0.0076***	0.0206***	0.0066***
	[0.0018]	[0.0004]	[0.0006]	[0.0005]
N	206429	206429	206429	206429
r2	0.013	0.962	0.962	0.970
F	451.618	318622.752	.	.
ll	-1.514e+05	184827.300	186002.831	210568.671

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 6: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0014	-0.0024***	-0.0043***	-0.0053***
	[0.0014]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x Pleasanton	-0.0015	0.0043***	0.0038***	0.0030***
	[0.0018]	[0.0003]	[0.0003]	[0.0003]
Total Pollen x San Jose	0.0026	0.0034***	0.0010**	0.0041***
	[0.0016]	[0.0003]	[0.0003]	[0.0003]
Pleasanton	0.0278***	0.0088***	0.0143	0.0129
	[0.0080]	[0.0016]	[36.4714]	[.]
San Jose	0.0237**	0.0028	0.0054	0.0050
	[0.0078]	[0.0016]	[38.9312]	[.]
Revenuejt	0.0866***	0.0085***	0.0215***	0.0072***
	[0.0016]	[0.0003]	[0.0005]	[0.0005]
N	241347	241347	241347	241347
r2	0.014	0.961	0.962	0.970
F	569.768	378837.988	.	.
ll	-1.759e+05	214782.662	216169.725	245528.667

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 7: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0015	-0.0053***	-0.0062***	-0.0070***
	[0.0016]	[0.0005]	[0.0005]	[0.0005]
Total Pollen x Pleasanton	0.0022	0.0066***	0.0060***	0.0052***
	[0.0020]	[0.0006]	[0.0006]	[0.0005]
Total Pollen x San Jose	-0.0007	0.0036***	0.0009	0.0027***
	[0.0018]	[0.0005]	[0.0006]	[0.0005]
Pleasanton	-0.0107	-0.0120***	0.0089	0.0081
	[0.0084]	[0.0025]	[0.0064]	[0.0057]
San Jose	0.0181*	0.0011	0.0287***	0.0307***
	[0.0081]	[0.0025]	[0.0059]	[0.0053]
Revenuejt	0.0314***	0.0049***	0.0139***	-0.0016
	[0.0018]	[0.0005]	[0.0010]	[0.0009]
N	58907	58907	58907	58907
r2	0.007	0.903	0.904	0.920
F	70.232	.	.	.
ll	-7203.048	61297.305	61618.155	67118.186

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 8: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0022	-0.0052***	-0.0061***	-0.0076***
	[0.0013]	[0.0004]	[0.0004]	[0.0004]
Total Pollen x Pleasanton	0.0013	0.0062***	0.0058***	0.0053***
	[0.0017]	[0.0005]	[0.0005]	[0.0005]
Total Pollen x San Jose	-0.0020	0.0035***	0.0008	0.0033***
	[0.0015]	[0.0005]	[0.0005]	[0.0004]
Pleasanton	-0.0026	-0.0111***	0.0150*	0.0100
	[0.0071]	[0.0022]	[0.0063]	[0.0055]
San Jose	0.0262***	-0.0001	0.0292***	0.0279***
	[0.0067]	[0.0021]	[0.0057]	[0.0050]
Revenuejt	0.0323***	0.0047***	0.0126***	-0.0010
	[0.0015]	[0.0005]	[0.0008]	[0.0007]
N	80415	80415	80415	80415
r2	0.008	0.903	0.904	0.921
F	104.782	.	.	.
ll	-9597.112	83923.615	84337.250	91928.792

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 9: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0025*	-0.0049***	-0.0059***	-0.0076***
	[0.0012]	[0.0004]	[0.0004]	[0.0004]
Total Pollen x Pleasanton	0.0003	0.0059***	0.0056***	0.0053***
	[0.0015]	[0.0005]	[0.0005]	[0.0004]
Total Pollen x San Jose	-0.0018	0.0033***	0.0007	0.0035***
	[0.0014]	[0.0004]	[0.0004]	[0.0004]
Pleasanton	0.0038	-0.0107***	0.0197***	0.0107*
	[0.0064]	[0.0019]	[0.0059]	[0.0053]
San Jose	0.0246***	-0.0005	0.0335***	0.0279***
	[0.0062]	[0.0019]	[0.0052]	[0.0047]
Revenuejt	0.0323***	0.0049***	0.0127***	-0.0012
	[0.0014]	[0.0004]	[0.0007]	[0.0007]
N	93674	93674	93674	93674
r2	0.008	0.903	0.904	0.921
F	119.084	.	.	.
ll	-10784.468	98077.945	98568.636	107512.896

