Faculdade de Economia,
Administração e Contabilidade
de Ribeirão Preto
Universidade de São Paulo

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Dynamic Price Competition in Allergy Pharmaceutical Markets

Prof. Dr. Renato Seixas

Av. Bandeirantes, 3900 - Monte Alegre - CEP: 14040-905 - Ribeirão Preto - SP
Fone (16) 3315-3884 - e-mail: posgrad@fearp.usp.br site: www.fearp.usp.br

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Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto
Avenida dos Bandeirantes,3900
14040-905 Ribeirão Preto – SP

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Dynamic Price Competition in Allergy Pharmaceutical Markets

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Renato Seixas*

This paper studies the behavior of mark-up for antihistaminic medicines, used as a treatment for allergy symptoms caused by seasonal high concentration of pollen 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.

Keywords: Dynamic Price Competition, Cyclical Demand, Oligopoly, Allergy Drugs

* Postdoctoral Research Fellow at FEA-RP/USP. (rnlseixas@usp.br). 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.

1 Introduction

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-industry studies in the industrial organization literature.

In this paper 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: in the northern hemisphere, 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. We 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.

My results show that profit margins respond positively to expected demand in cities with high levels and high variation of pollen concentration. The magnitudes of the coefficients are

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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.

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 paper 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 paper 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.

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]

[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 (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 p^m. This result is known in the literature as *tacit collusion*, in the sense that the collusive result (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

[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).

shown that, for some range of the discount parameter, collusion ($p_i = p_m$) 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 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. 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

[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.

at 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, we 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, we 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).

I check for the comparability of the two groups of stores, by looking 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 we can see 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

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

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 we 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 – 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. We 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 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, that 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).

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:

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

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.

5. Results

Tables 4 – 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].

[8] Results for other distances (10 km, 15 km and 20 km) are qualitatively similar and are available upon request.

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. We 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 $Pollen \times Pleasanton$ and $Pollen \times San\, Jose$ 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 different specifications. We 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, we take the statistical significance and the sign of the coefficients of interst 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:

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

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). We 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. We take this as an indication of robustness of our estimates and of the conclusions of the empirical exercise.

6. Conclusion

In this paper 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 paper 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.

