NORTHWESTERN UNIVERSITY

Internet-based Firms Entering Offline Channels: Empirical Models & Analysis

A DISSERTATION

SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

for the degree

DOCTOR OF PHILOSOPHY

Field of Marketing

By

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EVANSTON, ILLINOIS

June 2008

ABSTRACT

Internet-based Firms Entering Offline Channels: Empirical Models & Analysis

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This dissertation consists of three empirical essays on issues related to Internet-based firms entering the offline channel. Issues arising from offline entry include the potential spillovers in online revenue, online customer acquisition, and online customer activity. Over the past decade, there has been considerable research examining brick & mortar companies entering the online channel. The maturation of the Internet industry has led to several established online-based firms that have opened physical stores.

The first essay of the dissertation investigates the impact of an online e-commerce marketplace provider opening physical stores. The focus is on the spillover effects with respect to online seller revenue, online seller acquisition, and online seller activity. The analysis finds store entry leads to a positive revenue spillover, however store entry cannibalizes new online sellers as well as online seller listings. The positive online revenue spillover may be due to the relative rise in the average selling price of products sold online in regions with store entry.

The focus of the second essay is on the role of offline store entry on online consumer purchase behavior; in particular, the spillover effects with respect to online buyer revenue, online buyer acquisition, and online bidding activity. The analysis finds store entry engenders positive online buyer sales and positive online buyer acquisition spillover. The analysis also finds a positive spillover for the average price of products purchased online in regions with store entry. The increase in average sales price for products purchased may be explained by both a change in the assortment of products being purchased and an increase in the price expectation for products sold through the firm.

The third essay extends the study of the relationship between the study of product quality and market size to an Internet setting. Additionally, the empirical essay examines the link between firm specialization and market size, as well as product quality, in an Internet setting. The results indicate that similar to other settings, there is a positive relationship between market size and market concentration. However, unlike previous studies, there is an overall negative link between market size and product quality. The analysis also finds that the level of firm specialization diminishes with increases in market size, but there is a positive link between the level of firm specialization and the product quality of firms. The product quality findings of the study may be explained by the partially hidden nature of quality in this setting.

Acknowledgements

I would like to thank all of those who have made the last five years at Northwestern a truly wonderful experience.

First, I would like to thank my advisor, Professor Dipak C. Jain, for his guidance and feedback during this process. Professor Jain's insights and philosophy on research have been invaluable. I am forever indebted to my other committee members: Shane Greenstein, Eric Anderson, and Karsten Hansen. They have been tremendously generous with their time and expertise. Without the support and encouragement of my committee, the process of completing a dissertation would have been unbearable and impossible.

I would like to thank my family. Thank you to my father, for his advice and guidance while I trained for the family profession. Thank you to my mother, for her encouragement, and her eternal optimism on all facets of life. Finally, I would like to thank my brother, Aashish, for his humor, and his reminders that there is a world outside academia.

I have been extremely fortunate to have a large cohort of Marketing graduate students. I would like to thank them for their support and encouragement during this process. Special thanks to Jeffrey Shulman, Sandeep Conoor, Federico Rossi, Kanishka Misra, Derek Pai, Ryan Hamilton, and Breagin Riley. I would also like to thank my cohort for the new expressions I have learned in Italian, Mandarin, Polish, Hindi, and Tamil while at Northwestern.

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CHAPTER 1

Introduction

The maturation of the Internet industry has led to several established online-based firms that have opened physical stores. Examples of firms entering the offline channel include online services firms (financial, e-commerce) as well as online retailers. This dissertation focuses on issues related to Internet-based firms entering the offline channel. Issues arising from offline entry include the potential spillovers in online revenue, online customer acquisition, and online customer activity. Additionally, the opening of physical stores raises questions regarding market size, product quality, and firm specialization.

Over the past decade, there has been considerable research examining factors that influence online purchasing by consumers (Peterson, Balasubramanian, and Bronnenberg 1997; Swaminathan, Lepkowska-White, and Rao 1999; DeRuyter, Moorman, and Lemmink 2001). However, there is no research examining the effect that a firm entering the offline channel has on customer online purchasing behavior. Offline entry might influence online purchase behavior through increasing firm brand awareness and increasing consumer trust.

In addition to spillovers on online purchasing behavior, there is a lack of research examining offline entry spillover on online service adoption. E-commerce firms represent one of the types of online services that are entering the offline channel. These firms may enter the offline channel to exploit heterogeneity across customer preferences or overcome the lack of interpersonal trust online. This entry may lead to market expansion or cannibalization of sales.

The first essay provides an empirical analysis of the impact of an online e-commerce marketplace provider opening physical offline stores. The focus is on the spillover effects with respect to online seller revenue, online seller acquisition, and online seller activity. The study uses a novel data set from an online e-commerce marketplace provider, eBay, with offline store-level data, as well as five-digit zip code level sales, seller acquisition, and seller listing observations. Propensity scoring methods from biostatistics are adopted to control for the endogeneity of store entry. While there is a positive seller revenue spillover into the online channel resulting from offline entry, the finding is not driven by increased online seller acquisition or increased existing online seller activity that might be expected. Rather, the positive revenue spillover can be linked to a positive change in the average selling price of items sold by the online channel sellers in regions with offline store entry.

The implications of this essay are manifold. The research underscores the importance of analyzing spillover beyond the effect on revenue. By examining metrics other than revenue in this high new customer growth market, the analysis finds that the entry of stores has a negative effect on new online sellers in regions with offline store entry. The finding of a positive average selling price spillover raises the question: is this increase due to a change in the assortment of products sold or in a change of selling ability?

The focus of the second essay is on the role of offline store entry on online consumers purchase behavior. In particular, the spillover effects with respect to online buyer revenue, online buyer acquisition, and online bidding activity. The same store-level eBay data as in the first essay is used. However, this study employs five-digit zip code level sales, buyer acquisition, and buyer bidding observations. A similar methodology as the first essay is used to control for the endogeneity of store entry.

While there is positive buyer revenue spillover into the online channel resulting from offline entry, the finding is not driven by increased online new buyer acquisition or an increased number of products purchased that might be expected. Rather, the positive revenue spillover can be linked to a positive change in the average selling price of items purchased by the online channel customers in regions with offline entry. The results also indicate a positive initial spillover in new buyer acquisition. The study does not find any significant online spillover with respect to online bids (purchase activity).

The third essay extends the study of the relationship between product quality and market size to an Internet setting. Additionally, the empirical essay examines the link between firm specialization and market size, as well as product quality, in an Internet setting. Empirical examination of the relationship between product quality and market size was popularized by Berry and Waldfogel (2003). In addition to the recent interest in product quality and market size, there has also been empirical work relating firm specialization and market size (Garicano and Hubbard 2007); that finds firms become more specialized as the market size increases. The study uses store-level eBay data that includes the specific products listed and sold by the stores, the sales price, as well as the average online feedback ratings (product quality) for the offline stores.

The study finds that market concentration increases with market size, however, there does not seem to be a lower bound to the market share of the largest store in the market. Also, the study finds a negative relationship between firm quality and market size. Furthermore, increases in market size seem to grow both the number of high and low quality stores in the market. Finally, firm specialization is examined, and a negative relationship between the degree of firm specialization and market size, and a positive relationship between the degree of firm specialization and product quality is discovered. There are several possible explanations for these empirical findings. It is possible that the process through which consumers discover product quality may be partially responsible for the negative relationship between product quality and market size, as well as the negative relationship between firm specialization and market size. Also, unobserved advertising by stores may be influencing these empirical observations.

Together, all three of these essays help to enrich the literature regarding offline entry by Internet-based firms. The effect of offline entry on the existing online business is examined for both product & services type firms as well as online-retailing type firms. Furthermore, the nature of competition in the offline channel and its implication on product quality is described in the dissertation. The introduction of these issues arising from offline entry in this dissertation engenders several novel areas for additional research that are described in section 5.3.

CHAPTER 2

Channel Spillovers from Offline Entry: A Seller Analysis

2.1. Introduction

> *For web companies to succeed, they're going to have to establish brand attributes that are tangible.* - Jeffrey Mallet, ex-President & COO, Yahoo! Inc. (Weintraub 2000)

> *When they see it, even if they are just driving by, people feel like it's a real company.* - Michael Curcio, EVP, e*Trade (Milbourn 2004)

Over the past decade, there has been considerable research examining brick & mortar companies entering the online channel (Gulati and Garino 2000; Geyskens, Gielens, and Dekimpe 2002; Deleersnyder et al. 2002; Zettelmeyer 2000). These studies have primarily been focused on retailers seeking to enter an additional distribution channel. The online channel has been dissected with respect to *cannibalization* of sales (Balasubramanian 1998; Fox, Montgomery, and Lodish 2006; Deleersnyder et al. 2002), and its ability for *market expansion*; i.e. attracting new sales (Alba et al. 1997; Shankar, Smith, and Rangaswamy 2003). The research examining entry into the brick & mortar channel, however, is limited (Avery et al. 2007).

The maturation of the Internet industry has led to several established online-based firms that have opened physical stores. This phenomenon leads to several interesting questions regarding the reasons a firm enters the brick & mortar channel, and the impact of this additional channel. This chapter examines the consequences of an Internet-based firm entering the offline channel. The study seeks to determine the effect of offline entry on online firm revenue, customer acquisition, and customer behavior.

The motivations for a firm to establish a "brick experience" are manifold. Some of the reasons may overlap with rationale used by brick & mortar firms to go online: *brand credibility* (Gulati and Garino 2000), exploiting *heterogeneity* across customers (Alba et al. 1997) and across purchase occasions (Shankar, Smith, and Rangaswamy 2003). Internet firms may be trying to overcome the lack of *interpersonal trust* online (Lim et al. 2006), or attempting some type of *status differentiation* (Grewal, Iyer, and Levy 2004) by creating a brick experience. These reasons are not limited to just Internet-based firms. Non-traditional retailer firms such as Apple and Gateway have also had tremendously successful and unsuccessful entries, respectively, into the offline channel.

The studies of moving from "bricks to clicks" have mostly been limited to traditional retailers in mature industries such as groceries and apparel; however firms setting up a brick experience seem to be quite diverse. For example there are online-trading service providers such as DLJ Direct and e*Trade that have opened brick & mortar stores. Travel engine Travelocity has established "Travelocity on Location" kiosks. The diversity and novelty of these industries introduces a new set of metrics for analysis. These firms with "new" products or services are deeply concerned with customer acquisition, customer quality, and product usage, as well as revenue.

In this chapter, a novel dataset from an online e-commerce marketplace provider, eBay[1], is used to study the spillover in terms of revenue, customer acquisition, and product

[1]This essay was not created in conjunction with eBay and the views expressed in this chapter are solely those of the author and do not in any way reflect the views of eBay.

use by online sellers over time that results from entry into the brick & mortar channel. The research objective is to understand market growth or cannibalization that results from entry into the brick & mortar channel. This phenomenon is examined over time, and the focus is not just on the effect on revenue, but also online seller acquisition, product usage, and average selling price.

Empirical results indicate that store entry results in a positive spillover in terms of revenue from sellers. However, the increase in revenue is not due to an increase in the number of sellers. In fact, store entry results in a cannibalization of sellers; that is, there is negative spillover with respect to seller acquisition in zip-codes with stores. The positive revenue spillover is also not the result of increased product usage. The study finds that total product listings in a region are also negatively impacted by store entry. The increase in revenue may be caused by an increase in average selling price of products listed in regions where there is store entry.

The results also indicate that the positive effect of store entry on online revenue and the negative effect of store entry on online seller acquisition spillover do not diminish over time. However, the positive effect of offline entry on average selling price and the negative effect on product usage do diminish over time.

This research makes both substantive and methodological contributions, in addition to being the first to comprehensively study an Internet-based firm both prior to and after its entry into the brick & mortar channel. First, is the use of a novel dataset to examine spillover not just from the revenue perspective, but also using metrics that are important in emerging markets. Use of metrics such as marketplace listings and new customer acquisition gives us a deeper understanding of the impact of entering the offline channel.

The second contribution is the use of a novel methodology from the biometrics literature that is employed to control for the endogeneity of store entry into a region: Inverse Probability of Treatment Weighted (IPTW) estimation (Robins 1997; Hernan, Brumback, and Robins 2001) to control for the selection bias related to store openings in certain regions. IPTW estimation generalizes propensity score matching to situations where the treatment (store entry) is staggered over time. The IPTW propensity scoring method is combined with a difference-in-differences fixed effects model to discern the impact of store entry.

The remainder of this chapter is organized as follows. In ∮ 2.1.1, some previous research in channel evaluation is reviewed. In ∮ 2.2, a formal model is presented for identifying the online spillover resulting from offline entry in a field-based study, while accounting for the endogeneity related to store openings. In ∮ 2.3, the methods used to estimate the model are discussed. The data set is introduced in ∮ 2.4. The findings from the model estimation are presented in ∮ 2.5 and the essay concludes in ∮ 2.5.3 & ∮ 2.6 with a review of the findings, limitations and opportunities for future work.

2.1.1. Conceptual Background

The existing literature provides evidence for the entry in the brick & mortar channel leading to either positive or negative spillover in the online channel. The key factor in determining the direction of the spillover is the relative strengths of substitution and complementarity between the channels. In this section, the literature related to substitution and complementarity with respect to multi-channel strategies is reviewed.

Both substitution and complementarity across the channels can be linked to heterogeneity across consumers. For example, multiple studies show that consumers are heterogeneous in their use of channels across purchase occasions (Shankar, Smith, and Rangaswamy 2003) and stages of the buying process (Frambach, Roest, and Krishnan 2007). There is also heterogeneity across customers for their channel preferences (Alba et al. 1997). Neslin et al. (2006) provide a survey of the literature regarding the determinants of channel selection. Finally, since the study is examining web-based firms which provide new services like e-commerce, the literature on new product adoption is also applicable. Chatterjee and Eliashberg (1990) describe customers as heterogeneous with respect to the amount of information they need to reduce the perceived uncertainty surrounding the true quality of a new product. The entry into the offline channel is a mechanism for providing information to customers regarding the firm's product.

The relative extent of substitution and complementarity will depend on the overlap of the two channels across the dimensions of heterogeneity described above. Greater overlap will favor substitution across the channels. Previous studies have empirically demonstrated this cannibalization across the online and offline channels (Deleersnyder et al. 2002; Fox, Montgomery, and Lodish 2006).

The goal in this essay is to examine which of these two forces has a greater effect across various dimensions of customer metrics such as revenue, acquisition, and activity.

2.2. Model

The primary goal of this essay is to study the impact of the presence of brick and mortar stores on the overall non-store seller activity of an Internet-based firm. Essentially, the spillover effects from the offline channel to the online channel with respect to sales and seller acquisition is of primary interest. Since the entry of stores into particular locations is not randomized, the use of non-experimental methods to control for entry endogeneity is necessary. In this section, the empirical model and strategy for controlling for factors that could bias the findings is presented.

2.2.1. Difference-in-Differences Model for Seller Spillover

If the presence of a store in an area i at time t is considered to be analogous to a treatment ($S_{i,t}$), then a difference-in-differences (DID) estimator can be used to analyze the impact of physical stores on online seller activity. Let $Y_{i,t}$ be the outcome of interest, for example, non-store based revenues or new monthly customers for an Internet firm in area i at time t.

Let $S_{i,t} = 1$ if there is a store present in area i for $t' \leq t$, (*Treatment Group*)

otherwise,

let $S_{i,t} = 0$. (*Control Group*)

Then the basic DID framework (Ashenfelter and Card 1985) supposes that the outcome variable is generated by a components of variance process:

$$Y_{i,t} = \delta(t) + \alpha S_{i,t} + \eta(i) + \xi_{i,t} \tag{2.1}$$

where α is the impact of store presence, $\delta(t)$ is a time-specific component, $\eta(i)$ is an area-specific component, and $\xi_{i,t}$ is an individual transitory shock that is mean zero. Only $Y_{i,t}$ and $S_{i,t}$ are observed; thus in order to identify α it must be assumed that selection for treatment does not depend on the area-transitory shocks; e.g., one period advertising spend by eBay in a region. Thus, it is assumed

$$P(\xi_{i,t}|S_{i,t}) = 0 \tag{2.2}$$

Equation (2.2) implies that in the absence of new store entry, the average outcome for areas with store entry (treatment group) and no store entry (control group) would have followed parallel paths over time. However, unlike traditional experiments where treatment and control groups are based on random assignment, here the creation of treatment and control groups (areas with and without stores) is not randomized. There may be certain market factors (i.e. area population and area income) which affect both the entry of stores into an area and the subsequent outcome of interest (customer behavior) in the area.

2.2.2. Endogeneity of Entry

Non-experimental data often suffers from the endogeneity of the treatment of interest (Meyer 1995; Besley and Case 2000). In the model, the entry of a store into an area i may be influenced by the population, income, or other unobserved factors in the area that also affect the customer behavior outcomes. Failure to account for the endogeneity of entry can lead to biased treatment effects (Heckman 1978). A common method to control for the endogeneity of treatment is instrumental variables (IV) (Heckman 1978; Heckman 1979; Meyer 1995). However, it is difficult to identify powerful instruments for store entry. Therefore, in lieu of IVs, matching methods, such as the Propensity Score Estimator, are employed that can be used to transform the non-experimental data into quasi-experimental data. The following two sections provide an explanation of the implemented matching methods.

2.2.2.1. Propensity Score Estimator. Propensity Scoring (Heckman, Ichimura, and Todd 1998) is a matching method that can weight store entry based on characteristics of the region. The goal of this method is to balance treated (regions with a store) and untreated (regions without a store) groups based on observed factors. Propensity Scoring Estimators are identified by relaxing assumption (2.2).

Assumption (2.2) can be considered too severe if treated and untreated areas are unbalanced in covariates, $X_{i,t}$, that are believed to be linked to the dynamics of the outcome variable, Y (Ashenfelter's dip, Ashenfelter (1978)). For example, consider a region in the San Francisco Bay Area (S_1) where there is store entry, and a region in Montana (S_2) where there is no store entry. Assume there is interest in the impact of store entry on the online sales (Y) in the region. Observed factors such as the population and income of the region ($X_{i,t}$) may influence both the entry of a store in a region and the level of online sales. Thus, a conditional identification restriction:

$$P(S_{i,t} = 1 | \xi_{i,t}, X_{i,t}) = P(S_{i,t} = 1 | X_{i,t}) \tag{2.3}$$

is useful in the DID framework when $X_{i,t}$ is believed to be related to the outcome dynamics (i.e. online revenue in a region over time), and their distributions differ between treated and control groups.

Now matching methods can be used that assume that conditional on the $X_{i,t}$'s, the observed outcome distribution of the units in the control group is the same as the outcome distribution of the treated units. Thus, in the example above, the region with a store in the Bay Area (S_1) would be compared with a control region that was similar in terms of observed factors such as population and income, not a region in Montana (S_2). The strong underlying assumption here is that there is no selection into treatment on the basis of unobservables. If there is matching on the basis of the covariates, the analysis is hindered by the curse of dimensionality; that is, it is difficult to match regions on multiple observed factors.