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 10: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0114**	-0.0066***	-0.0052***	-0.0065***
	[0.0043]	[0.0010]	[0.0010]	[0.0011]
Total Pollen x Pleasanton	0.0063	0.0108***	0.0094***	0.0079***
	[0.0052]	[0.0011]	[0.0011]	[0.0012]
Total Pollen x San Jose	0.0139**	0.0078***	0.0053***	0.0056***
	[0.0047]	[0.0010]	[0.0011]	[0.0012]
Pleasanton	0.0507*	0.0312***	0.0210**	0.0047
	[0.0231]	[0.0047]	[0.0072]	[0.0070]
San Jose	0.0003	0.0417***	0.0402***	0.0208**
	[0.0222]	[0.0046]	[0.0067]	[0.0064]
Revenuejt	0.0499***	0.0014	0.0013	-0.0017
	[0.0041]	[0.0008]	[0.0014]	[0.0012]
N	11948	11948	11948	11948
r2	0.022	0.963	0.964	0.970
F	43.790	24306.276	5258.461	8754.388
ll	-2445.899	17138.820	17221.908	18449.073

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 11: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	-0.0097*	-0.0060***	-0.0047***	-0.0063***
	[0.0038]	[0.0009]	[0.0009]	[0.0010]
Total Pollen x Pleasanton	0.0047	0.0098***	0.0086***	0.0074***
	[0.0045]	[0.0010]	[0.0010]	[0.0010]
Total Pollen x San Jose	0.0118**	0.0070***	0.0047***	0.0053***
	[0.0041]	[0.0009]	[0.0009]	[0.0010]
Pleasanton	0.0671***	0.0354***	0.0232***	0.0070
	[0.0201]	[0.0041]	[0.0069]	[0.0066]
San Jose	0.0203	0.0452***	0.0417***	0.0216***
	[0.0192]	[0.0040]	[0.0064]	[0.0060]
Revenuejt	0.0525***	0.0018*	0.0007	-0.0014
	[0.0036]	[0.0007]	[0.0012]	[0.0010]
N	16163	16163	16163	16163
r2	0.026	0.963	0.963	0.970
F	67.465	32435.881	5477.744	8984.425
ll	-3365.424	23058.483	23173.301	24763.838

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 12: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(5)
Total Pollen	-0.0089*	-0.0056***	-0.0044***	-0.0061***
	[0.0035]	[0.0008]	[0.0008]	[0.0009]
Total Pollen x Pleasanton	0.0040	0.0093***	0.0082***	0.0071***
	[0.0041]	[0.0009]	[0.0009]	[0.0009]
Total Pollen x San Jose	0.0107**	0.0065***	0.0041***	0.0049***
	[0.0038]	[0.0008]	[0.0009]	[0.0009]
Pleasanton	0.0645***	0.0340***	0.0301***	0.0408***
	[0.0182]	[0.0037]	[0.0081]	[0.0085]
San Jose	0.0214	0.0463***	0.0775***	0.0814***
	[0.0177]	[0.0037]	[0.0084]	[0.0088]
Revenuejt	0.0537***	0.0025***	0.0012	-0.0010
	[0.0033]	[0.0007]	[0.0011]	[0.0010]
N	18995	18995	18995	18995
r2	0.024	0.963	0.963	0.970
F	75.552	37716.495	5632.533	9324.731
ll	-4023.064	26938.103	27106.792	28957.879