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Tables and Figures

Figure 1: Dynamics of Margins with Cyclical Demand

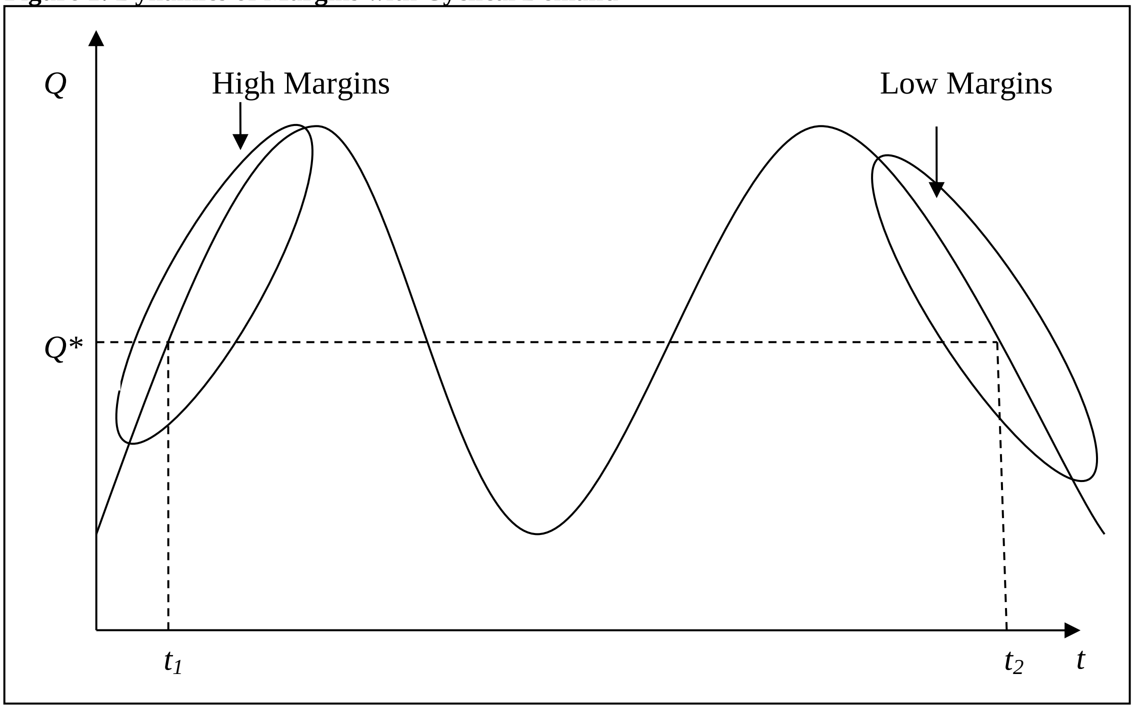

Figure 2

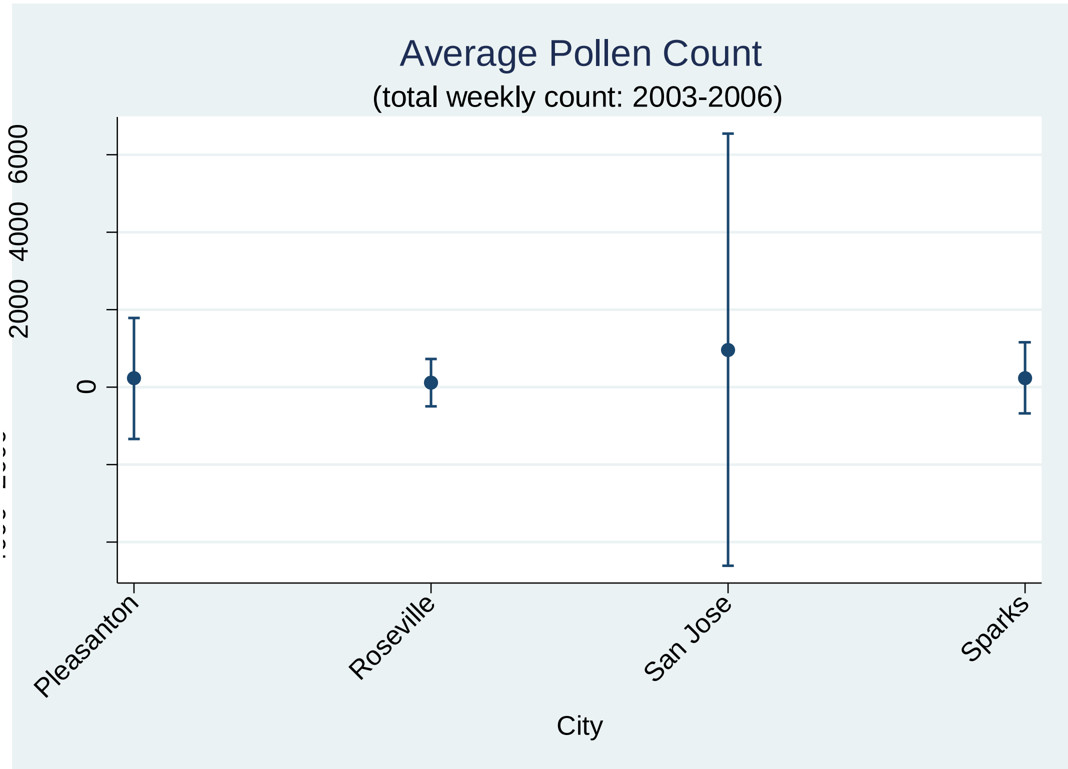

Figure 3

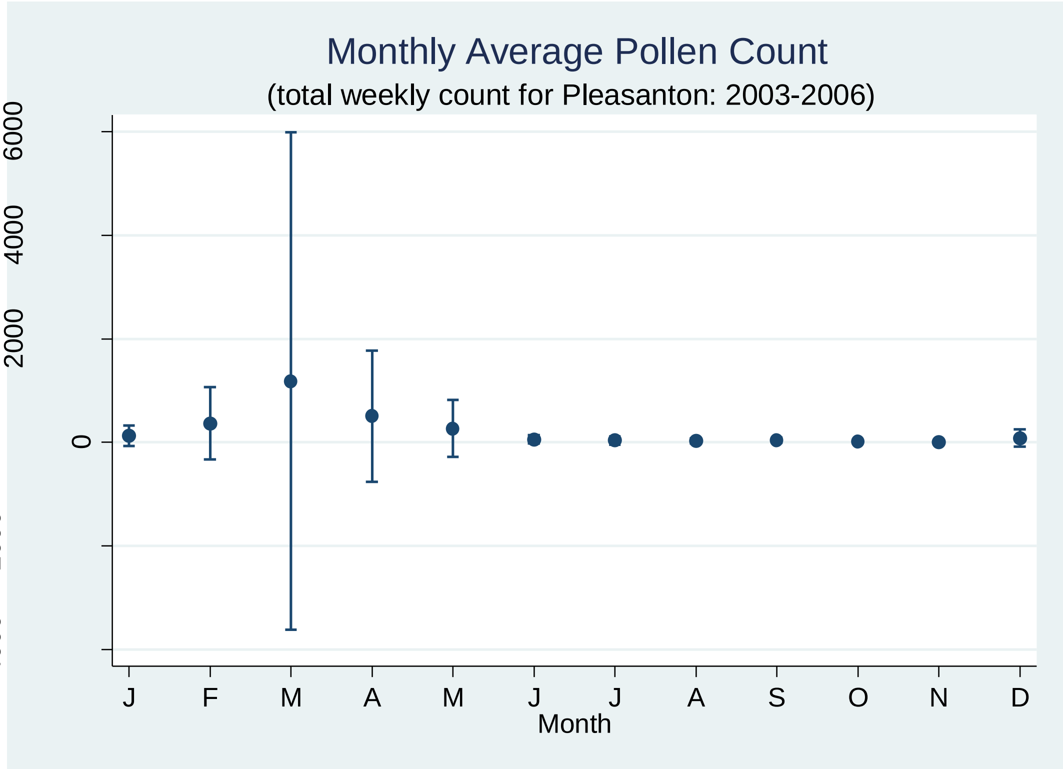