In order to deal with the issue of dimensionality, Rosenbaum and Rubin (1983) establish that if $P(x) = Pr(S_{i,t} = 1 | \ X_{i,t})$ and

$$0 < P(X) < 1 \tag{2.4}$$

then the conditional identification restriction can be:

$$P(S_{i,t} = 1 | \xi_{i,t}, P(X)) = P(S_{i,t} = 1 | P(X)) \tag{2.5}$$

Rosenbaum and Rubin refer to equations 2.4 and 2.5 together as a "strong ignorability" condition. This result is helpful in applications since it simplifies the matching of multiple dimensions problem to matching on a scalar. In the context of the example above, matching the Bay Area region with a store (S_1) with a control region can become difficult as there is an increase in the number of observed factors (i.e. population, income) that are being matched on. $P(X)$ is a function of the observed factors that gives a scalar value that represents the probability of store entry in a region, given the values for the observed factors in the region. Now one can just find a region with no store entry (control) that has a similar scalar $P(X)$ value to S_1, rather than match across multiple dimensions. Thus, one can construct a propensity score for treatment based on covariates, and create a sample of treated and untreated regions that lie on the common support of $P(X)$. One way to achieve this is to use a logit specification for $P(\widehat{X})$ (Gertler and Simcoe 2006).

2.2.2.2. Inverse Probability of Treatment Weighted estimation. While the propensity score matching model helps to solve the selection on observables problem, the phenomenon of store entry occurring in different regions at different times poses an additional complication. Researchers who typically use DID models generally study programs where the "before" and "after" periods can be easily defined for the control and treated regions. However, stores can enter at different times, and thus an untreated region may be a good control for a treated region in one time period, but a bad control for the same treated area in another time period.

In order to overcome the timing related issue, one can use a method from biostatistics, Inverse Probability of Treatment (IPTW) estimation (Hernan, Brumback, and Robins 2001; Azoulay, Ding, and Stuart 2006). The IPTW is an extension of propensity score matching techniques to time-varying treatments. IPTW estimation allows the recovery of average treatment effects in the presence of *time-varying confounders.*

Time-varying confounders, $Z_{i,t}$, are variables that predict treatment selection, are correlated with future values of the outcome variable, and are themselves predicted by past treatment history. Examples of $Z_{i,t}$ include store openings in adjoining regions and number of customers in a region.

If it is assumed that selection is based on observables, the bias created by *time-varying confounders* can be removed by weighting the regression by:

$$w_{i,t} = \frac{1}{\prod_{k=0}^{t} Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{Z_{i,k-1}}, \widetilde{X_{i,k}})} \tag{2.6}$$

where $\widetilde{Z_{i,k-1}}$ refers to the whole history of variable vector Z up to time $k-1$. Also, where $X_{i,t}$ are a set of exogenous, potentially time-varying covariates, and $\widetilde{X_{i,k}}$ refers to the whole history of variable vector X up to time k. The probability that a region followed its own treatment history up to time t is represented by the regression weight $w_{i,t}$.

When *time-varying confounders* are associated strongly with treatment, there can be tremendous variability in the regression weights. Thus Robins (1997) introduce a "stabilized" weight that does not influence the consistency of IPTW estimators, but does increase their efficiency. The stabilized weight, $W_{i,t}$ is defined as:

$$W_{i,t} = \prod_{k=0}^{t} \frac{Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{X_{i,k}})}{Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{Z_{i,k-1}}, \widetilde{X_{i,k}})} \tag{2.7}$$

Both regression weights are straightforward to estimate, and the estimation procedure is discussed in section 2.3.1.

IPTW estimation, while intuitive and relative simple to implement, has a few limitations. First, is the strong assumption of no unobserved confounding factors. Second, the causal effect estimated by these models in the average treatment effect over the entire population, not the effect of treatment on the treated.

Incorporating equation (2.7) into equation (2.1):

$$Y_{i,t} = \alpha_0 + \alpha_1 X_{i,t} + \alpha_2 W_{i,t} S_{i,t} + \eta(i) + \delta(t) + \xi_{i,t} \tag{2.8}$$

In the context of model (2.8), in addition to the issue of endogeneity, the estimation of the DID model is also subject to a potentially severe *serial correlation* problem. Bertrand, Duflo, and Mullainathan (2004) argue that three factors lead to the potential serial correlation problem in DID models. First, DID models typically use a fairly long time series. Second, the dependent variable in DID models is usually highly positively serially correlated. Finally, the treatment variable, $S_{i,t}$, changes infrequently within an area i over time. They present several techniques to correct for the serial correlation in DID models. The arbitrary variance-covariance matrix method, a technique that is shown to perform well when there are a large number of areas, i, in the study is employed; the technique is explained below.

2.2.3. Serial Correlation in DID Models

In order to deal with serial correlation, a variance-covariance matrix is estimated for equation (2.8) that is consistent in the presence of any correlation pattern within areas i over time periods t. It is difficult to consistently estimate each element of the variance-covariance matrix, but a generalized White-like formula is used to calculate the standard errors (White 1984; Kezdi 2002). The estimator for the variance-covariance matrix is defined as:

$$W = (V'V)^{-1}(\sum_{j=1}^{N} u_j' u_j)(V'V)^{-1} \tag{2.9}$$

where N is the total number of areas, V is the matrix of independent variables, and u_j is defined for each area to be:

$$u_j = \sum_{t=1}^{T} \upsilon_{j,t} k_{j,t} \tag{2.10}$$

where $\upsilon_{j,t}$ is the estimated residual for area i at time t and $k_{j,t}$ is a row vector of dependent variables. Kezdi (2002) demonstrates that the estimator of the variance-covariance matrix is consistent for fixed panel length as the number of areas tends to infinity.

In addition to accounting for serial correlation, there is another factor that needs to be considered before estimating equation (2.8); this factor is referred to as *neighborhood effects*. That is, the impact of store entry in one region on the behavior of customers and the probability of store entry in adjacent regions is incorporated in the analysis.

2.2.4. Neighborhood Effects

Consider two adjacent regions, i and j, and assume that a store opens in region j at time $t-1$. The presence of a store in j may lead to change in the conditional probability of a store opening in i (Bronnenberg and Mela 2004), that is:

$$P(S_{i,t} = 1 | S_{j,t-1} = 1) \neq P(S_{i,t} = 1 | S_{j,t-1} = 0) \tag{2.11}$$

Furthermore, consider an area, i, where store entry has not yet occurred; there is the possibility for customers in area i to hear about, observe, or use a store in the adjacent region j (Bell and Song 2004). Thus customer behavior in region i can be impacted by store entry in region j.

The effect of adjacent region store presence can enter the model both in equation (2.8) as the impact on customer behavior and in equation (2.6) as the impact on store entry. The additive effect of adjacent region activity in the two equations is introduced through $g(\cdot)$:

$$g_{i,t}(\cdot) = g(\{S_\upsilon(u)\}, \upsilon = 1, ..., \Upsilon_i; u = 1, ..., t-1) \tag{2.12}$$

where υ indexes the neighbors of focal region i and $g(\cdot)$ is a function of past store entry by these neighbors. In this essay, a model of contiguity relationships among regions is used and an equal weighting is assigned across neighbors in their influence on decision making in the focal region (Anselin 1988; Bell and Song 2004); that is $g(\cdot)$ is a weighted linear function. Using the estimation technique defined in Bell and Song (2004), $g_{i,t}(\cdot)$ results in a scalar variable bounded between zero and one.

2.3. Estimation

In order to properly estimate equation (2.8), the weights, $W_{i,t}$, must first be estimated. The overall equation can be estimated through a least-squares regression. In this section, the weights estimation is described in detail.

2.3.1. Weights Estimation

The presence of a physical store in a particular region could be considered a *flow* or a *regime* change (Azoulay, Ding, and Stuart 2006). If treatment is a flow, then it is not necessarily the case that the entry of a store has a lasting, constant impact on a region. A regime formulation, however, represents a one-time shift on the outcome of interest.

In a flow formulation of the treatments, the whole dataset is used to compute $W_{i,t}$. To compute the denominator of $W_{i,t}$ consider:

$$\hat{p}_{i,t} = logitprob(S_{i,t} = 1) = \eta_0 + \eta_1 S_{i,t-1} + \Phi(\widetilde{Z}_{i,t-1}, \eta_2) + \eta_3 X_{i,t} + \theta(t) \tag{2.13}$$

where δ_t are time effects, and $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is a parametric function of past values for time-varying confounders. If T_1 is the set of time periods where one observes the presence of a store in a region, and T_2 is the set of time periods when the presence of a store in a region is not observed, then the denominator of $W_{i,t}$ is defined as: $\prod_{t \in T_1} \hat{p}_{i,t} \prod_{t \in T_2} (1 - \hat{p}_{i,t})$.

To compute the numerator of $W_{i,t}$ in the flow formulation, the same procedure as the denominator is followed, but $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is excluded.

In a regime formulation of treatment, the probability of treatment is assumed to be equal to one after the time t when entry is first observed. Thus, only the subset of data for a region of before entry occurs is needed in order to estimate the weights. Now the denominator of $W_{i,t}$ is defined as:

$$\hat{p}_{i,t} = logitprob(S_{i,t} = 1) = \eta_0 + \Phi(\widetilde{Z}_{i,t-1}, \eta_2) + \eta_3 X_{i,t} + \theta t \tag{2.14}$$

and the numerator is once again the same except $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is excluded. Thus, the estimate of $W_{i,t}$ for region i in time t is $\prod_{k=0}^{t}(1 - \hat{p}_{i,k})$ if there is no entry by time t, and $\left[\prod_{k=0}^{t-1}(1 - \hat{p}_{i,k})\right] \hat{p}_{i,t}$ if entry in time t is observed. A similar method is used for the numerator.

2.4. Data

The data are drawn from two sources. First, the firm data come from an e-commerce Internet-based firm, eBay, that is starting to establish a brick & mortar presence. eBay provides an e-commerce marketplace where sellers can sell durable and non-durable goods. The second source of data is the 2000 United States Census.

2.4.1. eBay data

In this study, a novel dataset provided by eBay[2] is used. eBay has been an e-commerce platform since the late 1990s. Beginning in 2003, individuals in the United States were

[2] The financial data in this essay have been modified to preserve confidential information.

able to open franchise brick & mortar stores where customers could bring in goods for sale. These franchise stores sell the goods using eBay's e-commerce platform to buyers across the world. Applications to open a franchise store are available through the Internet.

There are three major firms that provide franchises across the United States. These firms have arms-length agreements with eBay such that eBay only provides the franchisers with limited marketing materials and the consent to use eBay's logo. Anecdotally, the majority of the advertising done by the franchisers is through the Internet, and is not targeted by geography. However, specific franchiser advertising is not observed. Technically, franchises provided by these three firms can be opened anywhere in the United States.

eBay also provides a directory of "Enablers" on its web-site. Enablers are customers that use the eBay e-commerce to sell goods belonging to other individuals. Enablers essentially perform a similar function as the franchise stores, except they do not have a brick and mortar presence. Rather, the Enablers typically pick-up the goods to be sold from the individual. Franchise stores create their revenue by retaining a percentage of the final sales price of the sold good. The percentage amount is based on a non-linear tiered pricing system.

eBay obtains its revenue by collecting transaction fees on goods sold using its e-commerce platform. In the dataset provided by eBay, franchise store, Enabler, and aggregate five-digit zip code level seller data on a quarterly basis are observed; starting in the second calendar quarter of 2000 and ending in the third calendar quarter of 2006.

Figure B.1 shows the locations of franchise stores in the United States using annual snapshots starting in 2003 and through the third calendar quarter of 2006. In Q3 2006, there are 489 stores in the United States. The revenue made by eBay from each store and the gross sales volume on a quarterly basis is observed. Also the total number of goods listed for sale by the franchise store and the number of goods successfully sold on a quarterly basis are observed. Table A.1 provides summary statistics at the franchise store level. These statistics are for Q3 2006, the last quarter in the dataset. The conversion rate is calculated by simply dividing the number of goods successfully sold by the total number of goods that were listed for sale.

The dataset also has eBay aggregate seller data at the five-digit zip code level. The aggregate data includes the franchise stores and the Enablers. Thus, the total quarterly revenue from sellers, quarterly total listings, and quarterly total successful listings in 23,163 zip codes are observed. Additionally, the number of new sellers that sell at least one good in each zip code on a quarterly basis is observed. Finally, the number of Enablers in each zip code on a quarterly basis is observed.

Figure B.4 plots the average revenue for eBay on a quarterly basis. Not surprisingly, for a growing Internet-based firm, the average quarterly revenue is increasing. Figure B.3 plots the quarter-over-quarter growth rate of the number of sellers. With the exception of two quarters, the growth rate is positive across the dataset time period.

In Table A.2, eBay sales, total listings, conversion rates, number of sellers, and number of Enablers in five-digit zip codes that have a franchise store in Q3 2006 are compared against five-digit zip codes that do not have a store. Zip codes that contain stores seem to have greater sales, listings, number of sellers, and number of Enablers. The conversion rates between the two groups seem similar.

2.4.2. Census data

The study takes advantage of having eBay data at the five-digit zip code level by merging it with five-digit zip code data available from the 2000 U.S. Census. While census tract data might be more optimal in terms of smaller, homogeneous, contiguous markets, the study is constrained by the eBay data being available only at the five-digit zip code level. The demographic data from the U.S. Census is only for the year 2000. It is recognized that there are demographic trends between 2000-2006 that are not being captured through the cross-sectional data.

Table A.2 manifests that zip codes that have franchise stores tend to have higher levels of median household income, educational attainment (college graduates), and overall population size. They also tend to be smaller in terms of land area. This is not surprising, as one would predict sales to be positively correlated with income and population size. Also, educational level has been shown to be positively correlated with new technology adoption, thus the demographic differences between zip codes with stores and without stores are to be expected.

2.5. Results & Discussion

All of the results incorporate the arbitrary variance-covariance matrix described in section (2.2.3) to correct for serial correlation. Furthermore, neighborhood effects as described in section (2.2.4) are included. The results are divided into two main sections. Table A.3 displays the factors associated with creating a balanced sample through "traditional" propensity scoring methods. Tables A.4-A.7 examine the results using the IPTW regime propensity scoring method. The results using the IPTW flow propensity scoring method are not presented because store closing is not observed in the data. Thus, once a store appears, it remains in the sample, which is theoretically congruous to the concept of a regime change. Propensity scores using the IPTW flow method were estimated, and the results were directionally equivalent to the regime method. The results using the "traditional" propensity scoring method are also not presented. These results are available upon request.

2.5.1. Traditional Propensity Score Results

Rosenbaum and Rubin (1983) show that matching on the basis of a propensity score, $\widehat{p(X)}$, is equivalent to matching them on the covariates X. Thus, one can construct a propensity score for treatment based on covariates, and create a sample of treated and untreated regions that lie on the common support of $P(X)$. To create the balanced sample the method used in Gertler and Simcoe (2006) is employed. A propensity score, $\widehat{P(X)}$, is created using eight covariates. Zip codes with no store entry (control) where there is no support for $\widehat{P(X)}$ in the propensity score distribution of area codes with store entry (treated) are eliminated. This is accomplished by trimming the top and bottom quartiles of the control $\widehat{P(X)}$ distribution. Now, when the mean covariate values for the treated and control sample are compared, it is not possible to reject the univariate t-tests of equality of means. Thus, the balanced sample is created by combining the control and treated zip codes that lie on the common support of $\widehat{P(X)}$.

Table A.3 manifests the covariates used to create the propensity score and the probability of entry using the full and balanced sample. The land area and education level in a region seem to have a clear impact on the entry decision of a store. Not surprisingly, there is a strong time trend that influences the store entry decision as well. Similar to the procedure in (Gertler and Simcoe 2006), the data is not re-weighted, but the DID model is estimated using the balanced sample data on the common support of $\widehat{P(X)}$.

2.5.2. IPTW Propensity Score Results

Tables A.4-A.7 examine the results using the IPTW regime propensity scoring method. In order to create the regime propensity score weights, the same covariates used in the traditional propensity score creation as the $X_{i,t}$ are used. Also, a set of time varying confounders, $\widetilde{Z}_{i,t-1}$, are introduced for the creation of the regime weights. The time varying confounders are one quarter lagged variables of metrics for the entire zip code, not just non-store values. Thus, the one-period lagged values of total zip-code revenue, total zip-code number of enablers, total zip-code number of listings, and existence of a store within 50 miles are used as the $\widetilde{Z}_{i,t-1}$. IPTW weights for the full sample are created and the full sample is used for an analysis similar to the one described in section (2.5.1).

Table A.4 presents the results from the DID model with fixed effects using the natural log of non-store quarterly revenue at the five digit zip code level as the dependent variable. The full sample with the IPTW regime propensity weights is used. The first column of results does not interact store entry into yearly effects, whereas the second column does. The parameter coefficients are presented with the 95% confidence interval beneath them. Store entry appears to have a significant positive effect of approximately 2% on the non-store revenue. The second column of results shows that the effect does not change over time. Using the IPTW method decreases the magnitude of the effect as compared to the traditional propensity score method, but the effect is still positive and significant.

Table A.5 performs a similar analysis using the natural log of quarterly new non-store cusotmers at the five digit zip code level as the dependent variable. Again, the results are directionaly the same as the traditional propensity scoring method, but the magnitude of the effect is reduced.

The IPTW regime weighted full sample is used to examine the effect of store entry on the natural log of quarterly total non-store listings at the zip code level. Table A.6 presents the results of the estimation. Store entry has a significant negative effect of approximately 2% on the listings. While the magnitude of the effect is similar to the traditional method, it is directionaly opposite. The second column of results show that the magnitude of the effect seems to be diminishing over time. Finally, Table A.7 shows a simliar analysis but employs the natural log of quarterly average selling price of products sold by non-store customers. Store entry seems to positively impact the average selling price (2%). The magnitude of the effects seems to diminish over time, as shown in column two of the results. Again, with respect to the natural log of quarterly average selling price of products sold by non-store customers, the magnitude of the impact of store entry is found to be similar to the traditional propensity score method, but directionaly opposite.

2.5.3. Discussion

There seems to be a positive seller revenue spillover that results from the entry of stores into the five-digit zip code market. This result is confirmed both by the traditional method of propensity scoring and the IPTW method. Previous literature would suggest that positive revenue spillover results from stores building brand awareness or increasing trust, thus bringing new customers into the existing online channel. However, even though the total number of customers in the zip codes is growing over time, a negative spillover is observed in terms of new seller acquisition and the number of non-store listings. Thus, the entry of a store in a particular region is impacting the online channel through a decrease in online customer growth and a decrease in product usage (listings).

The empirical analysis also seems to indicate an increase in the average selling price of items sold by online customers in regions with store entry. There are two factors that could be influencing the average selling price. First, there is a change in the mix of types of products being sold by the non-store customers. Second, non-store customers improve their abilities to price and sell products (Li, Srinivasan, and Sun 2005), thus garnering higher prices than prior to store entry for similar types of products. These sets of results on metrics other than just revenue help to provide a deeper understanding of the impact of store entry. In this section, potential interpretations of the results of treatment models are examined, and the managerial implications of the study are provided.