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 13: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0335***	0.0004	0.0001	-0.0007
	[0.0051]	[0.0010]	[0.0010]	[0.0009]
Total Pollen x Pleasanton	-0.0167*	0.0014	0.0018	0.0001
	[0.0068]	[0.0012]	[0.0012]	[0.0011]
Total Pollen x San Jose	-0.0327***	0.0017	0.0019	0.0007
	[0.0059]	[0.0011]	[0.0011]	[0.0009]
Pleasanton	0.1544***	0.0483***		
	[0.0325]	[0.0057]		
San Jose	0.1580***	-0.0024	0.0388***	0.0107
	[0.0299]	[0.0054]	[0.0110]	[0.0097]
Revenuejt	0.0184**	-0.0019	-0.0035	-0.0024
	[0.0059]	[0.0013]	[0.0019]	[0.0016]
N	8087	8087	8087	8087
r2	0.022	0.955	0.956	0.969
F	29.568	20102.413	4132.282	7034.968
ll	-2624.209	9853.473	9904.647	11273.664

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 14: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0310***	0.0004	0.0010	-0.0004
	[0.0043]	[0.0008]	[0.0008]	[0.0007]
Total Pollen x Pleasanton	-0.0146*	0.0015	0.0018	0.0002
	[0.0058]	[0.0010]	[0.0010]	[0.0009]
Total Pollen x San Jose	-0.0264***	0.0012	0.0017	0.0007
	[0.0049]	[0.0009]	[0.0009]	[0.0008]
Pleasanton	0.1384***	0.0473***	0.0522***	0.0748***
	[0.0277]	[0.0048]	[0.0088]	[0.0081]
San Jose	0.1190***	0.0029	0.0024	0.0195**
	[0.0246]	[0.0043]	[0.0081]	[0.0067]
Revenuejt	0.0282***	-0.0006	-0.0056***	-0.0030*
	[0.0051]	[0.0011]	[0.0016]	[0.0013]
N	11238	11238	11238	11238
r2	0.022	0.957	0.958	0.970
F	43.325	28927.255	4507.724	7899.960
ll	-3731.553	13798.958	13918.203	15838.448

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 15: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen	0.0318***	0.0002	0.0012	-0.0003
	[0.0039]	[0.0007]	[0.0007]	[0.0007]
Total Pollen x Pleasanton	-0.0210***	0.0014	0.0013	-0.0001
	[0.0052]	[0.0009]	[0.0009]	[0.0008]
Total Pollen x San Jose	-0.0277***	0.0012	0.0013	0.0007
	[0.0045]	[0.0008]	[0.0008]	[0.0007]
Pleasanton	0.1788***	0.0408***	0.0247*	-0.0061
	[0.0243]	[0.0042]	[0.0110]	[0.0091]
San Jose	0.1296***	0.0011	0.0398***	0.0106
	[0.0228]	[0.0040]	[0.0106]	[0.0094]
Revenuejt	0.0261***	0.0023*	-0.0052***	-0.0031*
	[0.0047]	[0.0010]	[0.0015]	[0.0012]
N	13115	13115	13115	13115
r2	0.024	0.957	0.958	0.970
F	54.745	33402.508	4544.223	8100.396
ll	-4242.193	16174.598	16398.655	18628.510

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 16: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0046**	-0.0042***	-0.0060***	-0.0059***
	[0.0014]	[0.0003]	[0.0003]	[0.0003]
Total Pollen (-1) x Pleasanton	-0.0018	0.0067***	0.0058***	0.0029***
	[0.0018]	[0.0003]	[0.0004]	[0.0003]
Total Pollen (-1) x San Jose	-0.0035*	0.0026***	-0.0000	0.0024***
	[0.0017]	[0.0003]	[0.0003]	[0.0003]
Pleasanton	0.0222**	0.0013	-0.0035	-0.0077
	[0.0081]	[0.0016]	[238.3163]	[197.0014]
San Jose	0.0359***	0.0125***	0.0009	-0.0122
	[0.0080]	[0.0017]	[227.2392]	[204.5524]
Revenuejt	0.0734***	0.0080***	0.0235***	0.0077***
	[0.0016]	[0.0003]	[0.0006]	[0.0005]
N	208133	208133	208133	208133
r2	0.013	0.959	0.959	0.967
F	439.195	169943.768	.	.
ll	-1.320e+05	198712.370	200106.015	221906.544

Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 17: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(5)
Total Pollen (-1)	0.0044***	-0.0039***	-0.0058***	-0.0067***
	[0.0012]	[0.0002]	[0.0003]	[0.0002]
Total Pollen (-1) x Pleasanton	-0.0010	0.0065***	0.0059***	0.0036***
	[0.0016]	[0.0003]	[0.0003]	[0.0003]
Total Pollen (-1) x San Jose	-0.0032*	0.0024***	0.0000	0.0033***
	[0.0014]	[0.0003]	[0.0003]	[0.0003]
Pleasanton	0.0221**	0.0006		
	[0.0069]	[0.0014]		
San Jose	0.0372***	0.0112***	0.0264	0.0043
	[0.0066]	[0.0014]	[.]	[59.0770]
Revenuejt	0.0744***	0.0079***	0.0219***	0.0082***
	[0.0014]	[0.0003]	[0.0005]	[0.0004]
N	282326	282326	282326	282326
r2	0.013	0.959	0.960	0.967
F	616.908	239362.837	.	.
ll	-1.789e+05	270698.755	272409.502	302074.059

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 18: Reduced Form Model with Treatment and Control (OLS). Category: All Allergy Drugs. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0045***	-0.0035***	-0.0055***	-0.0068***
	[0.0011]	[0.0002]	[0.0002]	[0.0002]
Total Pollen (-1) x Pleasanton	-0.0022	0.0059***	0.0055***	0.0035***
	[0.0014]	[0.0003]	[0.0003]	[0.0002]
Total Pollen (-1) x San Jose	-0.0036**	0.0020***	-0.0003	0.0034***
	[0.0013]	[0.0003]	[0.0003]	[0.0002]
Pleasanton	0.0251***	0.0015	1.9137***	1.8988***
	[0.0061]	[0.0012]	[0.0067]	[0.0078]
San Jose	0.0427***	0.0123***	1.9187***	1.8916***
	[0.0062]	[0.0013]	[0.0067]	[0.0078]
Revenuejt	0.0761***	0.0087***	0.0226***	0.0087***
	[0.0013]	[0.0003]	[0.0004]	[0.0004]
N	329914	329914	329914	329914
r2	0.014	0.958	0.959	0.967
F	756.108	282791.066	161371.513	265074.570
ll	-2.075e+05	314819.204	316821.373	352251.801

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 19: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0014	-0.0033***	-0.0055***	-0.0049***
	[0.0020]	[0.0004]	[0.0004]	[0.0004]
Total Pollen (-1) x Pleasanton	-0.0004	0.0061***	0.0051***	0.0018***
	[0.0025]	[0.0005]	[0.0005]	[0.0004]
Total Pollen (-1) x San Jose	0.0016	0.0022***	-0.0004	0.0022***
	[0.0023]	[0.0004]	[0.0005]	[0.0004]
Pleasanton	0.0239*	0.0044*		
	[0.0113]	[0.0022]		
San Jose	0.0215	0.0123***	-0.0157	-0.0540
	[0.0112]	[0.0022]	[.]	[152.3021]
Revenuejt	0.0845***	0.0094***	0.0274***	0.0102***
	[0.0021]	[0.0004]	[0.0007]	[0.0006]
N	137445	137445	137445	137445
r2	0.013	0.962	0.963	0.970
F	296.434	246574.814	.	.
ll	-1.012e+05	123111.427	124153.621	139918.671

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 20: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0014	-0.0030***	-0.0054***	-0.0058***
	[0.0017]	[0.0003]	[0.0003]	[0.0003]
Total Pollen (-1) x Pleasanton	0.0003	0.0060***	0.0054***	0.0027***
	[0.0021]	[0.0004]	[0.0004]	[0.0003]
Total Pollen (-1) x San Jose	0.0016	0.0021***	-0.0003	0.0032***
	[0.0019]	[0.0004]	[0.0004]	[0.0003]
Pleasanton	0.0240*	0.0029	1.8993***	1.8825***
	[0.0097]	[0.0019]	[0.0085]	[0.0103]
San Jose	0.0252**	0.0105***	1.8985***	1.8671***
	[0.0093]	[0.0018]	[0.0086]	[0.0104]
Revenuejt	0.0844***	0.0093***	0.0258***	0.0109***
	[0.0019]	[0.0004]	[0.0006]	[0.0005]
N	186079	186079	186079	186079
r2	0.013	0.963	0.963	0.971
F	402.680	343028.620	164028.643	238416.007
ll	-1.369e+05	167536.030	168834.594	190249.373