Figure 4

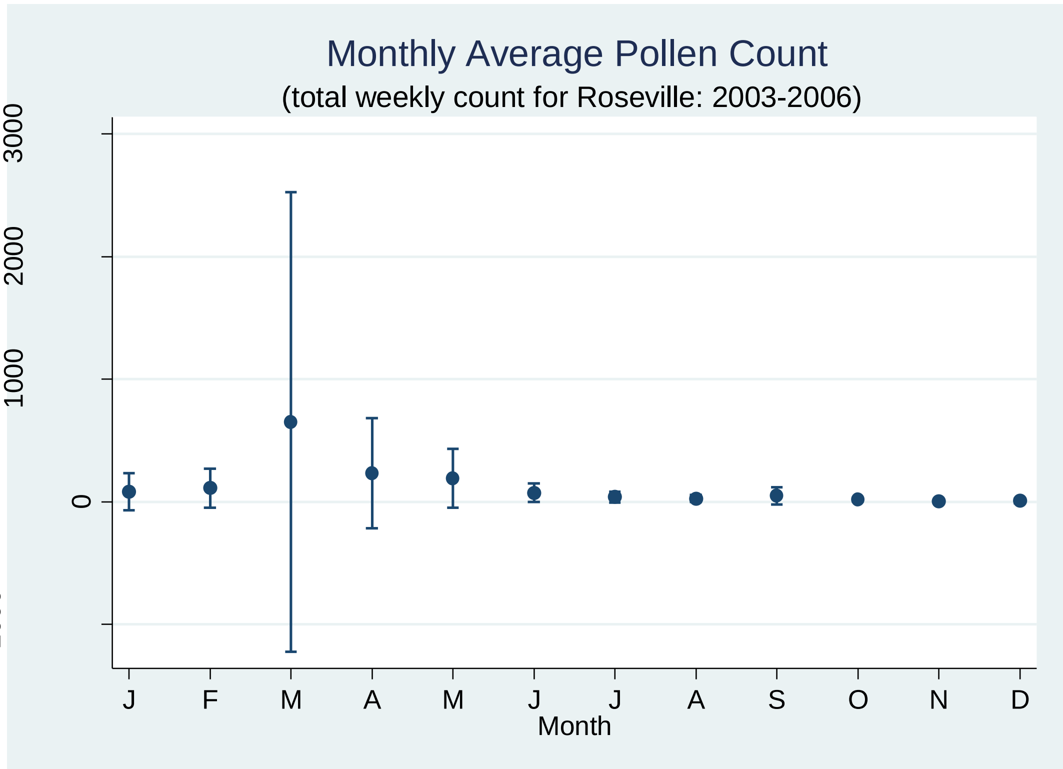

Figure 5

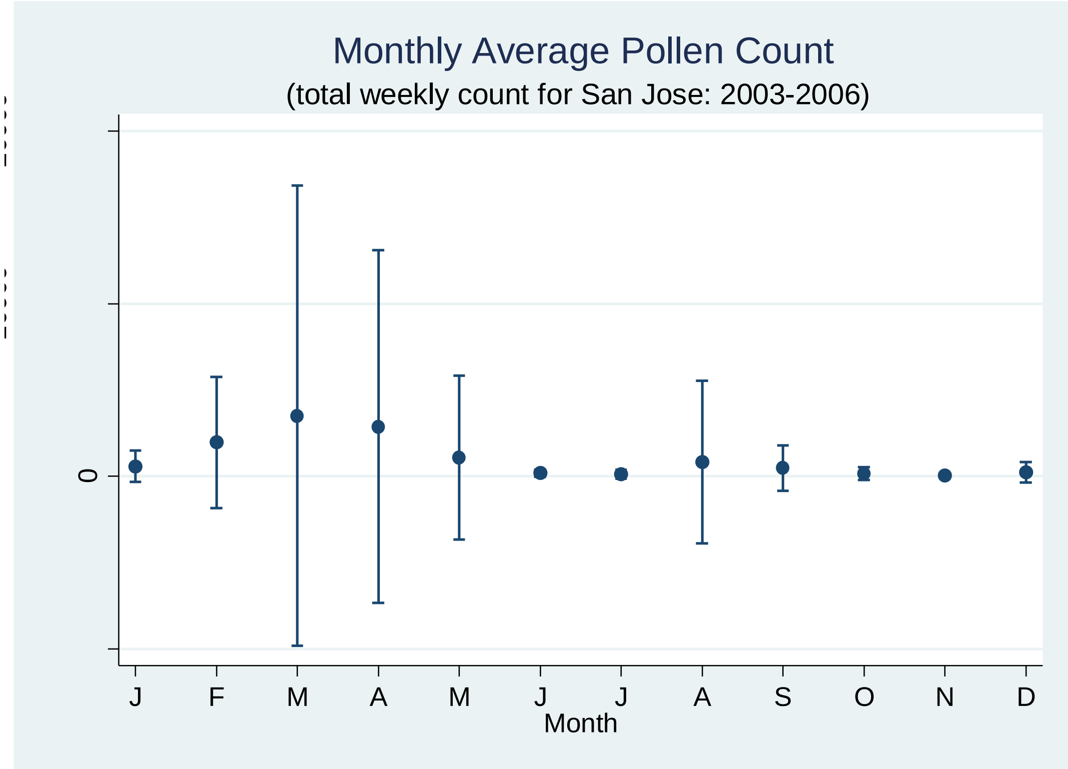

Figure 6

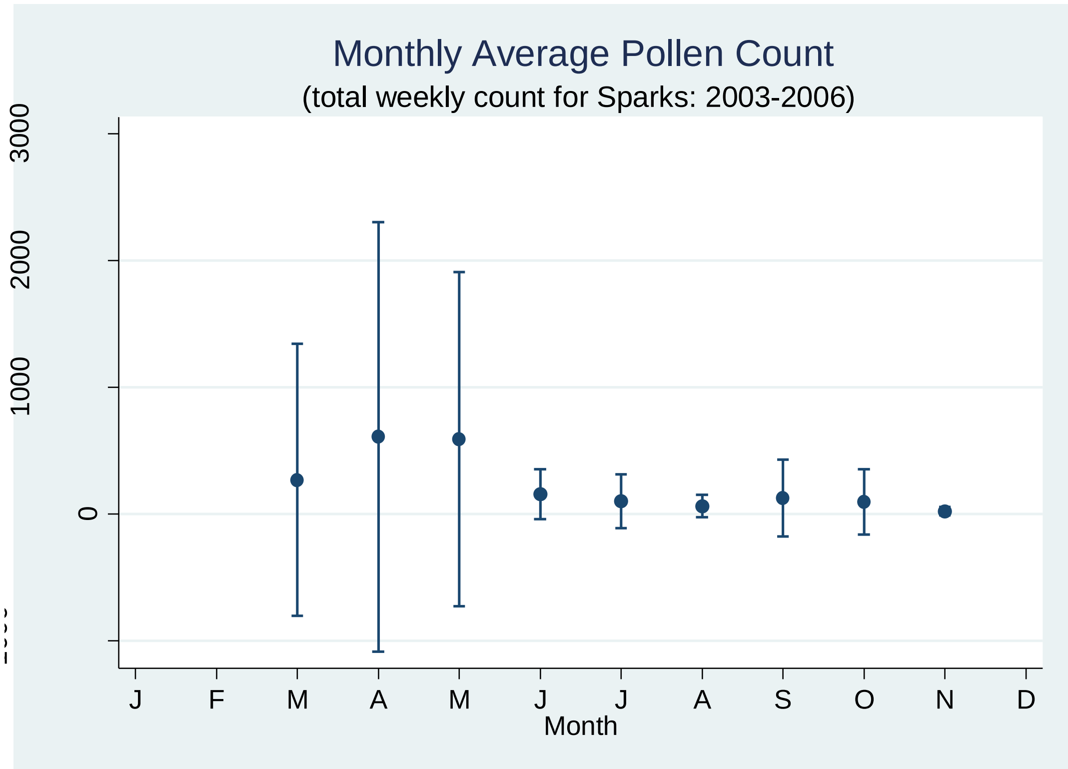

Figure 7: Average Daily Sales

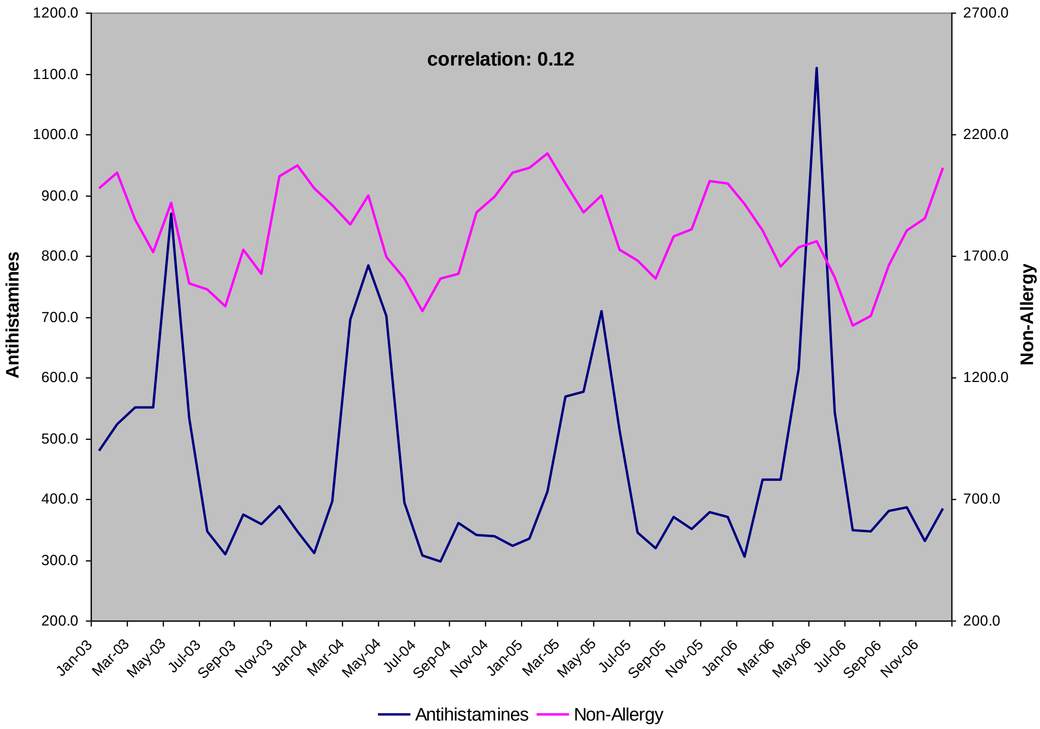

Figure 8: Average Monthly Price