First, the negative spillover in non-store seller acquisition related to store entry is examined. A likely explanation of this phenomenon is that there is a strong substitution effect between the online and offline channel for new users. Thus, new customers who would have sold their items directly online, are going to the stores instead. The other potential effect is a combination of complementarity and brand spillover. These theories suggests that the introduction of stores will induce a new segment of customers to use the product either through the stores (complementarity), or through the online channel (spillover). Complementarity would also suggest that customers can be heterogeneous across purchase occasions in terms of the channel they employ (Shankar, Smith, and Rangaswamy 2003). Similarly, the stores could be an entry point for customers who are uncomfortable with new technologies, and who migrate to the online channel after using the stores. Given the data set, the number of customers that use the stores cannot be identified since only the sales of the stores are observed. Therefore, the overall number of sellers in a zip code may be positively impacted by the entry of a store, however only the aggregate non-store customers in a region are observed. In these regions, the substitution effect seems stronger than the brand spillover or migration of customers from stores to the online channel. The negative spillover in terms of non-store seller acquisition seems to be stable over time (Table A.5). The strength of the substitution effect may be partially attributed to the nature of the e-commerce marketplace industry. There is high growth is terms of the number of new users, and the stores may be capturing the segment of customer who would have used the product even in the absence of a store, but strictly prefer the brick & mortar shopping experience.

Next, the impact of store entry on customer activity is considered. A measure of customer activity is the number of products that are listed in the e-commerce marketplace. The number of non-store seller quarterly listings in a zip code is negatively correlated with the entry of a store in the zip code. One explanation is that the number of new customers decreases, as discussed above, and thus there are fewer total listings. Another possible factor is that existing users list certain items on their own and use the stores to sell other items. There is a strong negative correlation between total store listings in a region and total non-store listings. This is evidence of substitution of listings between the channels, however it is not possible to discern between the listings of new users that decide to enter through the offline channel and the expropriation of the listings of existing customers.

Finally, the effect of store entry on the types of products being sold in the e-commerce marketplace is studied. In Table A.7, positive spillover in terms of the average sales price (ASP) of products not sold through stores is observed. There are several possible explanations for the increase in ASP. First, the segment of customers that choose to use the stores tend to sell lower priced items. Second, customers that stay in the online channel are good at selling products online, and thus are able to command higher prices for products. If the ratio of ASP for products sold in stores is compared with the ASP for non-store products sold in the same zip code in the same quarter, it is found that $\mu_{asp} = 0.24$ ($std. = 0.43$). Assuming that store operators are skilled online sellers, this difference in ASP would provide some empirical evidence of lower priced items being sold through the stores.

An overview of the results demonstrates that there are several metrics in addition to seller revenue that are impacted by the entry of a store into a region, including seller activity, seller acquisition, and seller product type. While it is difficult to identify the singular impact of the relative forces driving the various types of spillover, it is possible to the discern the aggregate effect of these forces. Also, since it is observed that the level of total listings and number of new non-store customers is negatively impacted by the entry of a store, and the conversion rate of listings seems to be unaffected, it can be assumed that the positive revenue spillover is being driven by positive spillover on non-store seller ASP.

2.5.3.1. Managerial Implications. The managerial implications of this study are manifold. First, the research underscores the importance of analyzing spillover beyond the effect on revenue. By examining metrics other than revenue, it is noted that in this high new customer growth market, the entry of stores has a negative effect on new non-store customers in a zip-code. If these new sellers are entering through the stores instead of directly online, the firm needs to examine the risks of the brick experience. In the case of eBay, the stores are franchise stores that are not run by eBay. Thus, a negative brick experience is not under eBay's control. Also, given the cost structure of a firm, these customers could be less valuable.

In addition to the customer acquisition spillover, this study shows the importance of examining customer activity (listings) and type of activity (ASP). If stores are truly selling lower ASP products, than this provides firms with important information as to the types of customers and listings that not best served through the online channel. Firms can change their online product offering to account for these types of listings and the preferences of these customers.

Finally, the study shows that there may be transferable learnings from the offline channel to the online channel. If the ratio of conversion rates for products listed in stores is compared with the conversion rate for non-store products listed in the same zip code in the same quarter, it is discovered that $\mu_{conv} = 1.35$ ($std. = 0.94$). Stores are selective as to the types of products they elect to list and may also possess superior abilities to sell a product as compared to the non-store customers. If eBay studies the behavior of the store sellers, it may be able to share insights with its non-store customers to help with their listing and conversion skills.

2.6. Conclusion

This essay has examined the the impact of entering the brick & mortar channel on the existing online channel in terms seller revenue, seller acquisition, and the nature of seller activity. While there is positive revenue spillover into the online channel resulting from offline entry, the finding is not driven by increased online seller acquisition or increased existing online seller activity that might be expected. Rather, the positive revenue spillover can be linked to a positive change in the average selling price of items sold by the online channel customers. This study underscores the importance of analyzing metrics other than just revenue when determining the impact of entry into a new channel. The study also employs the IPTW propensity scoring method to control for the staggered entry over time of brick & mortar stores. This is a powerful methodology that has not been previous used when studying multi-channel problems. The methodology does have limitations, however. The assumption of selection through observables demands exhaustive use of covariates, and still does not preclude a bias resulting from an omission. Unfortunately, this bias is not testable in this framework.

There are at least two areas of promising future work. First, the entry decision could be modeled in a dynamic framework. This study would provide a deeper understanding of the factors that influence the forward-looking decision of a firm to enter a particular zip code market. Second, there is great potential for a study that employs cost data to model the nature of entry and to compare the relative values of online and store customers. By using cost data, eBay's decision to use a franchise approach to enter the offline market could be structurally modeled, and policy experiments on alternative methods of entry could be analyzed.

CHAPTER 3

Channel Spillovers from Offline Entry: A Buyer Analysis

3.1. Introduction

Over the past decade, there has been considerable research examining factors that influence online purchasing by consumers (Peterson, Balasubramanian, and Bronnenberg 1997; Swaminathan, Lepkowska-White, and Rao 1999; DeRuyter, Moorman, and Lemmink 2001). These studies have primarily been focused on pure play Internet firms (Haubl and Trifts 2000) or existing brick & mortar firms entering the online channel (Deleersnyder et al. 2002; Zettelmeyer 2000). However, there does not seem to be any research examining the effect of a firm entering the offline channel on customer online purchasing behavior.

The maturation of the Internet industry has led to several established online-based firms that have opened physical stores. This phenomenon leads to interesting questions regarding the reasons a firm enters the brick & mortar channel, and the impact of this additional channel. This chapter examines the consequences of an Internet-based firm entering the offline channel. Specifically, it seeks to determine the effect of offline entry on online purchase revenue, customer acquisition, and purchase behavior.

The antecedents for a customer to shop online are manifold. The motivations can broadly be grouped into consumer characteristics, website & product characteristics, and perceived characteristics of the Internet as a sales channel (Chang, Cheung, and Lai

2005). The research examining online shopping behavior has been limited to single channel Internet firms or to the overall impact of brick & mortar firms entering the online channel. Spillover effects across channels, however, have not been closely studied. Firms establishing a "brick experience" may influence online purchase behavior through influencing perceived characteristics of the Internet as a sales channel such as trust disposition (Moore et al. 1987) and perceptions of risk (Cox 1967). Furthermore, the creation of a brick experience could also influence consumer characteristics such as lack of familiarity with the medium, as well as low technology readiness (Parasuraman 2000). Finally, firm entry into a new channel such as the offline channel may create brand awareness (Gulati and Garino 2000) which can lead to an increase in the likelihood that the brand will be subsequently purchased (Hoyer and Brown 1990).

The studies of moving from "bricks to clicks" have mostly been limited to traditional retailers in mature industries such as groceries and apparel; however firms setting up a brick experience seem to be quite diverse. For example there are online-trading service providers such as DLJ Direct and e*Trade that have opened brick & mortar stores. Travel engine Travelocity has established "Travelocity on Location" kiosks. The diversity and novelty of these industries introduces a new set of metrics for analysis. These firms with "new" products or services are deeply concerned with customer acquisition, customer activity, as well as revenue.

In this chapter, a novel dataset from an online e-commerce marketplace provider, eBay[1], is used to study the online spillover in terms of buyer revenue, buyer acquisition, and purchase activity over time that results from entry into the brick & mortar channel.

[1]This essay was not created in conjunction with eBay and the views expressed in this chapter are solely those of the author and do not in any way reflect the views of eBay.

The research objective of the essay is to understand the influence of physical stores on online buyer behavior. This phenomenon is examined over time, and the focus is not just on the effect on purchase revenue, but also customer acquisition, purchase activity, and price expectation.

The findings indicate that store entry results in a positive spillover with respect to revenue in zip-codes with stores. This positive revenue spillover may be linked to a positive spillover in customer acquisition as well as a positive spillover in average sales price of products purchased online by buyers in zip-codes with stores. The entry of a physical store does not seem to effect the number of online bids (purchase activity) in a region. While there is a positive spillover in revenue, customer acquisition, and average sales price, there is also a slight negative spillover in the number of products sold online in a region with store entry near the end of the sampled time period. Possible explanations for this phenomenon are examined, including unobserved competitive effects.

The results also indicate that the positive spillover with respect to buyer acquisition is only manifested in the first year after initial store entry in the sample. The positive spillover with respect to revenue occurs in the second year after initial store entry in the sample, and then diminishes over time. The positive spillover with respect to average sales price begins in the second year after initial store entry in the sample, and seems to increase over time.

This research makes both substantive and methodological contributions, in addition to being the first to comprehensively study an Internet-based firm both prior to and after its entry into the brick & mortar channel. First, the novel dataset is used to examine online spillover not just from the revenue perspective, but also using metrics that are important in emerging markets. Use of metrics such as bidding activity, new customer acquisition, and average sales price of products purchased online provides a deeper understanding of the impact of entering the offline channel on the existing online channel.

The second contribution is the use of a novel methodology from the biometrics literature that is employed to control for the endogeneity of store entry into a region. Inverse Probability of Treatment Weighted (IPTW) estimation (Robins 1997; Hernan, Brumback, and Robins 2001) is used to control for the selection bias related to store openings in certain regions. IPTW estimation generalizes propensity score matching to situations where the treatment (store entry) is staggered over time. IPTW propensity scoring is combined with a difference-in-differences fixed effects model to discern the impact of store entry.

The remainder of this chapter is organized as follows. In $\oint$ 3.1.1, some previous research in online purchase antecedents and brand awareness is reviewed. In $\oint$ 3.2, a formal model for identifying the online spillover resulting from offline entry in a field-based study, while accounting for the endogeneity related to store openings is presented. In $\oint$ 3.3, the methods used to estimate the model are discussed. The data set is introduced in $\oint$ 3.4. The findings from the model estimation are presented in $\oint$ 3.5 and the essay concludes in $\oint$ 3.5.3 & $\oint$ 3.6 with a review of the findings, limitations and opportunities for future work.

3.1.1. Background Literature

Previous research on antecedents of online shopping adoption includes a few models of customer online purchase behavior. Ranaweera, McDougall, and Bansal (2005) present a theoretical model of online customer behavior where the focal construct is website satisfaction. In this theoretical model, the behavioral outcome of purchase likelihood is driven by dimensions of website quality as well as characteristics such as the technological readiness, trust disposition, and risk perceptions of customers. Schlosser, White, and Lloyd (2006) propose a model of converting website browsers into buyers and conclude that investments in website quality serve as a signal to consumers which can increase trust and consequently lead to a higher purchase likelihood. Chang, Cheung, and Lai (2005) identify major antecedent factors significant to online shopping and develop reference models of online shopping adoption. Trust disposition, perceived risk, and technological readiness are also antecedents of the usage of online shopping in their proposed reference model. Since these three factors may be influenced by the opening of physical stores, previous research in these areas is closely examined in this section. Also, previous research in brand awareness leading to an increase in purchase propensity is considered; as physical stores could be considered mechanisms to increase brand awareness.

Moore et al. (1987) manifested the moderating link between trust disposition and the buying behavior of consumers. Within an online setting, Kim and Prabhakar (2002) demonstrated through a survey study that only users that trust in the electronic channel as a transaction medium will adopt Internet banking. Trust can also increase the price expectation and willingness to pay of consumers, as demonstrated in lab experiments (Grewal et al. 2003). Jarvenpaa et al. (1999) posit that increasing the perceived size of a firm can increase the trust of consumers. The researchers recommend physical outlets for Internet firms as a mechanism for increasing the perceived size of the firm. In a proposed framework of online trust, Riegelsberger, Sasse, and McCarthy (2005) identify stable identity and social presence as factors that influence online trust. It is possible that entry into the offline channel can accrete a firms social presence and stable identity. Another factor that has been shown to influence initial and repeat surveyed online trust in perceived situational normality (Kong and Hung 2006).

Cox (1967) demonstrated the moderating link between consumers perception of risk and their buying behavior. In a survey study, Chang, Cheung, and Lai (2005) show that increased brand awareness can decrease perceived risk and increase purchase propensity. Physical stores may act as billboard-type advertisements for the firm. Previous lab research has also demonstrated that increased brand awareness can increase purchase likelihood (Hoyer and Brown 1990).

The opening of physical stores may result in some customers entering the stores and having having face to face interactions with firm representatives. Also, observing store signs may make some customers more familiar with the firm. Parasuraman (2000) demonstrates that lack of familiarity can decrease online purchase probability. Also, Grabner-Krauter and Kaluscha (2003) show that lack of face to face interactions can decrease the likelihood of purchase.

Empirical field studies with regards to trust and online purchase behavior are extremely limited. Teltzrow, Meyer, and Lenz (2007) conduct surveys in physical stores of an established European firm with both an online and offline presence. The survey results demonstrate that trust is an important factor in online purchase propensity for first-time customers and existing customers who are unfamiliar with Internet retailing.

3.2. Model

The primary goal of this essay is to study the impact of the presence of brick and mortar stores on the online buyer activity of an Internet-based firm. Essentially, the study is interested in the spillover effects from the offline channel to the online channel with respect to sales, customer acquisition, and customer behavior. Since the entry of stores into particular locations is not randomized, non-experimental methods must be used to control for entry endogeneity. In this section, the empirical model and strategy for controlling for factors that could bias the findings are presented.

3.2.1. Endogeneity of Entry in Buyer Analysis

The model uses a similar DID framework as the one presented in section 2.2.1. Non-experimental data often suffers from the endogeneity of the treatment of interest (Meyer 1995; Besley and Case 2000). In the model, the entry of a store into an area i may be influenced by the population, income, or other unobserved factors in the area that also affect the customer behavior outcomes. Failure to account for the endogeneity of entry can lead to biased treatment effects (Heckman 1978). A common method to control for the endogeneity of treatment is instrumental variables (IV) (Heckman 1978; Heckman 1979; Meyer 1995). However, it is difficult to identify powerful instruments for store entry. Therefore, in lieu of IVs, matching methods, such as the Propensity Score Estimator, are employed that can be used to transform the non-experimental data into quasi-experimental data. The following two sections provide an explanation of the implemented matching methods.

3.2.1.1. Propensity Score Estimator. Propensity Scoring (Heckman, Ichimura, and Todd 1998) is a matching method that can weight store entry based on characteristics of the region. The goal of this method is to balance treated (regions with a store) and untreated (regions without a store) groups based on observed factors. Propensity Scoring Estimators are identified by relaxing assumption (2.2).

Assumption (2.2) can be considered too severe if treated and untreated areas are unbalanced in covariates, $X_{i,t}$, that are believed to be linked to the dynamics of the outcome variable, Y (Ashenfelter's dip, Ashenfelter (1978)). For example, consider a region in the Bay Area (S_1) where there is store entry, and a region in Montana (S_2) where there is no store entry. Assume there is interest in the impact of store entry on the online sales (Y) in the region. Observed factors such as the population and income of the region ($X_{i,t}$) may influence both the entry of a store in a region and the level of online sales. Thus, a conditional identification restriction:

$$P(S_{i,t} = 1|\xi_{i,t}, X_{i,t}) = P(S_{i,t} = 1|X_{i,t}) \tag{3.1}$$

is useful in the DID framework when $X_{i,t}$ is believed to be related to the outcome dynamics (i.e. online revenue in a region over time), and their distributions differ between treated and control groups.

Now matching methods can be used that assume that conditional on the $X_{i,t}$'s, the observed outcome distribution of the units in the control group is the same as the outcome distribution of the treated units. Thus, in the example above, the region with a store in the Bay Area (S_1) would be compared with a control region that was similar in terms of observed factors such as population and income, not a region in Montana (S_2). The strong underlying assumption here is that there is no selection into treatment on the basis of unobservables. If there is matching on the basis of the covariates, the analysis is hindered by the curse of dimensionality; that is, it is difficult to match regions on multiple observed factors.

In order to deal with the issue of dimensionality, Rosenbaum and Rubin (1983) establish that if $P(x) = Pr(S_{i,t} = 1|\ X_{i,t})$ and

$$0 < P(X) < 1 \tag{3.2}$$

then the conditional identification restriction can be:

$$P(S_{i,t} = 1|\xi_{i,t}, P(X)) = P(S_{i,t} = 1|P(X)) \tag{3.3}$$

Rosenbaum and Rubin refer to equations 3.2 and 3.3 together as a "strong ignorability" condition. This result is helpful in applications since it simplifies the matching of multiple dimensions problem to matching on a scalar. In the context of the example above, matching the Bay Area region with a store (S_1) with a control region can become difficult as there is an increase in the number of observed factors (i.e. population, income) that are being matched on. $P(X)$ is a function of the observed factors that gives a scalar value that represents the probability of store entry in a region, given the values for the observed factors in the region. Now one can just find a region with no store entry (control) that has a similar scalar $P(X)$ value to S_1, rather than match across multiple dimensions. Thus, one can construct a propensity score for treatment based on covariates, and create a sample of treated and untreated regions that lie on the common support of $P(X)$. One way to achieve this is to use a logit specification for $P(\widehat{X})$ (Gertler and Simcoe 2006).

3.2.1.2. Inverse Probability of Treatment Weighted estimation. While the propensity score matching model helps to solve the selection on observables problem, the phenomenon of store entry occurring in different regions at different times poses an additional complication. Researchers who typically use DID models generally study programs where the "before" and "after" periods can be easily defined for the control and treated regions. However, stores can enter at different times, and thus an untreated region may be a good control for a treated region in one time period, but a bad control for the same treated area in another time period.

In order to overcome the timing related issue, one can use a method from biostatistics, Inverse Probability of Treatment (IPTW) estimation (Hernan, Brumback, and Robins 2001; Azoulay, Ding, and Stuart 2006). The IPTW is an extension of propensity score matching techniques to time-varying treatments. IPTW estimation allows the recovery of average treatment effects in the presence of *time-varying confounders.*

Time-varying confounders, $Z_{i,t}$, are variables that predict treatment selection, are correlated with future values of the outcome variable, and are themselves predicted by past treatment history. Examples of $Z_{i,t}$ include store openings in adjoining regions and number of customers in a region.