Robust standard errors in brackets.
$* p < 0.05, ** p < 0.01, *** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 21: Reduced Form Model with Treatment and Control (OLS). Category: Adult. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0013	-0.0025***	-0.0051***	-0.0059***
	[0.0015]	[0.0003]	[0.0003]	[0.0003]
Total Pollen (-1) x Pleasanton	-0.0008	0.0052***	0.0049***	0.0026***
	[0.0019]	[0.0004]	[0.0004]	[0.0003]
Total Pollen (-1) x San Jose	0.0008	0.0015***	-0.0007*	0.0033***
	[0.0018]	[0.0003]	[0.0004]	[0.0003]
Pleasanton	0.0239**	0.0042*	-0.0452	-0.0260
	[0.0086]	[0.0017]	[177.8316]	[219.3797]
San Jose	0.0329***	0.0122***	-0.0438	-0.0332
	[0.0087]	[0.0017]	[199.6084]	[211.0554]
Revenuejt	0.0876***	0.0102***	0.0267***	0.0116***
	[0.0017]	[0.0003]	[0.0006]	[0.0005]
N	217603	217603	217603	217603
r2	0.014	0.962	0.962	0.970
F	507.577	417402.591	.	.
ll	-1.591e+05	194431.825	195941.270	221655.787

Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 22: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0017	-0.0057***	-0.0073***	-0.0080***
	[0.0017]	[0.0005]	[0.0006]	[0.0005]
Total Pollen (-1) x Pleasanton	0.0013	0.0061***	0.0055***	0.0037***
	[0.0022]	[0.0006]	[0.0006]	[0.0006]
Total Pollen (-1) x San Jose	-0.0025	0.0020**	-0.0009	0.0019***
	[0.0020]	[0.0006]	[0.0006]	[0.0006]
Pleasanton	-0.0091	-0.0100***		
	[0.0090]	[0.0027]		
San Jose	0.0244**	0.0108***	0.0232***	0.0190***
	[0.0091]	[0.0028]	[0.0047]	[0.0042]
Revenuejt	0.0308***	0.0065***	0.0194***	0.0031***
	[0.0019]	[0.0006]	[0.0010]	[0.0009]
N	52762	52762	52762	52762
r2	0.006	0.905	0.906	0.922
F	55.817	74783.311	27063.137	62573.708
ll	-6614.334	55186.432	55583.204	60482.247

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 23: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0027	-0.0055***	-0.0070***	-0.0086***
	[0.0014]	[0.0004]	[0.0005]	[0.0004]
Total Pollen (-1) x Pleasanton	0.0004	0.0058***	0.0054***	0.0041***
	[0.0018]	[0.0005]	[0.0005]	[0.0005]
Total Pollen (-1) x San Jose	-0.0039*	0.0019***	-0.0009	0.0027***
	[0.0016]	[0.0005]	[0.0005]	[0.0005]
Pleasanton	-0.0012	-0.0096***	0.0176*	0.0137*
	[0.0076]	[0.0023]	[0.0069]	[0.0061]
San Jose	0.0327***	0.0092***	0.0405***	0.0328***
	[0.0075]	[0.0023]	[0.0063]	[0.0056]
Revenuejt	0.0317***	0.0062***	0.0178***	0.0034***
	[0.0016]	[0.0005]	[0.0009]	[0.0008]
N	71743	71743	71743	71743
r2	0.007	0.904	0.906	0.922
F	83.061	109441.633	32715.595	72198.537
ll	-8808.003	75151.929	75658.204	82380.152