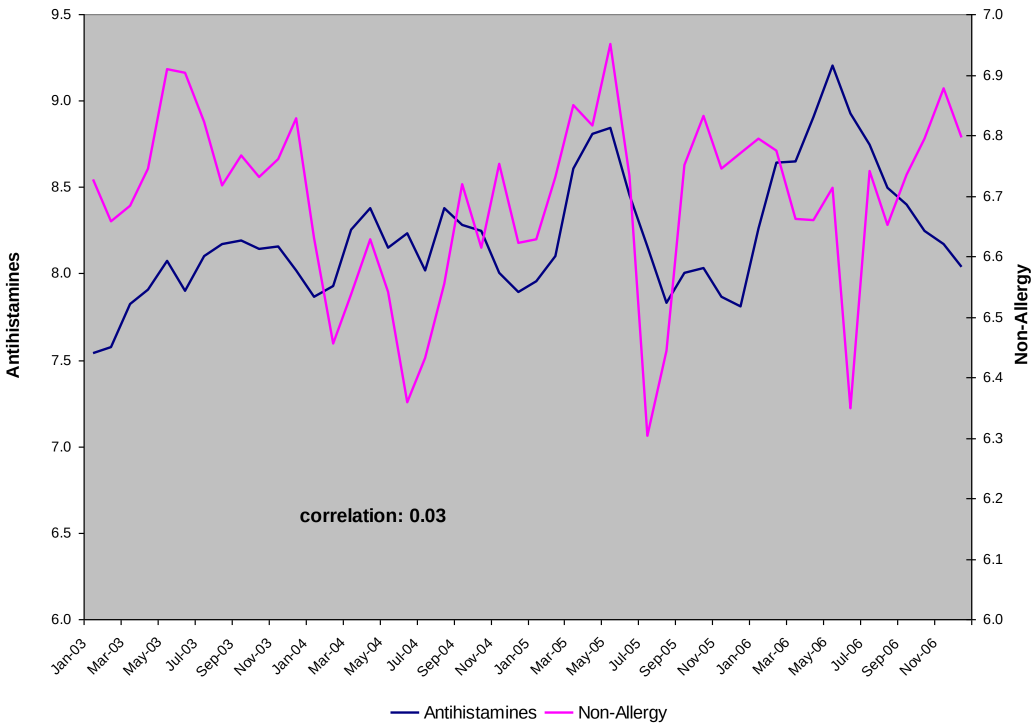

Table 1: Average Distance (Km) Between Stores (rows) and Pollen Count Stations (columns)

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 2: 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/m^3).

Table 3: 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 4: 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 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	-0.0051*	-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 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 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)	(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 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 (-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.