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Herd Behaviour and Preying on the Weak

- On Price Dispersion and the Intra-Distribution Mobility of Retailers in the Swedish Online Market

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Abstract
By examining six popular consumer electronic products in a detailed dataset gathered from a leading price comparison site, we show that retailers in the Swedish online market can be divided into two broad categories. The first group charge higher prices, change them frequently in response to competitors and have lower levels of customer satisfaction. In contrast, the other group of retailers exhibit lower prices, individual and less frequent changes with higher levels of customer satisfaction. These price setting behaviours cause local intra-distribution mobility not predicted by theory; firms frequently move up and down the cross-sectional price distribution at all levels, but do not move far from their initial position. Consistent with clearinghouse models of price dispersion, our findings support that uninformed consumers have much to gain from using price comparison sites.

JEL Classification No: D4, D83, L13.
Keywords: Price Dispersion, Intra-Distribution Mobility, Online Competition

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1. Introduction

1.1 Background

Historically, economists usually approached the question of information through a simple assumption; that it was perfectly shared by all participants. This was changed by George Stigler's (1961, p. 213) classical article on the economics of information. He eloquently states that:

> Ignorance is like subzero weather: by a sufficient expenditure its effects upon people can be kept within tolerable or even comfortable bounds, but it would be wholly uneconomic entirely to eliminate its effects. And, just as an analysis of man's shelter and apparel would be somewhat incomplete if cold weather is ignored, so also our understanding of economic life will be incomplete if we do not systematically take account of the cold winds of ignorance.

This spawned a new field of research and a plethora of papers on the impact of information. Some forty years later, Stigler's question of how information affects the efficiency of markets became actualised by the emergence of online markets and a fresh wave of research appeared. The so-called "New Economy" was to change the way of doing business altogether. Perfect information was to be fulfilled and online prices were to converge in accordance with the law of one price. Since then, researchers have established that price dispersion is a persisting feature of online markets. A less understood phenomena is that of the activity that goes on inside the price dispersion.

With this study, we shed light on the price changes that occur within the price dispersion and further the understanding of how and why firms move up and down the price distribution. An increased understanding of this is in the interest of retailers active in on- and offline markets as pricing decisions and strategies are all but set in isolation. Competitors' actions and reactions are of great importance. Consumers stand to gain much from learning of behaviours in online markets, as the Internet is an ever increasing platform for commerce and more and more people use it to purchase everything from consumer electronics to food.

Sweden provides an excellent base for further research within this area as there are numerous established e-commerce businesses that provide active markets to study. An effect of this thriving online retailing, and of particular importance for our study, is the widespread use of price comparison sites. The Swede's extensive use of these services can be illustrated by the fact that the two most popular price comparison sites, Prisjakt and PriceRunner, together achieve almost one million unique visitors every week out of a population of nine million[1]. The vast number of searches for products and potential purchases that pass through the price comparison sites creates a strong incentive for online retailers to list their prices with these clearinghouses. Having many visitors to these sites also ensure that the user contribution parts, such as reviews and ratings, are active and relevant.

[1] Sifo Research International, May 5, 2010

1.2 Overview and Contribution

With a detailed dataset describing the Swedish online market for six consumer electronics products, we take a closer look at the distribution of prices that make up the price dispersion. We conclude that price dispersion is evident and persistent in our dataset, as predicted by theoretical and empirical work.

The large number of price changes observed among the retailers charging higher prices in our dataset, even outnumbering those of the cheaper retailers, is contradicting of dominant theory. In a clearinghouse framework, firms either try to capture informed customers by competing at the bottom of the price distribution, or simply set a higher price and capture a fraction of the uninformed customers. The most intensive price competition is thus expected to take place in the lower region of the price distribution, with firms taking turns undercutting each other. Less price changing activity is expected from firms in the upper region of the distributions as they are selling to uninformed customers that purchase at random.

Varian's (1980) clearinghouse model predicts the use of frequent and random sale promotions to prevent uninformed consumers from identifying the low priced firms over time. The frequent price changing behaviour we observe leads to considerable movement up and down the distribution of prices, intra-distribution mobility, in all parts of the distribution. This mobility is however local, and firms do not move far from their initial position in the distribution. Our findings thus contradict those of Lach (2002) who finds strong support of the Varian model of sales. Instead we find support of Baylis and Perloff's (2002) empirical findings that firms are spread across the price distribution in a stationary manner to take advantage of uninformed customers, as originally proposed by Salop and Stiglitz (1977). Our findings thus provide clarification to the conflicting results of these particular parts of their studies, with clear answers from a recent high quality dataset.

Following Kauffman and Wood's (2007) methodology we find and present evidence of two broad groups of market participants: One group charge higher prices, change them frequently in response to competitor action and have lower levels of customer satisfaction. In contrast, the other group of retailers exhibit lower prices and less frequent changes with higher levels of customer satisfaction. We find that the price setting of the seemingly tacitly colluding group of firms to a large extent is explained by a *follower* behaviour with rapid responses to competitor price changes. We propose that firms either monitor the competition, or follow a similar set of business rules that govern their price setting behaviour, e.g. in relation to input prices from distributors. Arguably, this is a way for firms to reduce the managerial costs of strategic price setting. This is consistent with the lower levels of customer satisfaction that these *follower* firms exhibit. We conclude that there is evidently a large group of high-priced, low-service retailers that prey on uninformed consumers.