If it is assumed that selection is based on observables, the bias created by *time-varying confounders* can be removed by weighting the regression by:

$$w_{i,t} = \frac{1}{\prod_{k=0}^{t} Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{Z_{i,k-1}}, \widetilde{X_{i,k}})} \tag{3.4}$$

where $\widetilde{Z_{i,k-1}}$ refers to the whole history of variable vector Z up to time $k-1$. Also, where $X_{i,t}$ are a set of exogenous, potentially time-varying covariates, and $\widetilde{X_{i,k}}$ refers to the whole history of variable vector X up to time k. The probability that a region followed its own treatment history up to time t is represented by the regression weight $w_{i,t}$.

When *time-varying confounders* are associated strongly with treatment, there can be tremendous variability in the regression weights. Thus Robins (1997) introduce a "stabilized" weight that does not influence the consistency of IPTW estimators, but does increase their efficiency. The stabilized weight, $W_{i,t}$ is defined as:

$$W_{i,t} = \prod_{k=0}^{t} \frac{Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{X_{i,k}})}{Prob(S_{i,k} = s_{i,k} | \widetilde{S_{i,k-1}}, \widetilde{Z_{i,k-1}}, \widetilde{X_{i,k}})} \tag{3.5}$$

Both regression weights are straightforward to estimate, and the estimation procedure is discussed in section 3.3.1.

IPTW estimation, while intuitive and relative simple to implement, has a few limitations. First, is the strong assumption of no unobserved confounding factors. Second, the causal effect estimated by these models in the average treatment effect over the entire population, not the effect of treatment on the treated.

Incorporating equation (3.5) into equation (2.1):

$$Y_{i,t} = \alpha_0 + \alpha_1 X_{i,t} + \alpha_2 W_{i,t} S_{i,t} + \eta(i) + \delta(t) + \xi_{i,t} \tag{3.6}$$

In the context of model (2.8), in addition to the issue of endogeneity, the estimation of the DID model is also subject to a potentially severe *serial correlation* problem. Bertrand, Duflo, and Mullainathan (2004) argue that three factors lead to the potential serial correlation problem in DID models. First, DID models typically use a fairly long time series. Second, the dependent variable in DID models is usually highly positively serially correlated. Finally, the treatment variable, $S_{i,t}$, changes infrequently within an area i over time. They present several techniques to correct for the serial correlation in DID models. The arbitrary variance-covariance matrix method, a technique which is shown to perform well when there are a large number of areas, i, in the study is employed; the technique is explained below.

3.2.2. Serial Correlation in DID Models

In order to deal with serial correlation, a variance-covariance matrix is estimated for equation (3.6) that is consistent in the presence of any correlation pattern within areas i over time periods t. It is difficult to consistently estimate each element of the variance-covariance matrix, but a generalized White-like formula is used to calculate the standard errors (White 1984; Kezdi 2002). The estimator for the variance-covariance matrix is defined as:

$$W = (V'V)^{-1}(\sum_{j=1}^{N} u_j' u_j)(V'V)^{-1} \tag{3.7}$$

where N is the total number of areas, V is the matrix of independent variables, and u_j is defined for each area to be:

$$u_j = \sum_{t=1}^{T} \upsilon_{j,t} k_{j,t} \tag{3.8}$$

where $\upsilon_{j,t}$ is the estimated residual for area i at time t and $k_{j,t}$ is a row vector of dependent variables. Kezdi (2002) demonstrate that the estimator of the variance-covariance matrix is consistent for fixed panel length as the number of areas tends to infinity.

In addition to accounting for serial correlation, there is another factor that needs to be considered before estimating equation (2.8); this factor is referred to as *neighborhood effects*. That is, the impact of store entry in one region on the behavior of customers and the probability of store entry in adjacent regions is incorporated in the analysis. The analysis deals with *neighborhood effects* using the methods described in section 2.2.4.

3.3. Estimation

In order to properly estimate equation (3.6), the weights, $W_{i,t}$, must first be estimated. The overall equation can be estimated through a least-squares regression. In this section, the weights estimation is described in detail.

3.3.1. Weights Estimation

The presence of a physical store in a particular region could be considered a *flow* or a *regime* change (Azoulay, Ding, and Stuart 2006). If treatment is a flow, then it is not necessarily the case that the entry of a store has a lasting, constant impact on a region. A regime formulation, however, represents a one-time shift on the outcome of interest.

In a flow formulation of the treatments, the whole dataset is used to compute $W_{i,t}$. To compute the denominator of $W_{i,t}$ consider:

$$\hat{p}_{i,t} = logitprob(S_{i,t} = 1) = \eta_0 + \eta_1 S_{i,t-1} + \Phi(\widetilde{Z}_{i,t-1}, \eta_2) + \eta_3 X_{i,t} + \theta(t) \tag{3.9}$$

where δ_t are time effects, and $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is a parametric function of past values for time-varying confounders. If T_1 is the set of time periods where one observes the presence of a store in a region, and T_2 is the set of time periods when the presence of a store in a region is not observed, then the denominator of $W_{i,t}$ is defined as: $\prod_{t \in T_1} \hat{p}_{i,t} \prod_{t \in T_2}(1 - \hat{p}_{i,t})$. To compute the numerator of $W_{i,t}$ in the flow formulation, the same procedure as the denominator is followed, but $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is excluded.

In a regime formulation of treatment, the probability of treatment is assumed to be equal to one after the time t when entry is first observed. Thus, only the subset of data for a region of before entry occurs is needed in order to estimate the weights. Now the denominator of $W_{i,t}$ is defined as:

$$\hat{p}_{i,t} = logitprob(S_{i,t} = 1) = \eta_0 + \Phi(\widetilde{Z}_{i,t-1}, \eta_2) + \eta_3 X_{i,t} + \theta t \tag{3.10}$$

and the numerator is once again the same except $\Phi(\widetilde{Z}_{i,t-1}, \eta_2)$ is excluded. Thus, the estimate of $W_{i,t}$ for region i in time t is $\prod_{k=0}^{t}(1 - \hat{p}_{i,k})$ if there is no entry by time t, and $\left[\prod_{k=0}^{t-1}(1 - \hat{p}_{i,k})\right] \hat{p}_{i,t}$ if entry in time t is observed. A similar method is used for the numerator.

3.4. Data

The data are drawn from two sources. First, the firm data come from an e-commerce Internet-based firm, eBay, that is starting to establish a brick & mortar presence. eBay provides an e-commerce marketplace where sellers can sell durable and non-durable goods. The second source of data is the 2000 United States Census.

3.4.1. eBay data

This study uses a novel dataset provided by eBay[2]. eBay has been an e-commerce platform since the late '90s. Beginning in 2003, individuals in the United States were able to open franchise brick and mortar stores where customers could bring in goods for sale. These franchise stores sell the goods using eBay's e-commerce platform to buyers across the world. Applications to open a franchise store are available through the Internet.

There are three major firms that provide franchises across the United States. These firms have arms-length agreements with eBay such that eBay only provides the franchisers with limited marketing materials and the consent to use eBay's logo. Anecdotally, the majority of the advertising done by the franchisers is through the Internet, and is not targeted by geography. However, specific franchiser advertising is not observed in the dataset. Technically, franchises provided by these three firms can be opened anywhere in the United States. Franchise stores create their revenue by retaining a percentage of the final sales price of the sold good. The percentage amount is based on a non-linear tiered pricing system.

eBay also obtains its revenue by collecting transaction fees on goods sold using its e-commerce platform. In the dataset provided by eBay, franchise store and aggregate five-digit zip code level purchase data on a quarterly basis are observed; starting in the first calendar quarter of 2002 and ending in the third calendar quarter of 2006.

Figure B.1 shows the locations of franchise stores in the United States using annual snapshots starting in 2003 and through the third calendar quarter of 2006. In 2006, there are 489 stores in the United States. The revenue made by eBay from each store and the

[2]The financial data in this essay have been modified to preserve confidential information.

gross sales volume on a quarterly basis is observed. The total number of goods listed for sale by the franchise store and the number of goods successfully sold on a quarterly basis are also observed. Table A.8 provides summary statistics at the franchise store level. These statistics are for Q3 2006, the last quarter in the dataset. The conversion rate is calculated by simply dividing the number of goods successfully sold by the total number of goods that were listed for sale.

The dataset also has eBay aggregate buyer data at the five-digit zip code level. Thus, the total quarterly revenue from buyers, quarterly total bids, and quarterly total successful bids in 23,163 zip codes is observed. Additionally, the number of new buyers that bid on at least one good ("Buyers") in each zip code on a quarterly basis is observed.

Figure B.4 plots the average revenue for eBay on a quarterly basis. Not surprisingly, for a growing Internet-based firm, the average quarterly revenue is increasing. Figure B.5 plots the quarter-over-quarter growth rate of the number of buyers. With the exception of a couple quarters, the growth rate is positive across the dataset time period, and there seems to be a cyclical pattern of growth.

In Table A.9, the average eBay sales, total bids, successful bids, and number of buyers in five-digit zip codes that have a franchise store in Q3 2006 are compared against five-digit zip codes that do not have a store. Zip codes that contain stores seem to have greater sales, bids, successful bids, and number of buyers.

3.4.2. Census data

The study takes advantage of having eBay data at the five-digit zip code level by merging it with five-digit zip code data available from the 2000 U.S. Census. While census tract data might be more optimal in terms of smaller, homogeneous, contiguous markets, the eBay data is constrained by being available only at the five-digit zip code level. The demographic data from the U.S. Census is only for the year 2000. It is recognized that there are demographic trends between 2000-2006 that are not being captured through the cross-sectional data.

Table A.9 manifests that zip codes that have franchise stores tend to have higher levels of median household income, educational attainment, and overall population size. They also tend to be smaller in terms of land area. This is not surprising, as one would predict sales to be positively correlated with income and population size. Also, educational level has been shown to be positively correlated with new technology adoption, thus the demographic differences between zip codes with stores and without stores are to be expected.

3.5. Results & Discussion

All of the results incorporate the arbitrary variance-covariance matrix described in section (3.2.2) to correct for serial correlation. Furthermore, neighborhood effects, as described in section (2.2.4), are included. The results are divided into two main sections. Table A.10 displays the factors associated with creating a balanced sample through "traditional" propensity scoring methods. Tables A.3-A.15 examine the results using the IPTW regime propensity scoring method. The results using the IPTW flow propensity scoring method are not presented because store closing is not observed in the data. Thus, once a store appears, it remains in the sample, which is theoretically congruous to the concept of a regime change. Propensity scores using the IPTW flow method were estimated, and the results were directionally equivalent to the regime method. The results using the "traditional" propensity scoring method are also not presented. These results are available upon request.

3.5.1. Traditional Propensity Score Results

Rosenbaum and Rubin (1983) show that matching on the basis of a propensity score, $\widehat{p(X)}$, is equivalent to matching them on the covariates X. Thus, one can construct a propensity score for treatment based on covariates, and create a sample of treated and untreated regions that lie on the common support of $P(X)$. To create the balanced sample the method used in Gertler and Simcoe (2006) is employed. A propensity score, $\widehat{P(X)}$, is created using eight covariates. Zip codes with no store entry (control) where there is no support for $\widehat{P(X)}$ in the propensity score distribution of area codes with store entry (treated) are eliminated. This is accomplished by trimming the top and bottom quartiles of the control $\widehat{P(X)}$ distribution. Now, when the mean covariate values for the treated and control sample are compared, it is not possible to reject the univariate t-tests of equality of means. Thus, the balanced sample is created by combining the control and treated zip codes that lie on the common support of $\widehat{P(X)}$.

Table A.10 manifests the covariates used to create the propensity score and the probability of entry using the full and balanced sample. The land area and education level in a region seem to a clear impact on the entry decision of a store. Not surprisingly, there is a strong time trend that influences the store entry decision as well. Similar to the procedure in (Gertler and Simcoe 2006), the data is not re-weighted, but the DID model is estimated using the balanced sample data on the common support of $\widehat{P(X)}$.

3.5.2. IPTW Propensity Score Results

Tables A.3-A.15 examine the results using the IPTW regime propensity scoring method. In order to create the regime propensity score weights, the same covariates used in the traditional propensity score creation are used as the $X_{i,t}$. A set of time varying confounders, $\widetilde{Z}_{i,t-1}$, are introduced for the creation of the regime weights. The time varying confounders are one quarter lagged variables of metrics for the entire zip code. Thus, the one-period lagged values of total zip-code revenue, total zip-code number of enablers, total zip-code number of listings, total zip-code number of bids, total zip-code number of bidders, and a store within 50 miles are used as the $\widetilde{Z}_{i,t-1}$. IPTW weights for the full sample are created, and the full sample is used for an analysis similar to the one described in section (3.5.1).

Table A.11 presents the results from the DID model with fixed effects using the natural log of buyer quarterly revenue at the five digit zip code level as the dependent variable. The full sample is used with the IPTW regime propensity weights. The first column of results does not interact store entry into yearly effects, whereas the second column does. The parameter coefficients are presented with the 95% confidence interval beneath them. Store entry appears to have a significant positive effect of approximately 1.3% on the buyer revenue. The second column of results shows that the effect is present only in 2005. Figure B.6 decomposes the effect of store entry on buyer revenue on a quarterly basis. The effect is significant in quarters 9-12 (2005). Using the IPTW method decreases the magnitude of the effect as compared to the traditional propensity score method, but the effect is still positive and signigicant. Table A.12 performs a similar analysis using the natural log of quarterly new bidders at the five digit zip code level as the dependent variable. Again, the results are directionaly the same as the traditional propensity scoring method, but the magnitude of the effect is reduced. Figure B.7 decomposes the effect of store entry on new bidder acquisition on a quarterly basis. The effect is present primarily in 2004.

The IPTW regime weighted full sample is also used to examine the effect of store entry on the natural log of quarterly total bids at the zip code level. Table A.13 presents the results of the estimation. Store entry seems to have no significant effect on the number of bids. The same non-effect is found with the traditional method. Figure B.8 examines the effect over a quarterly basis and there are only two quarters (6,10) where the effect is significant. Table A.14 performs a similar analysis using the natural log of quarterly products purchased at the five digit zip code level as the dependent variable. There is no overall effect of store entry, however there is a small negative effect (-0.3%) in 2006. Again, the results are directionaly the same as the traditional propensity scoring method, but the magnitude of the effect is reduced.

Finally, Table A.15 shows a similar analysis but employs the natural log of quarterly average selling price of products purchased in a particular zip-code. Store entry positively impacts the average selling price (1.7%). The magnitude of the effects seems to increase over time, as shown in column two of the results. Again, with respect to the natural log of quarterly average selling price of products purchased, the results are directionaly the same as the traditional propensity scoring method, but the magnitude of the effect is reduced. Figure B.9 decomposes the effect of store entry on average sales price of products purchased into quarterly effects.

3.5.3. Discussion

There seems to be a positive new bidder spillover that results from the entry of stores into a particular five-digit zip code region. This result is confirmed both by the traditional method of propensity scoring and the IPTW method. There also seems to be a positive buyer revenue spillover that is confirmed by both the traditional method of propensity scoring and the IPTW method. Previous literature offers several explanations for the increase in the number of online bidders in areas that have offline store entry. The presence of a physical store could serve to increase the perceived size of the firm and thus increase consumer trust, and thus consequently influence adoption (Jarvenpaa et al. 1999). Additionally, the opening of stores could signal an investment in quality and thus increase trust in the firm (Schlosser, White, and Lloyd 2006). Potential new bidders may walk into a physical store and have face to face interactions with employees. This could increase familiarity with the firm and consequently influence online adoption (Parasuraman 2000; Grabner-Krauter and Kaluscha 2003). There could also be an increase in brand awareness about the firm through these stores serving as advertisements. All of these explanations would predict that there would be an increase in online adoption resulting from offline entry. The aggregate nature of the data does not allow discernment of which of these factors is primarily responsible for the positive new bidder spillover.

Empirically, the positive buyer revenue spillover can be a consequence of both more products being purchased in regions with store entry and higher average selling prices for products being sold in regions with store entry. One can eliminate more products being sold in regions with store entry as an explanation since there is a slight negative spillover in products sold in 2006, and no significant effect in other post-initial entry years of the sample. There does seem to be a positive average sales price of products purchased spillover that results from the entry of stores into a particular five-digit zip code region. This result is confirmed both by the traditional method of propensity scoring and the IPTW method. The increase in average sales price for products purchased may be explained by both a change in the assortment of products being purchased and an increase in the price expectation for products sold through the firm. The aggregate nature of the data does not allow us to test the relative importance of these factors. However, previous literature suggests that an increase in trust can raise the price expectation and willingness to pay of consumers (Grewal et al. 2003). Thus, it is possible that the increase in average sales price of products purchased could at least partially be explained through physical stores influencing the trust disposition of consumers.

It is unclear why the entry of offline stores leads to a slight negative online spillover in products sold in the particular zip code. One possible explanation in that the presence of physical stores changes the online purchasing preferences of customers. Another explanation is that there are competitive effects that are not being captured in the analysis. For example, regions that are conducive to physical store entry might also experience the opening of second-hand stores, flea markets, swap-meets, or new offline stores. All of these things serve as potential substitutes for purchasing products online through the firm. Thus, there is additional competitive data that must be added to the analysis in order to test this explanation.

3.5.3.1. Managerial Implications. The managerial implications of this study are manifold. First, the research underscores the importance of analyzing spillover beyond the effect on revenue. By examining metrics other than revenue in this market, it is demonstrated that the entry of stores has a positive effect on new bidders. Thus, the stores are serving as a vehicle for online customer acquisition.

In addition to the customer acquisition spillover, this study shows the importance of examining customer activity (number of products purchased) and type of activity (average sales price of products purchased). The positive spillover in average sales price underscores the need for firms to further examine the possible changes in product assortment or customer preferences caused by offline store entry. Finally, the study shows that there may be transferable learnings from the offline channel to the online channel. Customers online behavior may be influenced by face to face interactions at physical stores. Firms should consider surveying or tracking offline customers to see if their online behavior is altered through offline experience.

3.6. Conclusion

This essay has examined the the impact of entering the brick & mortar channel on the existing online channel in terms buyer revenue, new customer acquisition, and the nature of customer activity. While there is positive buyer revenue spillover into the online channel resulting from offline entry, the finding is not driven by increased online new customer acquisition or an increased number of products purchased that might be expected. Rather, the positive revenue spillover can be linked to a positive change in the average selling price of items purchased by the online channel customers. This study underscores the importance of analyzing metrics other than just revenue when determining the impact of entry into a new channel. The study also employs the IPTW propensity scoring method to control for the staggered entry over time of brick & mortar stores. This is a powerful methodology that has not been previous used when studying multi-channel problems. The methodology does have limitations, however. The assumption of selection through observables demands exhaustive use of covariates, and still does not preclude a bias resulting from an omission. Unfortunately, this bias is not testable in this framework.