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 24: Reduced Form Model with Treatment and Control (OLS). Category: Pediatric. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0027*	-0.0051***	-0.0067***	-0.0085***
	[0.0013]	[0.0004]	[0.0004]	[0.0004]
Total Pollen (-1) x Pleasanton	-0.0001	0.0054***	0.0052***	0.0040***
	[0.0017]	[0.0005]	[0.0005]	[0.0004]
Total Pollen (-1) x San Jose	-0.0036*	0.0016***	-0.0012*	0.0027***
	[0.0015]	[0.0005]	[0.0005]	[0.0004]
Pleasanton	0.0033	-0.0086***	0.0181**	0.0165**
	[0.0069]	[0.0020]	[0.0066]	[0.0059]
San Jose	0.0309***	0.0098***	0.0420***	0.0326***
	[0.0070]	[0.0022]	[0.0062]	[0.0056]
Revenuejt	0.0314***	0.0064***	0.0179***	0.0034***
	[0.0015]	[0.0005]	[0.0008]	[0.0007]
N	83561	83561	83561	83561
r2	0.007	0.904	0.905	0.922
F	93.434	131498.232	35682.263	77518.874
ll	-9916.482	87703.629	88290.572	96220.598

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 25: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0099*	-0.0063***	-0.0054***	-0.0065***
	[0.0046]	[0.0010]	[0.0011]	[0.0012]
Total Pollen (-1) x Pleasanton	0.0064	0.0119***	0.0106***	0.0077***
	[0.0055]	[0.0011]	[0.0012]	[0.0013]
Total Pollen (-1) x San Jose	0.0133**	0.0069***	0.0049***	0.0055***
	[0.0051]	[0.0011]	[0.0012]	[0.0012]
Pleasanton	0.0480	0.0242***		
	[0.0251]	[0.0050]		
San Jose	0.0003	0.0462***	0.0214**	0.0125*
	[0.0247]	[0.0051]	[0.0075]	[0.0064]
Revenuejt	0.0495***	0.0026**	0.0043**	0.0002
	[0.0044]	[0.0008]	[0.0015]	[0.0014]
N	10724	10724	10724	10724
r2	0.022	0.964	0.964	0.971
F	37.956	22209.317	4803.308	8056.765
ll	-2232.030	15430.741	15499.042	16568.624

Robust standard errors in brackets.
$* p < 0.05, ** p < 0.01, *** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 26: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0104*	-0.0061***	-0.0052***	-0.0068***
	[0.0041]	[0.0009]	[0.0010]	[0.0011]
Total Pollen (-1) x Pleasanton	0.0065	0.0113***	0.0102***	0.0078***
	[0.0049]	[0.0010]	[0.0010]	[0.0011]
Total Pollen (-1) x San Jose	0.0135**	0.0065***	0.0047***	0.0057***
	[0.0045]	[0.0010]	[0.0010]	[0.0011]
Pleasanton	0.0576**	0.0267***	0.0226**	0.0104
	[0.0219]	[0.0044]	[0.0073]	[0.0071]
San Jose	0.0106	0.0477***	0.0433***	0.0219***
	[0.0214]	[0.0044]	[0.0067]	[0.0063]
Revenuejt	0.0528***	0.0031***	0.0038**	0.0006
	[0.0039]	[0.0008]	[0.0013]	[0.0012]
N	14499	14499	14499	14499
r2	0.025	0.963	0.964	0.970
F	59.525	29590.603	4990.973	8209.855
ll	-3070.394	20737.097	20828.645	22209.131

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 27: Reduced Form Model with Treatment and Control (OLS). Category: General Eye Care. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	-0.0105**	-0.0060***	-0.0052***	-0.0070***
	[0.0037]	[0.0008]	[0.0009]	[0.0010]
Total Pollen (-1) x Pleasanton	0.0073	0.0109***	0.0099***	0.0076***
	[0.0044]	[0.0009]	[0.0009]	[0.0010]
Total Pollen (-1) x San Jose	0.0135**	0.0062***	0.0044***	0.0056***
	[0.0041]	[0.0009]	[0.0009]	[0.0010]
Pleasanton	0.0485*	0.0253***	0.0238**	0.0401***
	[0.0197]	[0.0040]	[0.0087]	[0.0091]
San Jose	0.0062	0.0481***	0.0744***	0.0776***
	[0.0196]	[0.0040]	[0.0090]	[0.0094]
Revenuejt	0.0544***	0.0039***	0.0046***	0.0014
	[0.0036]	[0.0007]	[0.0012]	[0.0011]
N	17057	17057	17057	17057
r2	0.024	0.963	0.964	0.970
F	66.861	34496.994	5136.021	8541.634
ll	-3674.033	24254.111	24386.989	26001.409