2. Theoretical Foundation

By examining empirical work and reviewing the theoretical models that have been formulated to predict and explain persistent price dispersion in equilibrium over the last decades, we conclude that the research field is, if not exhausted, mature to the point that economists now have sufficiently plausible explanations to why price dispersion still exists in online markets. Further insights will come from a more detailed analysis of how the intra-distribution of price setting firms work:

1. Price dispersion in the cross section is widespread across product categories, nations, and on- and offline markets. Price dispersion is also persistent over time, and the vast majority of empirical studies have found that online markets are not converging towards perfect competition.
2. Hidden product heterogeneity goes some way in explaining price dispersion. Search cost models and, more suitable for online markets, clearinghouse models take care of the rest.
3. New technology available to online retailers work to change their price setting behaviour, following its effects on, for example, menu costs and managerial costs.

2.1 Price Dispersion

Several factors have traditionally been studied when trying to determine the efficiency of a market or level of competition within an industry. Originally used to study the market conditions in traditional markets with bricks-and-mortar retailers, these dimensions were readily adopted to study the booming electronic commerce to see what impact, if any, this "New Economy" would have on competition.

Price level is the centre of attention in many classical microeconomic models where efficiency occurs when all firms are price takers and set their prices equal to marginal cost. A higher price deviating from this leads to inefficient markets since consumers are forced to refrain from trades that would otherwise have been socially efficient. Researchers have argued that consumer search costs are one of the causes for prices that are set higher than marginal cost even in clearing markets (Salop & Stiglitz, 1977; Stigler, 1961). Combining this with the theory of lower search costs on the Internet, Bakos (1997) concludes that the equilibrium price for goods should be lower in online markets than in their mundane counterparts. Brown and Goolsbee (2000) found that the emergence of the Internet did indeed have a lowering effect on prices in the life insurance industry.

Price dispersion is the term for a state where different retailers are quoting different prices for the same homogenous good, an obvious deviation from the law of one price. Multiple explanations for the phenomena have been proposed, including hidden product heterogeneity (e.g. different sellers offering different service levels), imperfect or asymmetric information, search costs, no transactions actually taking place on the upper range of the quoted prices (the price dispersion would then be merely illusory), and bounded rationality.

Scholten and Smith (2002, p. 1) use two datasets spanning a 24-year period to compare levels of retail pricing in 1976 with on- and offline retail pricing in 2000. They find that “the Information Age has done little to reduce price dispersion in retail and e-tail markets”. Brynjolfsson and Smith (2000) examine prices for books and CDs over a 15-month period, and find that ”Internet retailer prices differed by an average of 33 percent for books and 25 percent for CDs” and conclude that there is still considerable friction left in online markets. Comparative studies between national online markets have also been made, finding price dispersion across nations (Gatti & Kattuman, 2003).

Researchers have found that firms in online markets use a number of methods to differentiate their product offerings from competitors. These include, but are not limited to: safety-routines concerning payment, operating their own customer service, extending warranties and ease of navigation (Schmitz & Latzer, 2002). Hidden product heterogeneity is addressed by, amongst others, Lach (2002), Baye, Morgan and Scholten (2004c) and Baylis and Perloff (2002). The former two studies do so by introducing controls for a range of factors in their regressions to eliminate these effects. The latter find that some online sellers persistently offer high prices and poor service, or low prices and good service. This is contrary to what would be expected if price dispersion was a result of hidden product heterogeneity, as Kauffman and Lee (2004) argues.

Baye, Morgan and Scholten (2004a) try to take tackle the issue of not knowing whether there are transactions taking place at all of the quoted prices. They do so by arguing that most transactions should be taking place at the lowest prices, and that a lack of spread within these should be sufficient to conclude that the market actually is efficient. To try to capture this they introduce the measure Gap, defined as the difference between the second lowest and the lowest price. They do, however, in the same paper legitimise the price quotations in their dataset by the fact that it is costly to post prices on the site where their data is collected, and that it would be irrational to post prices that will not lead to transactions. A sizable amount of the products in their sample have an economically significant gap between the two lowest prices, and it is stable over time. They can thus not declare price dispersion to be non-existent.

For extensive reviews of the theories and empirical findings regarding online price dispersion, please see Pan, Ratchford and Shankar (2004) and Baye, Morgan and Scholten (2006).

2.2 Price Rigidity and Price Setting

Price rigidity is a consequence of firms' reluctance, inability or ignorance, resulting in that they do not instantly change their prices to reflect, for example, changes in costs or supply and demand. It contradicts the theoretical assumption that market participants continuously adjust their prices to mirror the underlying market fundamentals, and thus causes inefficiencies since, in theory, incorrect prices prevail.