There are at least two areas of promising future work. First, competitive effects could be included in the analysis. This study would provide a deeper understanding of the factors that influence the bidding and purchase behavior of customers. Second, there is great potential for a study that employs product and customer level data. The product level data could help researchers understand if store entry changes the types of products purchased by consumers, and thus consequently influencing the average sales price. Also, customer-level survey data with respect to trust disposition, perceived risk, and face to face interactions could help discern which factors are driving online adoption by customers.

CHAPTER 4

Market Size, Product Quality, and Firm Specialization: An Internet Study

4.1. Introduction

Empirical examination of the relationship between product quality and market size was popularized by Berry and Waldfogel (2003). By applying the Sutton (1991) theory of sunk costs and market structure, Berry & Waldfogel were able to characterize the process of quality competition in the newspaper and restaurant industries. Subsequently, there have been several studies focused on market structure and product quality. Industries examined include banking (Dick 2007; Cohen and Mazzeo 2007), health care (Kessler and Geppert 2005), and notary services (Nahuis et al. 2005). Despite the multitude of studies, there has been no research examining product quality and market structure on the Internet; an area originally singled out for investigation by Berry and Waldfogel (2003).

In addition to the recent interest in product quality and market size, there has also been empirical work relating firm specialization and market size (Garicano and Hubbard 2007). By examining the division of labor among law firms, Garicano and Hubbard (2007) find that firms become more specialized as the market size increases. Such an analysis can be extended to other industries. Furthermore, there is an open area of research for connecting the degree of firm specialization and product quality.

This chapter extends the study of product quality and market size to an Internet setting. Additionally, the link between firm specialization, market size, and product quality in an Internet setting is examined. The study employs a novel data set from an online e-commerce marketplace provider, eBay. In particular, the study examines physical eBay stores across the country. These offline stores act as a mechanism for sellers to collect the products of others and then sell them online. Physical stores compete in local markets for products to sell online. The types of products sold online through the physical stores as well as a proxy for quality, the feedback from the sales of products, are observed in the dataset. The results indicate that similar to other settings, there is a positive relationship between market size and market concentration. However, unlike previous studies, there is an overall negative link between market size and product quality, as well as market concentration and product quality. It seems that an increase in market size implies both more top quality and low quality firms. While the purpose of the study is descriptive, the findings suggest that the negative link between market size and product quality may be due to the partially "hidden" nature of product quality in this setting. However, this is an open issue for further research.

The results also indicate that in this setting, the level of firm specialization diminishes with increases in market size. However, there is a positive link between the level of firm specialization and the product quality of firms. It is posited that a possible explanation for the dearth of specialization as market size increases is the partially hidden nature of product quality; firms are not penalized for poor product quality. Again, this is an open issue for further research.

This research makes a substantive contribution to the product quality and market size literature by examining the process of quality competition in an Internet setting. A market is described where competition for attracting products to sell is on a local level, but the actual sale of the products is over a large market, the Internet. The second contribution of this research is the description of relationship between specialization and market size in an Internet setting. A final contribution of this research is that it attempts to show the relationship between the level of firm specialization and firm product quality.

The remainder of this essay is organized as follows. In ∮ 4.1.1, some previous research relating product quality to market size, as well as previous research linking firm specialization and market size is reviewed. In ∮ 4.2, a theoretical model of product quality is briefly reviewed. Then the data set is introduced in ∮ 4.3. The findings are presented in ∮ 4.4 and the chapter concludes in ∮ 4.4.3 & ∮ 4.5 with a review of the findings, limitations and opportunities for future work.

4.1.1. Background Literature

Shaked and Sutton (1987) argue that increases in quality can require increases in fixed or marginal costs. Furthermore, the link between market size and product quality depends on whether quality is produced mainly through variable or fixed costs. Thus, if marginal cost increases very slowly in quality, meaning the cost of quality comes primarily through fixed costs, then high quality producing firms can use price to undercut lower quality producing firms and drive them out of the market. This produces a lower bound on market share. If, however, the cost of quality is borne primarily through variable costs, then one expects a greater concentration of firms as market size increases, and there is an upper bound on the maximum quality level that increases in market size. It is this central idea that was first tested with respect to market size and concentration by Sutton (1991) and later Ellickson (2001).

Berry and Waldfogel (2003) were the first to empirically test the implications of the "endogenous sunk cost" models reviewed by Shaked and Sutton (1987) with respect to product quality and market size. Berry & Waldfogel examine the newspaper and restaurant markets. They claim that in the newspaper industry, the cost of quality should largely come through fixed costs, whereas in the restaurant industry the cost of quality should primarily come through variable costs. Using data from the respective industries, Berry and Waldfogel (2003) provide a descriptive analysis where they show that in the newspaper industry the number of dailies barely changes at all, while the quality of the product increases greatly in market size. In contrast, in the restaurant industry quality increases but the market fragments as size increases.

Following the Berry and Waldfogel (2003) study, there have been several papers that have extended the analysis to different industries. Cohen and Mazzeo (2007) find evidence that product differentiation creates additional profits for retail depository institutions. These additional profits help maintain smaller banks, while large banks expand their operations. Dick (2007) also examines the banking industry, and suggests that banks use fixed-cost quality investments to capture additional demand as market size grows. The findings also suggest that markets remain similarly concentrated regardless of size. Kessler and Geppert (2005) study competition in hospital services and find that low-risk patients in competitive markets receive less intensive treatment than in uncompetitive markets, but have statistically similar health outcomes. However, high-risk patients in competitive markets receive more intensive treatment than in uncompetitive markets, and have significantly better health outcomes. Marin and Siotis (2007) examine the relationship between market structure and R&D in the chemical industry. They find strong evidence that the ratio of market concentration to product concentration is bounded away from zero at high levels of product concentration only in high R&D markets. Finally, in a recent study of the Dutch notary profession, Nahuis et al. (2005) find that the quality of service is negatively affected by competition. They do not offer an explanation for this finding.

In addition to the vast amount of recent studies regarding product quality and market size, there has also been some work examining the relationship between the specialization level of firms and market size (Garicano and Hubbard 2007). The researchers study the composition of law firms in relatively isolated markets and test the Coasian ideas of organizational trade-offs versus demand-centric views of specialization. As part of their findings, the researchers show that holding constant the distribution of demands, as market size increases lawyers become more field-specialized. The researchers suggest examining specialization in other industries.

Finally, the study is in an Internet setting where the quality of a seller is determined by their online feedback. The online feedback may be unobserved by the consumer that is bringing their products to the store to be sold. It is possible that the consumer only learns about the quality of the seller through experience, or by eventually checking the feedback rating online. There is some theoretical work that examines the distribution of quality in a market where the quality is initially "hidden" from consumers. Orosel and

Zauner (2007) show that in such a situation, a possible equilibrium is extremely high levels and extremely low levels of product quality in a market. There is no empirical work examining this type of "hidden" quality situation.

4.2. Model

The empirical analysis documented in Berry and Waldfogel (2003) is used to describe the relationships between market size, market concentration, and product quality. In this section, a perfunctory review of Industrial Organization theory on product quality is provided in a similar fashion to Sutton (1991) and Berry and Waldfogel (2003).

Suppose that the utility to customer i of product j is:

$$u_{i,j} = \theta_i \delta_j - p_j \tag{4.1}$$

where δ_j is the product quality, and p_j is price. It is assumed that utility is measured in dollars and income effects are assumed away. Thus θ_i is distributed (0,∞) and is the consumer's willingness to pay. Additionally, it is assumed that there is an outside good of quality zero that is available at a price of zero.

In terms of cost, it is assumed that marginal cost, mc, is constant in quantity, q_j, and is weakly increasing in quality. Thus, variable cost is defined as:

$$C(q_j, \delta_j) = q_j mc(\delta_j) \tag{4.2}$$

It is assumed that fixed costs are weakly increasing in quality and that they are strictly positive. Fixed costs, FC, can be defined as:

$$FC = F(\delta_j) \tag{4.3}$$

In order to define firm j's profit function, the market size is assumed to be M, and some form of price-competition is assumed such that δ leads to some per-capita variable profit function $V(\delta_j,\delta_{-j})$. Thus firm j's profit function is:

$$\Pi_j = MV(\delta_j, \delta_{-j}) - F(\delta_j) \tag{4.4}$$

The key driver of empirical insights regarding product quality and market size stem from the relationship between costs and product quality; that is, are quality decision driven primarily through investments in fixed or variable costs. If marginal cost pricing is assumed, the utility function becomes:

$$u_{i,j} = \theta_i \delta_j - mc(\delta_j) \tag{4.5}$$

Thus, the first-order condition for consumer i's optimal quality is

$$\theta_i - \frac{\partial mc}{\partial \delta_j} \tag{4.6}$$

and the second-order condition is

$$\frac{\partial^2 mc}{\partial \delta_j^2} > 0 \tag{4.7}$$

It is apparent that the second-order condition is satisfied if marginal cost is convex in quality. Shaked and Sutton (1987) show that if marginal costs are increasing and convex in quality, the space of product qualities will fill in and the maximum quality offered in the market will increase as size increases. What the study attempts to observe empirically is that does marginal cost rise sufficiently fast in quality so that higher quality firms cannot undercut low quality firms in price and keep them out of the market. If marginal cost is constant in quality or if it is increasing but concave in quality, then higher-quality firms can undercut low-quality firms. In these situations, one can think of the cost of quality being borne in part by fixed costs. Shaked and Sutton (1987) also show that when quality improvements fall on fixed costs, concentration of products within the market will not go to zero as market size increases, but will have a lower bound. These different outcomes can be used for market concentration and product quality to empirically examine the process of quality competition in a given industry.

4.3. Data

The data are drawn from two sources. First, the store data comes from an e-commerce Internet-based firm, eBay, that is starting to establish a brick and mortar presence. eBay provides an e-commerce marketplace where sellers can sell durable and non-durable goods. The second source of data is at the Metropolitan Statistical Area (MSA) level, and it is taken from the 2000 United States Census.

4.3.1. eBay store data

This study uses a novel dataset provided by eBay[1]. eBay has been an e-commerce platform since the late '90s. Beginning in 2003, individuals in the United States were able to open franchise brick and mortar stores where customers could bring in goods for sale. These stores act as sellers and sell the collected goods using eBay's e-commerce platform to buyers across the world. Applications to open a franchise store are available through the Internet. Technically, franchises can be opened anywhere in the United States. There is an initial one time fee and a fixed recurring monthly charge in order to operate a store. These stores can be opened by any person that can pay the initial setup fee. Franchise stores create their revenue by retaining a percentage of the final sales price of the sold good. The percentage amount is based on a non-linear tiered pricing system.

Figure B.1 shows the locations of franchise stores in the United States using annual snapshots starting in 2003 and through 2006. At the end of 2006, there are 493 stores in the United States. Figure B.10 shows the proliferation of stores over time. In 2005, 2006, and 2007 the total number of physical stores has remained nearly constant. Since e-commerce is an emerging industry, it is difficult to definitively state that the store market has reached an equilibrium. However, for the purposes of the empirical analysis, it is assumed that the market is at equilibrium. The ramifications of this assumption are discussed in Section 4.4.3.

In the dataset, all of the product listings for the stores from 2006 are observed. These observations are at the store level. The product category of the listing, as well as if the listing was successfully sold is observed. Also the final sales price of the product is

[1]The financial data in this essay have been modified to preserve confidential information.

observed. Table A.16 provides a summary of the revenue, listings, and products sold by stores in 2006 across in the thirty-five major product categories. The dataset contains over 2.2 million product listings, with over one million products sold, at an approximate average sales price of $97.

4.3.1.1. Store Quality. In addition to product listings and sales data, the feedback received online by the sellers at the stores is observed. Customers who purchase products online from sellers have the option of providing a feedback score regarding the quality of the transaction. Sellers that have higher feedback ratings tend to convert more listings into sales as well as receive premiums on the final sales price (Li, Srinivasan, and Sun 2005). Since physical franchise stores are nearly identical in appearance, and provide a very similar experience on the front-end (collecting products to sell online), feedback may be a reasonable metric to access the quality of a store. It represents the perceived sales ability by online buyers of the seller. The feedback rating for all of the stores at the end of 2006 is observed in the dataset.

4.3.1.2. Specialization. The degree of specialization of a store is measured by the number of the thirty-five categories in which the store sells products. Thus, a store that sold products in fifteen categories in 2006 is less specialized than a firm which sells products in ten categories. Stores can emphasize to customers that want their product sold online that they are "experts" in particular categories. Furthermore, stores can decide to accept only products from certain categories. Thus, there is some decision being made by stores as to the level of specialization they desire. A specialization ratio (number of categories with products sold/total number of categories) is calculated for 2006 for each store in the sample.

4.3.2. Census data

The study takes advantage of having the five-digit zip code of the eBay store by merging it with Metropolitan Statistical Area (MSA) level data available from the 2000 U.S. Census. There are typically several five-digit zip codes within one MSA. Previous studies of market size and product quality have also used the MSA as the market level of analysis. Data from 144 MSAs are observed in the sample. MSA level demographic data is observed which includes the number of households, the median household income, the educational level, and the size of the MSA. The demographic data from the U.S. Census is only for the year 2000. It is recognized that there are demographic trends between 2000-2006 that are not being captured through the cross-sectional data. It is also acknowledged that there is an assumption that competition among stores for potential customers with products to sell is limited to within particular MSAs.

4.4. Results & Discussion

In the Internet setting, the quality of sellers is determined by their ability to sell. This includes the presentation of the product, the pricing strategy, and the fulfillment of an order. The quality of a seller seems to be an endogenous choice of the seller. Intuitively, it seems that an increase in marginal cost from high quality is sufficiently low such high quality seller stores can undercut lower quality stores, and therefore drive low quality competitors from the market. Given the beliefs about the cost structure of the industry, together with theoretical considerations, one would expect the following: 1) there should be a lower bound to the market share of the largest store in a market, 2) the number of stores will increase in market size, and 3) the quality of the best stores in a market will improve in market size.

Figure B.11 plots market concentration of a MSA in the form of the Herfindahl Index (HHI) by the population of the MSA. HHI's are the sum of squared percentage shares, so they vary from zero to 10,000. The plot seems to indicate that larger markets are more concentrated than smaller markets. In figure B.12, the market share of the largest firm in a MSA (C1) by the population of the MSA is plotted. Contrary to prior expectations, there does not seem to be a lower bound to the market share of the largest store in the market.

The relationship between market size and market concentration can be examined using regressions for tests of significance and controls. Instead of using raw numbers for the number of firms in a market as the dependent variable, the often used log of the "numbers equivalent" (the inverse HHI) is employed (Berry and Waldfogel 2003). Table A.17 shows the results of the regression between market concentration and market size. As expected, there is a significant positive relationship between market concentration and market size. There also seems to be a significant positive relationship between the percentage of college graduates in a region and the concentration of stores.

4.4.1. Product Quality

Figure B.13 plots the average feedback in a MSA by the population of the MSA. The plot does not seem to show a positive relationship between market size and product quality. In fact, product quality seems to be spread out across markets of all sizes, as might be expected in markets where marginal costs rise sufficiently fast in quality so that higher quality firms cannot undercut low quality firms in price and keep them out of the market. Table A.18 shows a regression analysis of quality (feedback) with market size, as well as market concentration. There is actually a significant negative relationship between market size and quality, and a negative relationship between market concentration and quality. The positive and significant coefficient on college education might indicate that educated sellers who open stores might have superior sales skills. This negative relationship between quality and market size has also been documented in the notary industry (Nahuis et al. 2005).

The relationship between product quality and market size is investigated further by specifically examining the number of "top" and "low" quality stores in MSAs. "Top" quality stores represent sellers that are in the top 20% of feedback for all physical store sellers on eBay. "Low" quality stores represent sellers that are in the bottom 20% of feedback for all physical store sellers on eBay. The study examines how market size affects the number of top quality and bottom quality stores in an MSA. The results of the regression are presented in table A.19. It seems that both the number of top and low quality stores increases with respect to increases in market size. This type of relationship again seems to be more consistent with the variable cost view of the process of quality competition.

4.4.2. Specialization

In addition to examining the relationship between product quality and market size, the link between market size and level of firm specialization is also investigated. Table A.20 shows the results of a regression where specialization, operationalized through the number of categories in which a store sells products, is the dependent variable. The results seem to indicate that stores become less specialized as market size increases. These results are in the opposite direction from a previous study of the law industry (Garicano and Hubbard 2007). Although, the results also seem to indicate that there is a positive relationship between the level of firm specialization and the level of firm quality. Possible explanations for all of these findings are offered in section 4.4.3.

4.4.3. Discussion

The findings from the empirical analysis seem to be contrary to prior beliefs about the nature of quality competition in this Internet setting. The empirical analysis describes a setting where the relationship between market concentration and market size is in between the metrics described for the restaurant (variable cost quality competition) and newspaper (fixed cost quality competition) (Berry and Waldfogel 2003). While the purpose of the study is purely descriptive, it can offer some possible explanations for the empirical findings.

There are several possible explanations for why a wide range of selling qualities are observed and there is not a lower bound for market share by the largest firm in a MSA. One possible explanation is that selling quality of these stores is "hidden" from customers looking to have their products sold online (Orosel and Zauner 2007). Since these physical stores are all very similar in their offline setup and operations, the ability of a particular store to successfully sell a product may be difficult for a consumer to discern. Possible mechanisms for the consumer to learn about the store's quality include going online and checking feedback scores and learning through personal experience with the stores, as well as the experiences of others. Additionally, it has been shown that advertising by Internet firms can serve as a signal of product quality (Latcovich and Smith 2001). It is possible that customers do not discover the online feedback of the stores, in fact the inability to use the Internet may be the motivation for these consumer to frequent the offline stores. If quality is hidden from consumers, then there is an equilibrium where there are very high and very low quality firm (Orosel and Zauner 2007).

Advertising as a signal of quality may be another explanation for the empirical findings. Advertising by firms is not observed in the dataset, however it is possible that low quality firms are using advertising as a vehicle for distorting their quality. Future studies that incorporate advertising data would be beneficial in describing this Internet setting.

An implication of these possible explanations is that the offline Internet store market has not yet reached an equilibrium. It could be argued that as consumers find ways to discern the true product quality, through experience or Internet adoption, higher quality firms will successfully undercut lower quality firms and the market structure will change. In fact, it has been posited that in the long run, as consumers become Internet savvy, the selling ability of consumers will become comparable to the firms, and these types of stores will no longer exist (Wang 2007). This is an open question which underscores the importance for future studies of this setting.

The empirical results from the study of firm specialization and market size seem to contrast with previous work in the law industry (Garicano and Hubbard 2007). Firms appear to become less specialized as market size increases, even though there seems to be a positive correlation between specialization and product quality. This may again be explained through the hidden nature of product quality. If firms realize that consumers are unable to discern product quality, there will be no incentive to make a possible investment in learning how to sell in a specific category. Stores may make false claims to expertise in multiple categories. This relationship between specialization and market size may change in the long run, if product qualities are indeed revealed to all consumers. Again, this is also an open question which should be studied with future data.