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 28: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0334***	0.0002	-0.0002	-0.0003
	[0.0055]	[0.0011]	[0.0011]	[0.0010]
Total Pollen (-1) x Pleasanton	-0.0165*	0.0025	0.0029*	-0.0006
	[0.0072]	[0.0013]	[0.0013]	[0.0012]
Total Pollen (-1) x San Jose	-0.0320***	0.0007	0.0013	-0.0000
	[0.0064]	[0.0012]	[0.0012]	[0.0010]
Pleasanton	0.1442***	0.0437***		
	[0.0349]	[0.0061]		
San Jose	0.1456***	0.0054	-0.0434***	-0.0558***
	[0.0329]	[0.0059]	[0.0089]	[0.0080]
Revenuejt	0.0155*	-0.0002	-0.0005	-0.0030
	[0.0063]	[0.0013]	[0.0022]	[0.0018]
N	7202	7202	7202	7202
r2	0.019	0.955	0.955	0.968
F	23.464	17825.909	3694.153	6541.667
ll	-2361.072	8710.059	8753.741	9977.166

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=10 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 29: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0296***	0.0005	0.0008	-0.0003
	[0.0046]	[0.0009]	[0.0009]	[0.0008]
Total Pollen (-1) x Pleasanton	-0.0125*	0.0021	0.0023*	-0.0005
	[0.0062]	[0.0011]	[0.0011]	[0.0010]
Total Pollen (-1) x San Jose	-0.0245***	-0.0000	0.0009	0.0001
	[0.0053]	[0.0010]	[0.0010]	[0.0009]
Pleasanton	0.1224***	0.0452***	0.0497***	0.0785***
	[0.0297]	[0.0051]	[0.0095]	[0.0088]
San Jose	0.1036***	0.0113*	0.0055	0.0222**
	[0.0271]	[0.0048]	[0.0086]	[0.0072]
Revenuejt	0.0248***	0.0011	-0.0023	-0.0027
	[0.0055]	[0.0012]	[0.0018]	[0.0015]
N	10005	10005	10005	10005
r2	0.019	0.956	0.957	0.969
F	33.527	25641.628	4002.343	7257.089
ll	-3345.564	12188.001	12281.359	13975.098

Robust standard errors in brackets.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=15 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.

Table A 30: Reduced Form Model with Treatment and Control (OLS). Category: Nasal. Dependent Variable: price of product i at store j on week t.

	(1)	(2)	(3)	(4)
Total Pollen (-1)	0.0300***	0.0002	0.0008	-0.0006
	[0.0042]	[0.0008]	[0.0008]	[0.0007]
Total Pollen (-1) x Pleasanton	-0.0174**	0.0024*	0.0022*	-0.0006
	[0.0055]	[0.0010]	[0.0010]	[0.0009]
Total Pollen (-1) x San Jose	-0.0255***	0.0002	0.0007	0.0003
	[0.0049]	[0.0009]	[0.0009]	[0.0008]
Pleasanton	0.1565***	0.0370***	0.0228*	-0.0051
	[0.0262]	[0.0046]	[0.0116]	[0.0096]
San Jose	0.1133***	0.0086*	0.0433***	0.0123
	[0.0253]	[0.0044]	[0.0113]	[0.0100]
Revenuejt	0.0225***	0.0040***	-0.0018	-0.0025
	[0.0050]	[0.0010]	[0.0017]	[0.0014]
N	11693	11693	11693	11693
r2	0.021	0.956	0.957	0.969
F	42.244	29517.635	4017.643	7401.283
ll	-3798.031	14301.898	14479.104	16441.170

Robust standard errors in brackets.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$
All variables in log form.
(2): UPC Fixed Effects
(3): UPC and store fixed effects
(4): UPC and store fixed effects and quadratic trend
Prices are deflated by cpi.
Lagged total pollen count per cubic meter of air at the nearest (<=20 Km) counting station.
Treatment: stores which have closest pollen count in Pleasanton and San Jose.
Total revenue of allergy drugs in store j and week t.