4.5. Conclusion

This essay has empirically examined the relationships between market size, market concentration, product quality, and firm specialization in the e-commerce industry. The study finds that market concentration does indeed increase with market size, however, there does not seem to be a lower bound to the market share of the largest store in the market. The study also finds a negative relationship between firm quality and market size. Furthermore, increases in market size seem to grow both the number of high and low quality stores in the market. Finally, the study investigates firm specialization, and discovers a negative relationship between the degree of firm specialization and market size, and a positive relationship between the degree of firm specialization and product quality. There are several possible explanations for these empirical findings. It is possible that the process through which consumers discover product quality may be partially responsible for the negative relationship between product quality and market size, as well as the negative relationship between firm specialization and market size. Also, unobserved advertising by stores may be influencing these empirical observations.

This research makes a contribution to the existing studies of market size and product quality, by examining a previously unexamined setting, physical access points for

Internet-based firms. An additional contribution of this research is that it investigates firm specialization and market size in an Internet setting, while also trying to relate product quality to firm specialization. There are several areas of promising future work. First, describing the order of entry of firms into the market. Do higher quality firms enter first? Second, it would be very interesting to examine this market in the future, to determine if customer actually do learn more about product quality, thus driving lower quality firms out of the market. Finally, another possible area of interest would be to further delve into the mechanism for firm specialization in the Internet setting.

CHAPTER 5

Conclusion

5.1. Summary of Results

This dissertation addresses several issues related to Internet-based firms entering the offline channel. While there is considerable research examining online entry by brick & mortar firms, the research on offline entry is limited. This dissertation identifies online spillovers from offline entry, and describes the nature of product quality, market concentration, and firm specialization with respect to the offline entry. The online spillovers are examined both from a consumer purchase behavior (buyers) and a consumer service adoption and usage (sellers) perspective.

There are several insights from the studies of the dissertation. The dissertation finds that in both the consumer purchase behavior study and the consumer service adoption study, there is a positive online revenue spillover from firm offline entry. It is posited that in the spillover analysis of online consumer purchase behavior, the positive online revenue spillover is driven by an increase in the average price of items purchased online by consumers located in regions with offline entry. Similarly, it is suggested that in the spillover analysis of online seller behavior, the positive online revenue spillover is driven by an increase in the average price of items sold online by sellers located in regions with offline entry. The findings from the dissertation also show that there is a positive relationship between market concentration and market size for the offline stores. However, there seems to be a negative link between the product quality of the offline stores and market size. Finally, a negative link between firm specialization and market size is identified, but a positive relationship between product quality and firm specialization is found in the offline Internet store setting. These findings illuminate several areas for future research that are described in section 5.3.

This research makes both substantive and methodological contributions, in addition to being the first to comprehensively study an Internet-based firm both prior to and after its entry into the brick & mortar channel. First, a novel dataset is used to examine spillover not just from the revenue perspective, but also using metrics that are important in emerging markets. Use of metrics such as marketplace listings, bidding behavior, average sales price, and new customer acquisition provides a deeper understanding of the impact of entering the offline channel. The second contribution is the use of a novel methodology from the biometrics literature that is employed to control for the endogeneity of store entry into a region. Third, this dissertation makes a contribution to the existing studies of market size and product quality, by examining a previously unexamined setting, physical access points for Internet-based firms. An additional contribution of this research is the investigation of firm specialization and market size in an Internet setting, while also trying to relate product quality to firm specialization. Thus, the contributions of this research to the study of offline entry are manifold.

5.2. Limitations of Work

While this dissertation does help contribute to the study of offline entry, there are several limitations to the research. The IPTW propensity scoring method is a powerful methodology that has not been previously used when studying multi-channel problems. The methodology does have limitations, however. The assumption of selection through observables demands exhaustive use of covariates, and still does not preclude a bias resulting from an omission. Unfortunately, this bias is not testable in the framework. One of the covariates that is not included in the three essays is external competitive effects. The inclusion of such effects would provide a richer understanding of offline entry.

The first two essays of this dissertation are also limited by the aggregate nature of the data and the results. It is not possible to determine the particular forces that drive the positive average selling and average purchase price spillover. A product and customer-level analysis of the offline entry would be useful in understanding specifically how customer move across channels, and potential changes in product assortment through offline entry. Finally, among the limitations of the third essay is the lack of additional proxies for firm quality and firm specialization. The findings would greatly benefit from additional proxies, and not just one metric for quality and one metric for specialization.

5.3. Future Direction

The scope for future research in this area is tremendous. With regards to the research focusing on online spillover, the findings would be greatly enhanced through a customer and product-level analysis. A customer-level analysis would include observations of customers who enter the offline stores to provide products for sale. Furthermore, the customer behavior across channels could be identified. Such a customer-level analysis would allow researchers to observe the ratio of new customers that go directly to the online channel as a result of offline entry versus new customers that try the offline channel first and then move to the online channel. One could study the differences in activity for customers that come directly to the online channel as compared to customers that use the offline channel as a gateway for entering the online channel.

A product-level analysis would be beneficial in determining potential changes in product assortment created through offline entry. The antecedents of the positive average sales price spillover could be clarified through a product-level study. That is, does the average sales price increase due to a change in the types of products sold online in regions where there is offline entry? If there is no change in product assortment, then it may be possible to attribute the increase in the average sales price to a change in the mix or ability of sellers.

All three essays can be enhanced through the addition of competitive effects. While the current spillover analyses account for neighboring offline stores that also belong to the firm, independent stores are not included. Independent stores could be pawn shops, second-hand stores, and unauthorized online sellers with an offline presence. Independent stores could also include brick & mortar retail stores, especially in the context firm specialization studies.

An additional area for study is firm entry and firm exit. Order of entry could be examined with respect to firm quality and firm level of specialization. It would be interesting to examine what types of firms are the early entrants in a market, as well as to describe the evolution of quality and specialization over time. In the future, if there is extensive firm exit in this market, a study of the determinants of firm exit would be quite beneficial in the overall understanding of this setting.

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APPENDIX A

Tables

Variable	***Q3 2006***
Sales	$763.79
Total Listings	244.10
Conversion Rate	0.57
N	489

Table A.1. Average Store Descriptives

Variable	***With Stores***	***Without Stores***
Zip Code Level eBay Metrics and Demographics		
Sales	\$606,186.71	\$144,085.45
Total Listings	36,702.10	9,361.24
Conversion Rate	0.42	0.44
Sellers	639.05	215.87
Enablers	4.70	1.62
Education	0.39	0.26
Income	\$53,973.66	\$42,317.12
Population	26,621.64	11,574.16
Area	43.62	83.01
HH	10,268.85	4,338.97
N	453	22,710

Table A.2. Q3 2006 Zip Code Level eBay Metrics and Demographics

Pr[Entry]	***Full***	***Marginal***	***Balanced***	***Marginal***
Total Households	0.00007 (0.00001)	0	0.00008 (0.00001)	0
Median Household Income	0.00001 (0)	0	0.00001 (0)	0
Population	0.00002 (0)	0	0.00001 (0)	0
Land Area	-0.00234 (0.00023)	-0.00001	-0.00158 (0.00026)	-0.00001
Education	2.3525 (0.12834)	0.00552	1.97902 (0.12971)	0.01677
2004	1.62721 (0.05473)	0.00382	1.15082 (0.05855)	0.00975
2005	2.08975 (0.05045)	0.0049	1.58548 (0.05551)	0.01343
2006	2.42526 (0.05038)	0.00569	1.91501 (0.05543)	0.01622
Constant	-8.23595 (0.06238)	0	-7.54223 (0.07749)	0
Observations	602,238		317,087	

Table A.3. Logit Estimates of Store Entry

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
Dependent Variable = Log(Non-store Revenue)		
log(total customers)	0.529 [0.524, 0.534]	0.529 [0.524, 0.534]
log(nonstore listings)	0.604 [0.602, 0.606]	0.604 [0.602, 0.606]
Number of Enablers	0.002 [0.001, 0.003]	0.002 [0.001, 0.003]
Neighborhood Effects	0.014 [-0.043, 0.07]	0.014 [-0.043, 0.07]
Listing Conversion	1.801 [1.79, 1.813]	1.801 [1.79, 1.813]
2001	0.002 [-0.002, 0.007]	0.002 [-0.002, 0.007]
2002	-0.015 [-0.019, -0.01]	-0.015 [-0.019, -0.01]
2003	-0.033 [-0.038, -0.027]	-0.033 [-0.038, -0.027]
2004	-0.011 [-0.016, -0.005]	-0.04 [-0.05, -0.03]
2005	0.025 [0.019, 0.031]	0.005 [-0.004, 0.013]
2006	0.056 [0.049, 0.062]	0.032 [0.02, 0.044]
Store Entry	0.022 [0.017, 0.026]	
Store Entry*2004		0.029 [0.021, 0.037]
Store Entry*2005		0.02 [0.013, 0.027]
Store Entry*2006		0.024 [0.014, 0.034]
Constant	2.595 [2.578, 2.613]	2.617 [2.6, 2.634]

Observations = 598,600, R-squared = 0.9083, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.4. Online Seller Revenue Spillover

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
Dependent Variable = Log(New Non-store Customers)		
log(nonstore revenue)	0.142 [0.14, 0.143]	0.142 [0.14, 0.143]
Number of Enablers	0 [0, 0.001]	0 [0, 0.001]
Neighborhood Effects	0.001 [-0.028, 0.03]	0.001 [-0.028, 0.03]
Listing Conversion	-0.008 [-0.015, -0.002]	-0.008 [-0.015, -0.002]
2001	0.143 [0.14, 0.145]	0.143 [0.14, 0.145]
2002	0.291 [0.289, 0.294]	0.291 [0.289, 0.294]
2003	0.479 [0.477, 0.482]	0.479 [0.477, 0.482]
2004	0.641 [0.638, 0.643]	0.647 [0.642, 0.652]
2005	0.644 [0.641, 0.647]	0.649 [0.645, 0.654]
2006	0.762 [0.759, 0.765]	0.768 [0.762, 0.774]
Store Entry	-0.005 [-0.007, -0.003]	
Store Entry*2004		-0.006 [-0.011, -0.002]
Store Entry*2005		-0.005 [-0.009, -0.002]
Store Entry*2006		-0.006 [-0.011, -0.001]
Constant	1.087 [1.077, 1.096]	1.082 [1.073, 1.091]

Observations = 598,600, R-squared = 0.772, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.5. Online New Sellers Spillover

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
DEPENDENT VARIABLE = LOG(NON-STORE LISTINGS)		
log(total customers)	0.547 [0.542, 0.551]	0.547 [0.542, 0.551]
Number of Enablers	0.003 [0.002, 0.004]	0.003 [0.002, 0.004]
Neighborhood Effects	0.002 [-0.053, 0.056]	0.002 [-0.053, 0.056]
Listing Conversion	-2.057 [-2.067, -2.046]	-2.057 [-2.067, -2.046]
2001	-0.023 [-0.027, -0.018]	-0.023 [-0.027, -0.018]
2002	-0.055 [-0.059, -0.05]	-0.055 [-0.059, -0.05]
2003	-0.107 [-0.112, -0.102]	-0.107 [-0.112, -0.102]
2004	-0.167 [-0.173, -0.161]	-0.132 [-0.142, -0.122]
2005	-0.201 [-0.207, -0.196]	-0.181 [-0.189, -0.172]
2006	-0.282 [-0.288, -0.275]	-0.262 [-0.274, -0.251]
Store Entry	-0.023 [-0.027, -0.019]	
Store Entry*2004		-0.035 [-0.043, -0.027]
Store Entry*2005		-0.021 [-0.027, -0.014]
Store Entry*2006		-0.019 [-0.029, -0.009]
Constant	0.567 [0.549, 0.585]	0.544 [0.526, 0.561]

Observations = 598,600, R-squared = 0.8991, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.6. Online Listings Spillover

parameter	*FE, No Time Interaction*	*FE, With Time Interaction*
DEPENDENT VARIABLE = LOG(AVERAGE SELLING PRICE OF NON-STORE PRODUCTS)		
log(total customers)	-0.058 [-0.059, -0.057]	-0.058 [-0.059, -0.057]
log(nonstore revenue)	0.986 [0.986, 0.987]	0.986 [0.986, 0.987]
log(nonstore listings)	-0.966 [-0.966, -0.965]	-0.966 [-0.966, -0.965]
Number of Enablers	0.001 [0.001, 0.001]	0.001 [0.001, 0.001]
Neighborhood Effects	0.003 [-0.006, 0.013]	0.003 [-0.006, 0.012]
Listing Conversion	-2.115 [-2.117, -2.113]	-2.115 [-2.117, -2.113]
2001	0.005 [0.004, 0.006]	0.005 [0.004, 0.006]
2002	0.007 [0.006, 0.008]	0.007 [0.006, 0.008]
2003	0.009 [0.008, 0.01]	0.009 [0.008, 0.01]
2004	0.018 [0.017, 0.019]	-0.005 [-0.006, -0.003]
2005	0.021 [0.02, 0.022]	0.003 [0.002, 0.005]
2006	0.036 [0.035, 0.037]	0.021 [0.019, 0.023]
Store Entry	0.017 [0.016, 0.018]	
Store Entry*2004		0.022 [0.021, 0.024]
Store Entry*2005		0.018 [0.017, 0.019]
Store Entry*2006		0.015 [0.013, 0.017]
Constant	1.886 [1.883, 1.889]	1.904 [1.901, 1.907]

Observations = 598,600, R-squared = 0.9813, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.7. Online Average Selling Price Spillover

Variable	***Q3 2006***
Sales	\$763.79
Total Listings	244.10
Conversion Rate	0.57
N	489

Table A.8. Average Store Descriptives

Variable	***With Stores***	***Without Stores***
Zip Code Level eBay Metrics and Demographics		
Sales	\$419,330.12	\$136,504.60
Total Bids	31,099.77	11,369.11
Successful Bids	9,836.13	3,567.42
Buyers	3,150.00	1,121.97
Education	0.39	0.26
Income	\$53,973.66	\$42,317.12
Population	26,621.64	11,574.16
Area	43.62	83.01
HH	10,268.85	4,338.97
N	453	22,710

Table A.9. Q3 2006 Zip Code Level eBay Metrics and Demographics

Pr[Entry]	***Full***	***Marginal***	***Balanced***	***Marginal***
Total Households	0.00008 (0.00001)	0	0.00008 (0.00001)	0
Median Household Income	0.00001 (0)	0	0.00001 (0)	0
Population	0.00002 (0)	0	0.00002 (0)	0
Land Area	-0.00251 (0.00024)	-0.00001	-0.00139 (0.00029)	-0.00001
Education	2.322 (0.13541)	0.00535	1.998 (0.14215)	0.01652
2004	1.73213 (0.05723)	0.00412	1.16124 (0.06118)	0.00991
2005	2.027562 (0.05917)	0.0058	1.6812 (0.05818)	0.01312
2006	2.85626 (0.05918)	0.00598	1.93456 (0.05873)	0.01279
Constant	-8.22172 (0.06812)	0	-7.19237 (0.07921)	0
Observations	427,346		219,254	

Table A.10. Logit Estimates of Store Entry

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
DEPENDENT VARIABLE = LOG(BUYER REVENUE)		
log(total bidders)	0.509 [0.507, 0.511]	0.509 [0.507, 0.510]
log(total bids)	0.524 [0.522, 0.527]	0.524 [0.522, 0.527]
Neighborhood Effects	0.013 [-0.002, 0.029]	0.013 [-0.002, 0.029]
2003	0.031 [0.030, 0.033]	0.031 [0.030, 0.033]
2004	0.038 [0.037, 0.039]	0.038 [0.037, 0.039]
2005	0.084 [0.083, 0.085]	0.084 [0.083, 0.085]
2006	0.137 [0.136, 0.139]	0.138 [0.136, 0.139]
Store Entry	0.013 [0.007, 0.019]	
Store Entry*2004		0.000 [-0.009, 0.010]
Store Entry*2005		0.015 [0.007, 0.022]
Store Entry*2006		0.000 [-0.008, 0.007]
Constant	3.14 [3.132, 3.154]	3.14 [3.132, 3.154]

Observations = 427,346, R-squared = 0.9536, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.11. Online Buyer Revenue Spillover

parameter	*FE, No Time Interaction*	*FE, With Time Interaction*
DEPENDENT VARIABLE = LOG(NEW BIDDERS)		
log(buyer revenue)	0.202 [0.201, 0.203]	0.202 [0.201, 0.203]
log(total bids)	0.396 [0.395, 0.397]	0.396 [0.395, 0.397]
Neighborhood Effects	0.001 [-0.009, 0.011]	0.009 [-0.009, 0.010]
2003	0.000 [-0.009, 0.001]	0.000 [-0.001, 0.007]
2004	0.112 [0.111, 0.112]	0.112 [0.111, 0.112]
2005	0.172 [0.171, 0.173]	0.172 [0.171, 0.174]
2006	0.228 [0.227, 0.229]	0.229 [0.228, 0.230]
Store Entry	0.008 [0.002, 0.018]	
Store Entry*2004		0.012 [0.006, 0.018]
Store Entry*2005		0.004 [-0.001, 0.009]
Store Entry*2006		-0.004 [-0.009, 0.001]
Constant	0.404 [0.397, 0.411]	0.404 [0.397, 0.411]

Observations = 427,346, R-squared = 0.9695, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.12. Online New Buyers Spillover

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
DEPENDENT VARIABLE = LOG(TOTAL BIDS)		
log(buyer revenue)	0.314 [0.313, 0.315]	0.314 [0.313, 0.315]
log(total bidders)	0.633 [0.631, 0.634]	0.633 [0.631, 0.635]
Neighborhood Effects	-0.003 [-0.015, 0.009]	-0.003 [-0.015, 0.009]
2003	-0.075 [-0.076, -0.074]	-0.075 [-0.076, -0.074]
2004	-0.129 [-0.130, -0.128]	-0.129 [-0.130, -0.128]
2005	-0.162 [-0.164, -0.162]	-0.163 [-0.164, -0.162]
2006	-0.235 [-0.236, -0.234]	-0.235 [-0.236, -0.234]
Store Entry	-0.009 [-0.014, 0.004]	
Store Entry*2004		-0.007 [-0.015, 0.001]
Store Entry*2005		-0.006 [-0.012, 0.001]
Store Entry*2006		-0.002 [-0.008, 0.004]
Constant	1.464 [1.455, 1.473]	1.464 [1.455, 1.473]

Observations = 427,346, R-squared = 0.9698, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.13. Online Bidding Spillover

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
DEPENDENT VARIABLE = LOG(PRODUCTS PURCHASED)		
log(total bids)	0.714 [0.711, 0.716]	0.714 [0.712, 0.716]
log(total bidders)	0.153 [0.151, 0.155]	0.153 [0.151, 0.155]
Neighborhood Effects	0.007 [0.009, 0.013]	0.007 [0.009, 0.013]
2003	-0.024 [-0.024, -0.023]	-0.024 [-0.024, -0.023]
2004	-0.002 [-0.002, -0.001]	-0.002 [-0.002, -0.001]
2005	0.017 [0.016, 0.018]	0.017 [0.016, 0.018]
2006	0.070 [0.069, 0.071]	0.070 [0.069, 0.071]
Store Entry	-0.002 [-0.003, 0.001]	
Store Entry*2004		-0.002 [-0.004, 0.001]
Store Entry*2005		-0.002 [-0.004, 0.001]
Store Entry*2006		-0.003 [-0.006, -0.001]
Constant	-1.002 [-1.014, -0.990]	-1.002 [-1.014 -0.990]

Observations = 427,346, R-squared = 0.9864, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.14. Products Purchased Online Spillover

parameter	***FE, No Time Interaction***	***FE, With Time Interaction***
Dependent Variable = Log(Average Sales Price)		
log(total bids)	-0.295 [-0.300, -0.291]	-0.296 [-0.299, -0.291]
log(total bidders)	0.343 [0.339, 0.347]	0.343 [0.339, 0.347]
Neighborhood Effects	-0.007 [-0.018, 0.005]	-0.007 [-0.018, 0.005]
2003	0.038 [0.036, 0.039]	0.038 [0.037, 0.040]
2004	0.012 [0.011, 0.013]	0.012 [0.011, 0.013]
2005	0.033 [0.032, 0.035]	0.033 [0.031, 0.034]
2006	0.027 [0.025, 0.028]	0.027 [0.025, 0.029]
Store Entry	0.017 [0.013, 0.020]	
Store Entry*2004		0.002 [-0.003, 0.007]
Store Entry*2005		0.013 [0.009, 0.018]
Store Entry*2006		0.020 [0.015, 0.024]
Constant	4.00 [3.98, 4.02]	4.00 [3.98, 4.02]

Observations = 427,346, R-squared = 0.1620, IPTW Propensity Scoring with Fixed Effects (FE)

Table A.15. Average Price of Products Purchased Online Spillover

Category	***Revenue***	***Listings***	***Sold Items***
Home & Garden	5.86%	18.96%	7.34%
Collectibles	9.97%	11.98%	15.89%
Sporting Goods	5.99%	4.56%	6.11%
Video Games	0.81%	0.63%	0.96%
Cell Phones & PDAs	2.39%	2.9%	2.01%
Books	0.81%	2.44%	1.61%
Toys & Hobbies	4.2%	4.72%	7.09%
Pottery & Glass	3.78%	4.43%	5.65%
Entertainment Memorabilia	0.52%	0.61%	0.66%
Cameras & Photo	6.53%	3.51%	4.68%
Jewelry & Watches	6.95%	4.04%	3.68%
Dolls & Bears	1.85%	2.4%	3.35%
Musical Instruments	5.62%	1.67%	2.62%
Consumer Electronics	15.14%	6.68%	7.67%
Clothing, Shoes, & Accessories	7.16%	9.62%	10.75%
Antiques	2.24%	1.97%	1.91%
Sports Memorabilia	1.70%	2.68%	2.6%
Computers & Networking	5.02%	3.22%	4.15%
Business & Industrial	5.53%	4.09%	3.58%
Tickets	0.78%	0.22%	0.28%
Art	2.12%	1.52%	1.36%
Health & Beauty	1.28%	1.36%	1.72%
Music	0.25%	1.16%	0.61%
Travel	0.33%	0.29%	0.27%
Baby	0.30%	0.37%	0.5%
Crafts	0.78%	0.78%	0.85%
Other	0.25%	1.7%	0.32%
Stamps	0.07%	0.13%	0.14%
Cell Phones	0.01%	0.01%	0.01%
Coins & Paper Money	1.28%	0.63%	0.84%
DVDs & Movies	0.34%	0.67%	0.77%
Gift Certificates	0.03%	0.02%	0.03%
Specialty Services	0.00%	0.01%	0.00%
Real Estate	0.13%	0.01%	0.00%
Partner	0.00%	0.00%	0.00%
TOTAL	$ 105,384,859	2,292,164	1,086,258

Table A.16. Distribution of Revenue, Listings, and Items Sold Across Categories

Dependent Variable = N-Equivalent(Concentration)		
log(MSA Population)	0.363* [0.298, 0.427]	0.406* [0.335, 0.476]
Household Size	-	0.000 [-0.001, 0.001]
Median Household Income	-	0.000 [-0.001, 0.001]
Land Area	-	0.001* [0.001, 0.001]
Education	-	0.385* [0.049, 0.721]
Constant	-13.37* [-14.17, -12.56]	-13.75* [-14.64, -12.86]
R-squared	0.609	0.631

*Significant at 5% Observations = 144

Table A.17. Market Size and Market Concentration

Dependent Variable = log(Feedback)		
log(MSA Population)	-0.448* [-0.593, -0.303]	-0.094* [-0.167, -0.022]
Household Size	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Median Household Income	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Land Area	-0.001* [-0.002, -0.001]	0.000 [-0.001, 0.001]
Education	0.393* [0.041, 0.745]	0.423* [0.024, 0.823]
log(products sold)	1.885* [1.443, 2.328]	1.603* [1.141, 2.065]
log(listings)	-0.676* [-1.169, -0.183]	-0.306* [-0.582, -0.031]
N-Equivalent	-	-1.030* [-1.375, -0.684]
Constant	2.975* [1.279, 4.670]	-11.342* [-16.986, -5.699]
R-squared	0.809	0.847

*Significant at 5% Observations = 144

Table A.18. Service Quality and Market Size

Parameter	***DV = Top Quality Firms***	***DV = Low Quality Firms***
log(Population)	0.747* [0.257, 1.237]	0.548* [0.257, 0.840]
Household Size	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Median Household Income	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Land Area	0.003* [0.000, 0.006]	0.005* [0.001, 0.009]
Education	1.024* [0.025, 2.023]	-0.500 [-1.423, 0.422]
Constant	-9.303* [-14.863, -3.744]	-5.595* [-8.748, -2.443]
R-squared	0.287	0.195

*Significant at 5% Observations = 144

Table A.19. Top & Low Quality Firms and Market Size

Dependent Variable = Percent of Categories Sold		
log(Population)	0.034* [0.013, 0.054]	0.030* [0.011, 0.050]
Household Size	0.019* [0.017, 0.020]	0.020* [0.019, 0.022]
Median Household Income	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Land Area	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]
Education	-0.049 [-0.133, 0.035]	-0.006 [-0.088, 0.076]
log(products sold)	0.107* [0.101, 0.114]	0.121* [0.108, 0.133]
N-Equivalent	0.026* [0.019, 0.032]	0.027* [0.019, 0.035]
log(feedback)	-	-0.014* [-0.024, -0.005]
Constant	-0.330* [-0.546, -0.114]	-0.239* [-0.459, -0.018]
R-squared	0.754	0.736

*Significant at 5% Observations = 493 with MSA Fixed Effects

Table A.20. Specialization, Service Quality and Market Size

APPENDIX B

Figures

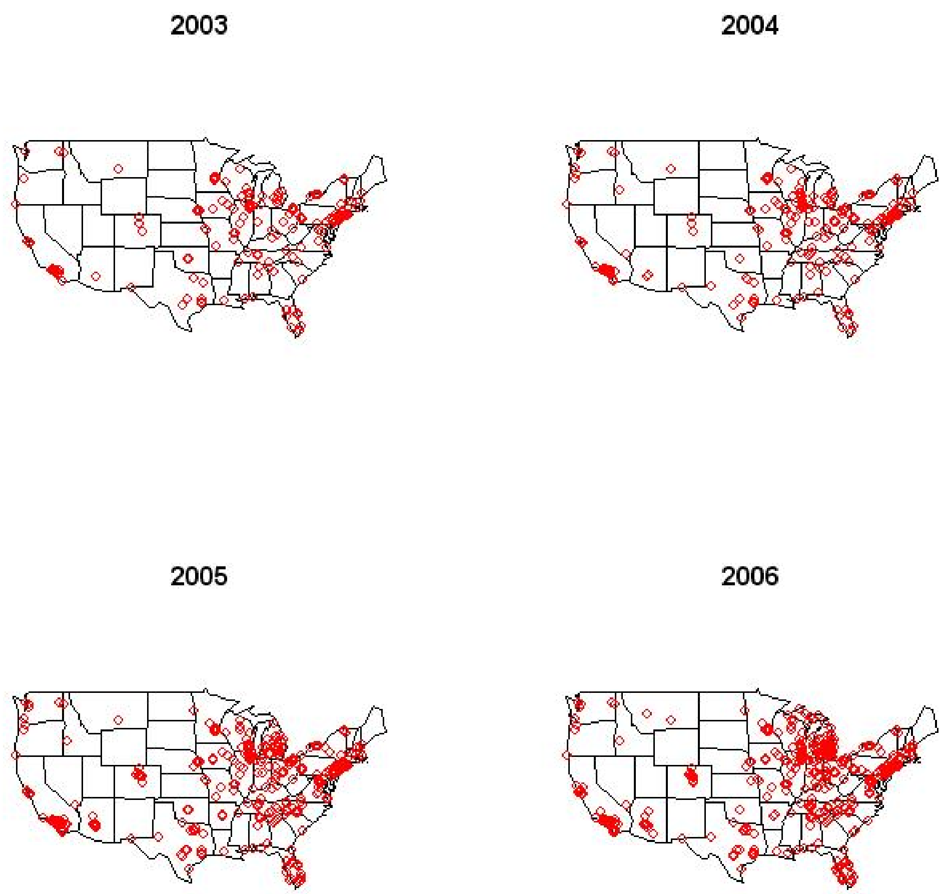

Figure B.1. Store locations, 2003 - 2006

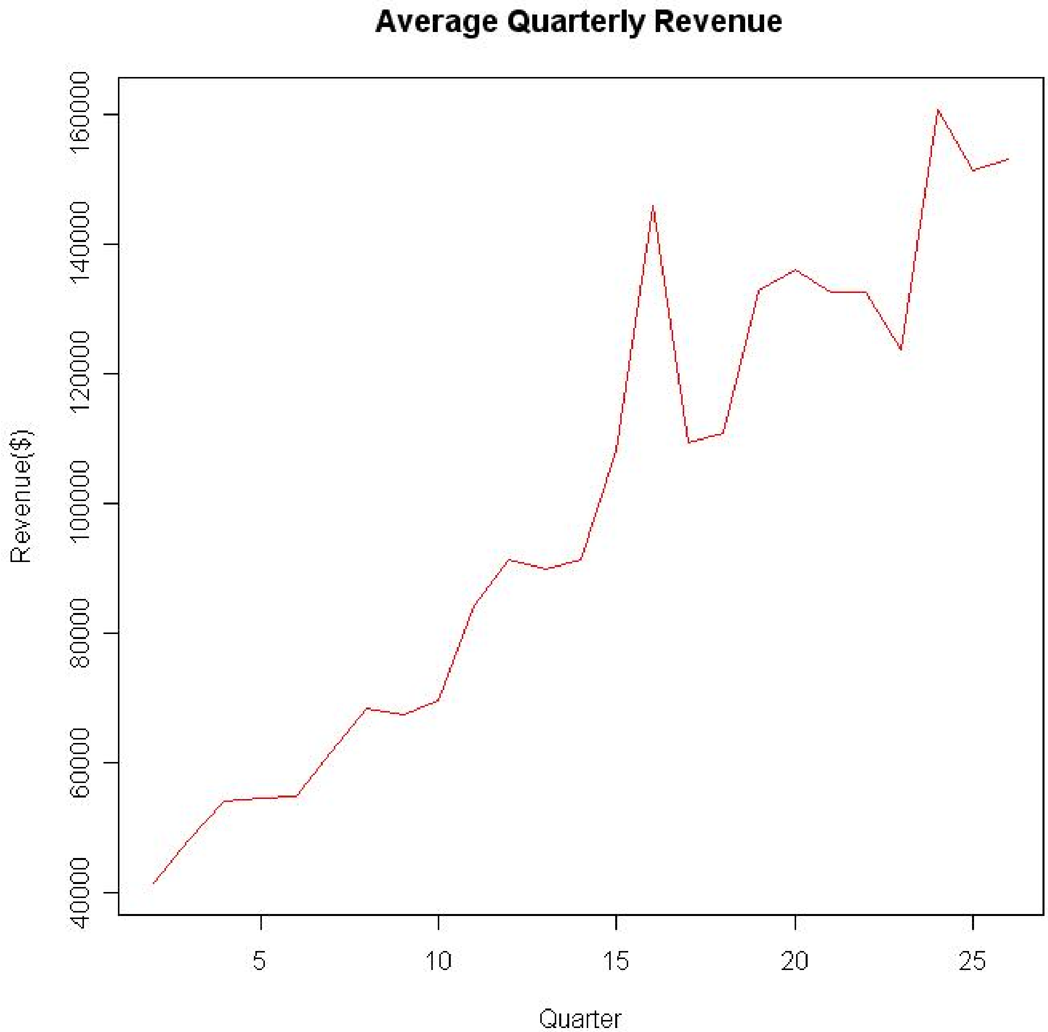

Figure B.2. Average Quarterly Revenue Across Zip Codes

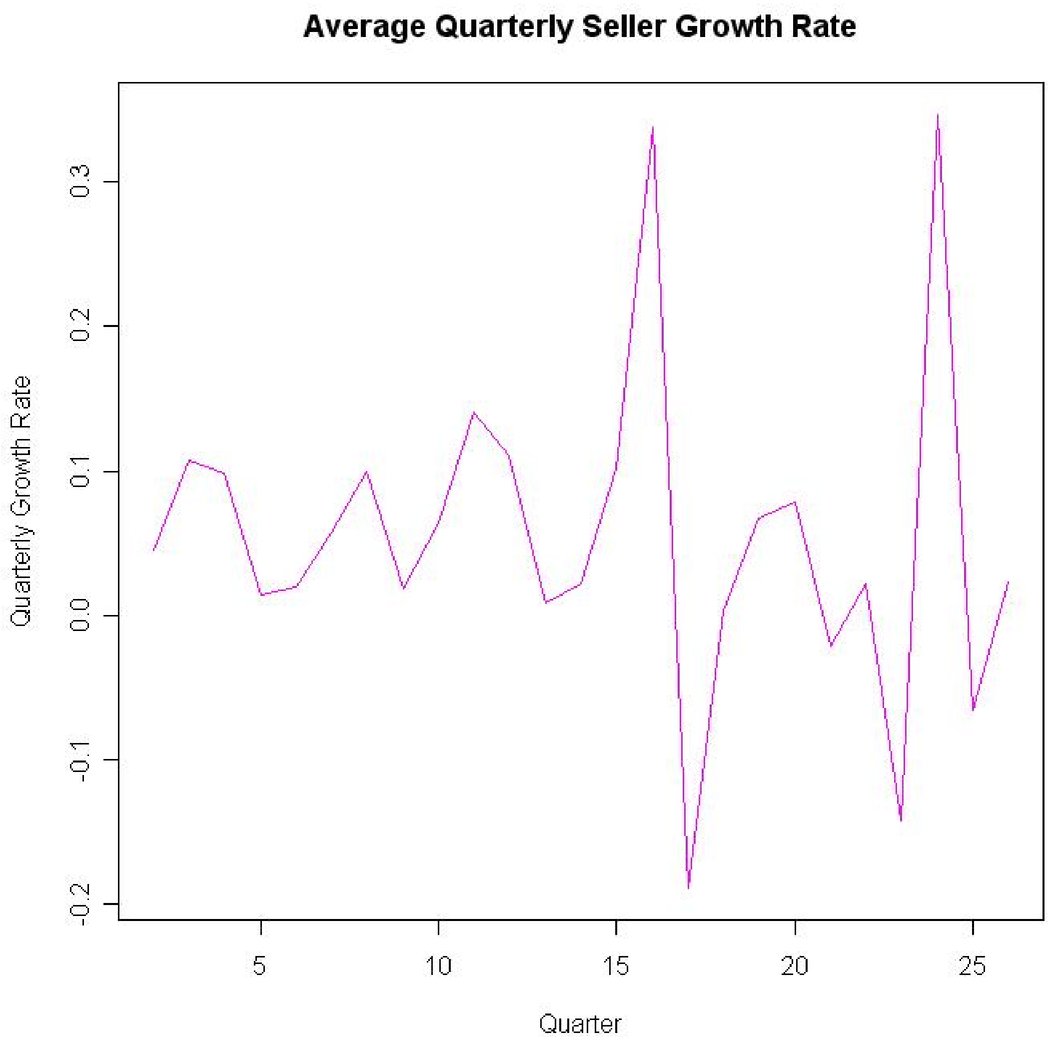

Figure B.3. Quarterly Seller Growth Rate

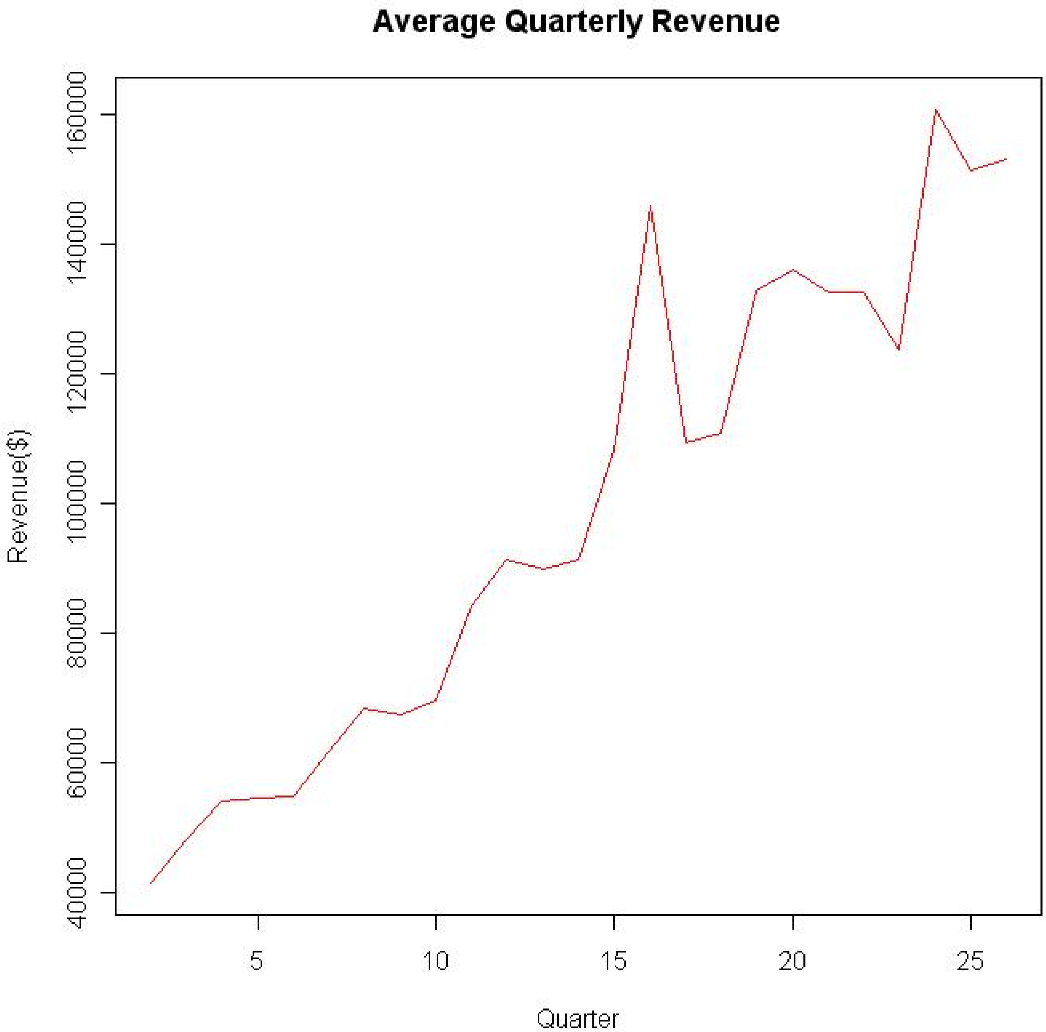

Figure B.4. Average Quarterly Revenue Across Zip Codes

Figure B.5. Quarterly Buyer Growth Rate

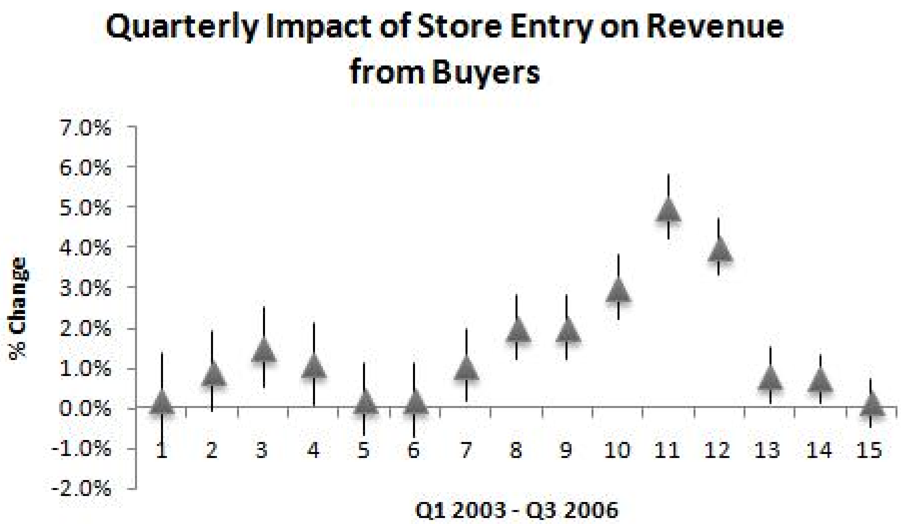

Figure B.6. Quarterly Impact of Store Entry on Revenue from Buyers

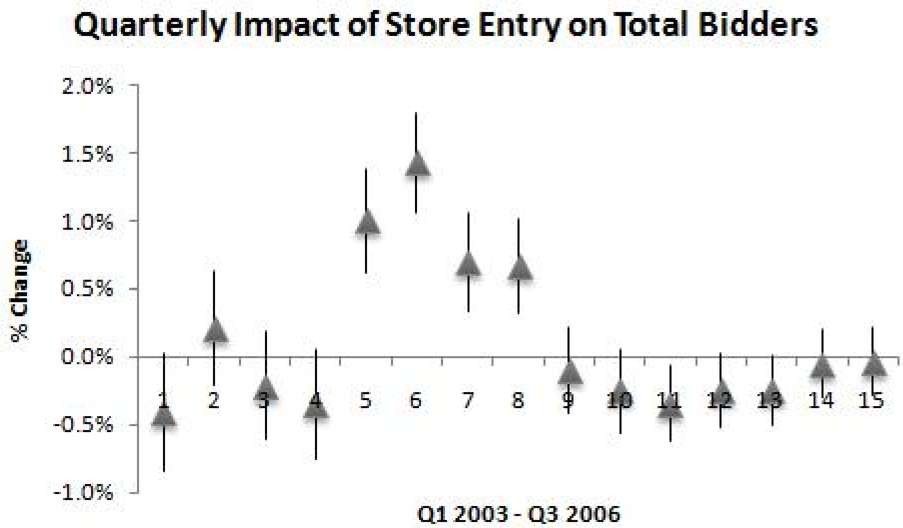

Figure B.7. Quarterly Impact of Store Entry on Total Bidders

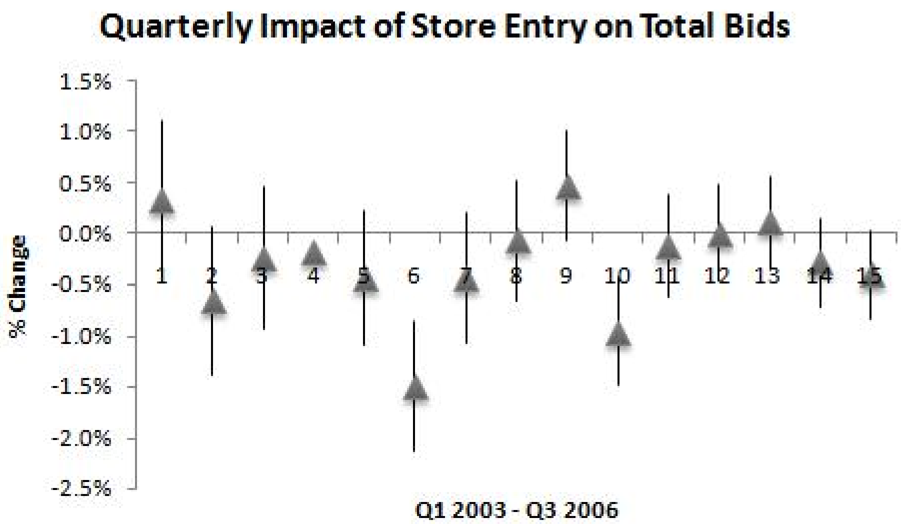

Figure B.8. Quarterly Impact of Store Entry on Total Bids

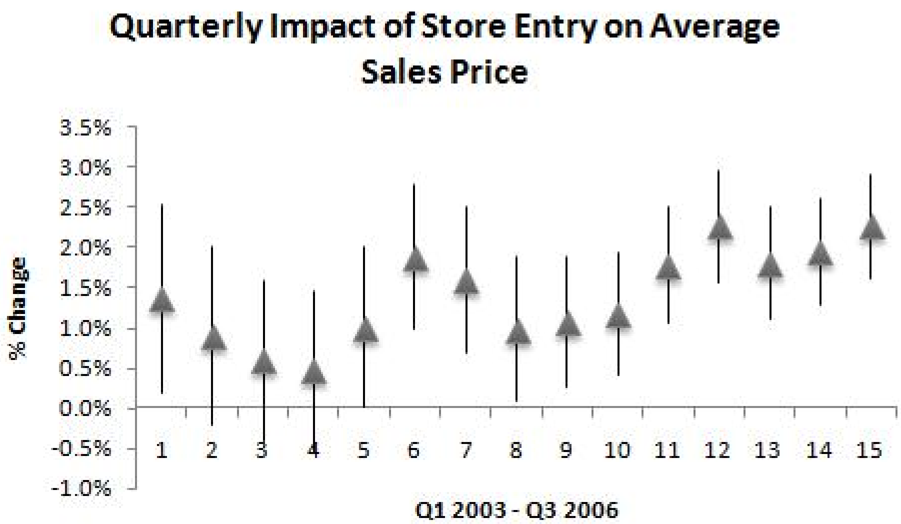

Figure B.9. Quarterly Impact of Store Entry on Average Sales Price

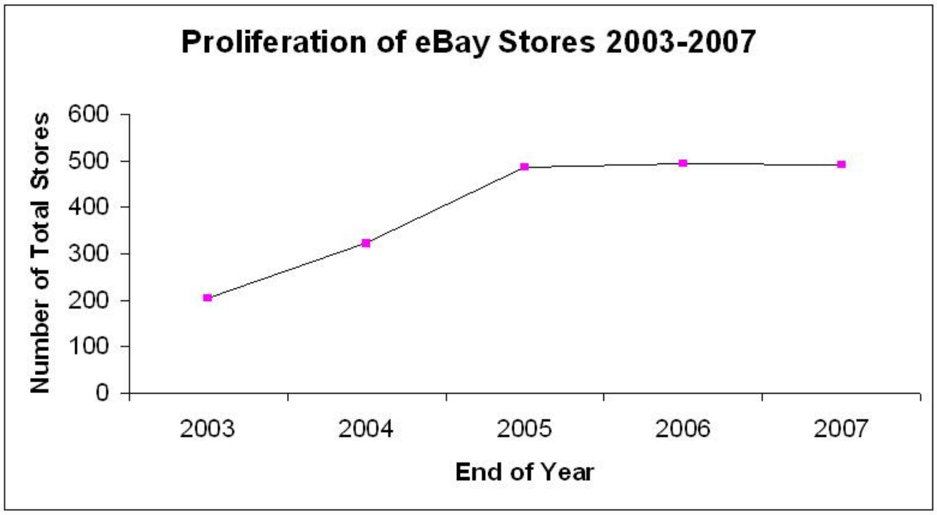

Figure B.10. Proliferation of eBay Stores

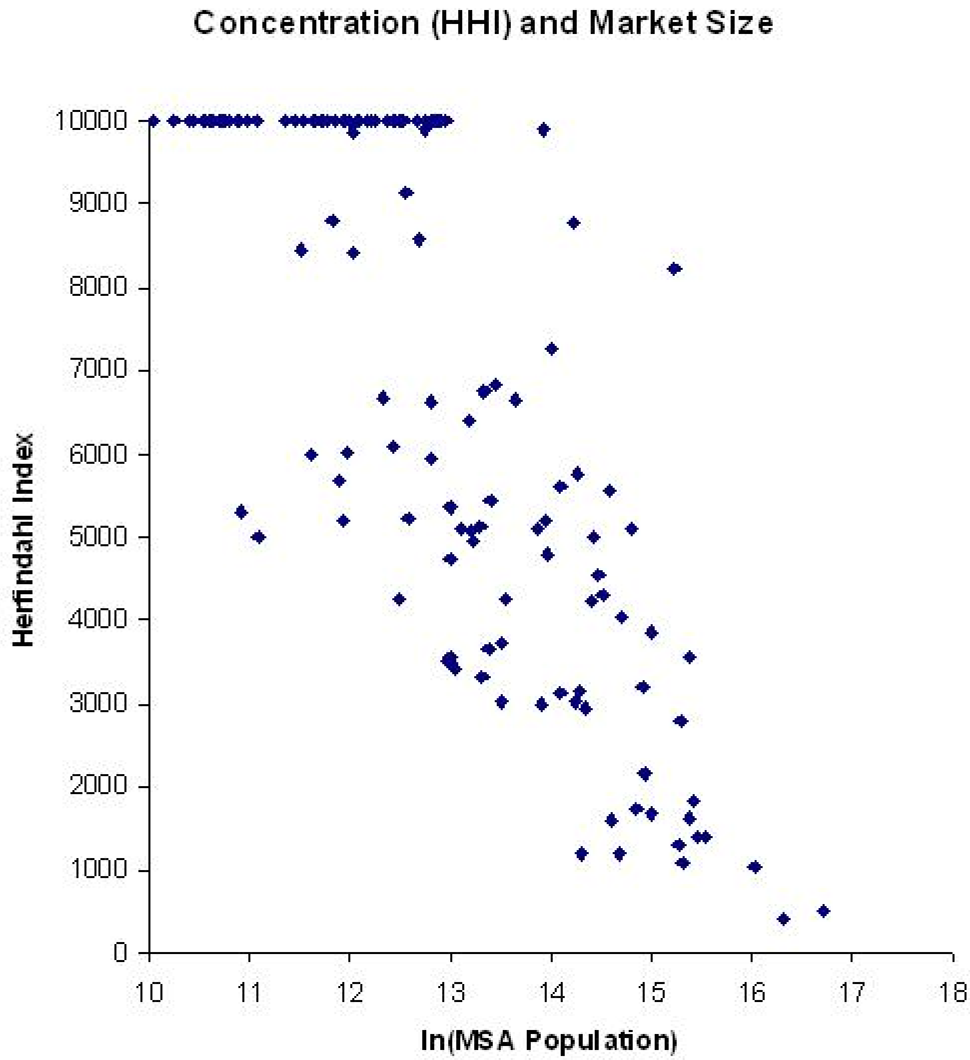

Figure B.11. Concentration (HHI) and Market Size

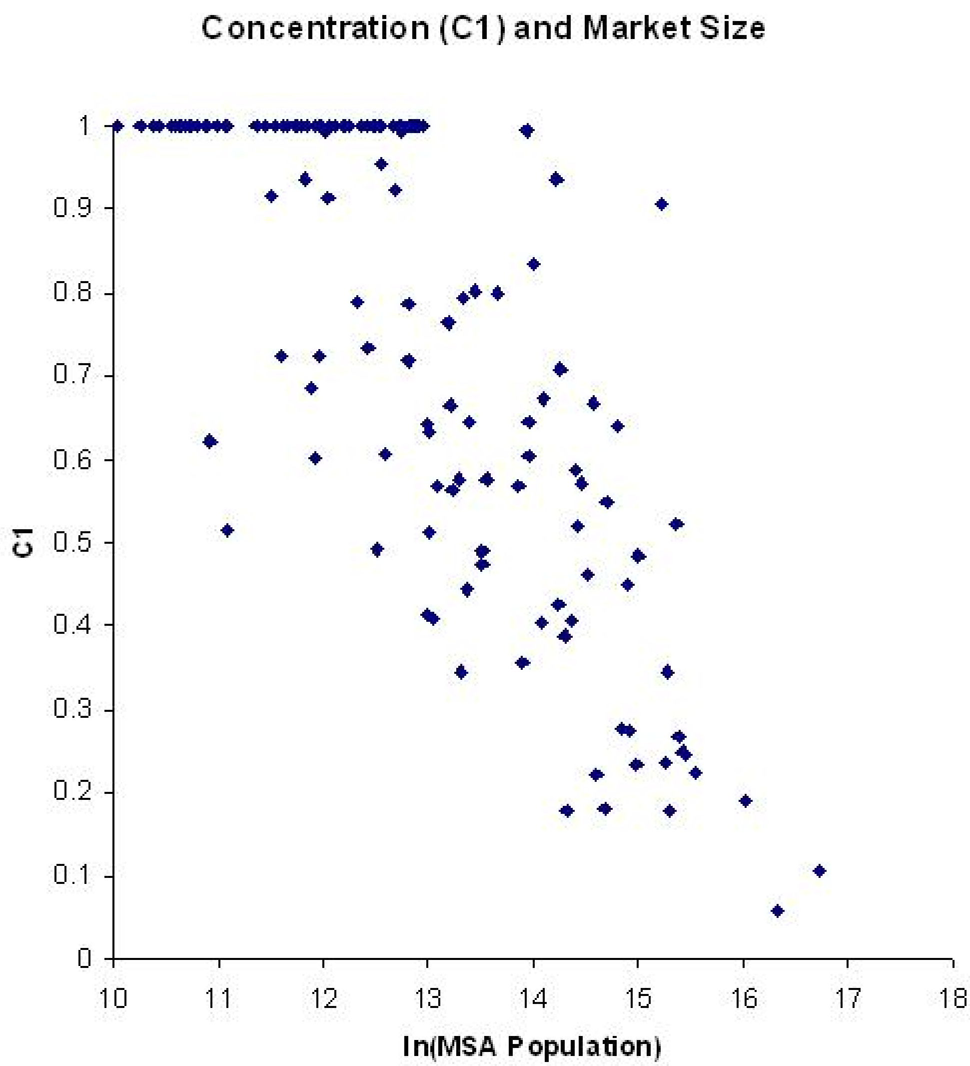

Figure B.12. Concentration (C1) and Market Size

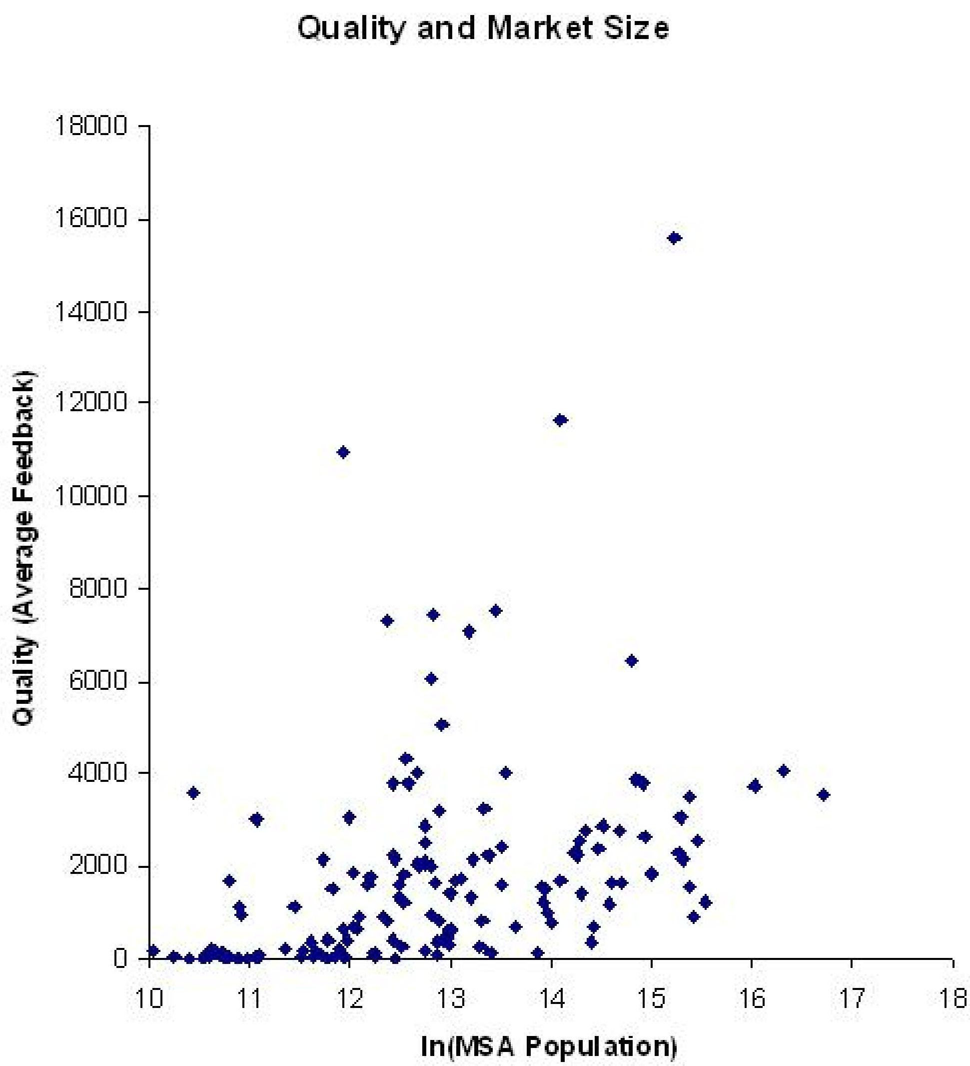

Figure B.13. Quality (Feedback) and Market Size