Menu costs, the costs that a retailer incur when making a price change, is the measure where the most conclusive research on online retailing can be found. The incurring of a cost every time a price change is made will obviously cause retailers to be less likely to change prices. Thus, higher menu costs lead to higher price rigidity. Following this reasoning, online retailers would be expected to change prices more often than their traditional counterparts as a result of their lower menu costs, some only having to change a single entry in their database to adjust all prices. A study on prices for matched sets of books and CDs find that "Internet retailers make price changes that are up to a 100 times smaller than the smallest price changes observed in conventional outlets" (Brynjolfsson & Smith, 2000).

Another expense for making price changes is the managerial costs. A price change is in many cases the result of a thought through decision from managers, and the cost of this process have been shown to be substantial (Zbaracki et al., 2004). The digitalisation of markets and internal information systems may nowadays be used to lessen these costs by setting up pricing schemes and rules in advance that automatically change prices on given signals. This kind of tools will be easily implemented by online retailers since they, as well as their direct competitors and the clearinghouses, are completely "digitalized" with prices and market communication readily available online.

The present asymmetric information in the relationship between the consumer and the retailer means that the consumer cannot with certainty know the level and quality of service that will be provided by the retailer. A good retailer will thus be interested in successfully signalling his superiority to be able to charge a premium for it. Taking into account the assumed relationship in markets that more expensive products are superior to cheaper ones, and a higher price thus signals quality, it has been shown that good retailers are reluctant to lower their prices to reflect, for example, lower costs, to not risk signalling a lowering of quality (Stiglitz, 1987). This contributes to price rigidity.

2.3 Theoretical Frameworks and Models

Founding Frameworks

We review a plethora of empirical research on the subject of the economics of information in general, and the efficiency of online markets in particular. This research was preceded and accompanied by a stream of theoretical models that have tried to predict or formalise these findings respectively.

As a starting point for a brief review of these models, we will consider the standard textbook case: In a world with homogenous sellers and buyers, that have perfect information regarding a homogenous good, the competitive price will be the unique Nash-equilibrium (otherwise known as the Bertrand outcome, giving rise to the "law of one price"). Although this is undoubtedly a useful conceptual tool, many have proven that there are important insights to be gained from relaxing these assumptions whilst studying the efficiency of markets.

Going back to early research, authors such as Hotelling (1929) and Chamberlin (1933) have shown that price dispersion can exist in equilibrium by modifying the assumptions regarding homogenous products and sellers. In their classical models, differentiated sellers (by geography), pass on their heterogeneity and thereby turn seemingly homogenous products into heterogeneous offerings – thus showing a theoretically valid basis for price dispersion.

Stigler (1961), however, argued in his seminal article that heterogeneity as the cause of price dispersion is but one piece of the puzzle, and instead introduced buyer search costs as a possible explanation for price dispersion.

Subsequently, this gave rise to several important theories that focus on assumptions regarding the buyer of a good. Below we will examine the main branches of this research that are relevant to our study. For a comprehensive review of theoretical models, see Baye, Morgan and Scholten (2006).

Search Cost Models

One of the earliest attempts at modelling price dispersion of homogenous products is the aforementioned Nobel laureate George Stigler's (1961) article. He finds that price dispersion arises due to the positive search costs that a consumer suffers when trying to find the best price, and concludes that price dispersion should decrease as search costs go down. Stigler's model builds on a fixed sample search where buyers decide on a fixed number of stores to obtain price quotes from and then go on to purchase at the lowest price found.

This model has come under critique for being too simplistic. Rothschild (1963) argued that if sequential search is assumed, i.e. that new information is uncovered during the course of searching for the lowest price, it will be optimal for buyers to have a stopping rule that will cause them to stop searching once they've found a sufficiently low price (this is a set reservation price, whereby gains from additional search are below the marginal cost of the search itself). Rothschild then introduces optimizing firms, and shows that under these conditions Stigler's model only creates a "partial-partial equilibrium" (Baye, Morgan & Scholten, 2006) where price dispersion in equilibrium is not certain.

Another important contradiction to Stigler's notion of costly search is the "Diamond paradox" (Diamond, 1971) where it is shown that in a setting with competing identical firms and positive search costs for buyers, the monopoly price is the equilibrium outcome.

These important doubts regarding if search costs alone could give rise to price dispersion spawned new research, and after several decades Burdett and Judd (1983) showed that *ex ante* identical buyers and sellers can give rise to price dispersion in equilibrium in a search-cost framework. They do this by establishing that in the process of sequential search, a fraction of buyers do not search for prices in the casual sense, but instead purchase from the first firm, and that the rest of the buyers are "shoppers" that compare two firms and choose the lowest one.

As we have seen in the review of empirical research, search costs can be practically non-existant in today's online markets, and thus the Burdett & Judd study is an important bridge to the next stream of research, clearinghouse models, where different buyer behaviour (shoppers and non-shoppers) instead drive price dispersion in equilibrium.

Clearinghouse or Tourists vs. Natives Models

Although not formally a clearinghouse model, we have chosen to start this section with Salop & Stiglitz' (1977) article on the concept of informed and un-informed buyers (i.e. shoppers and non-shoppers, or more popularly *tourists* and *natives*) under this heading since the intuition is very similar and it is indeed much of a predecessor to the formal clearinghouse models.

Salop (1977) showed that if buyers are heterogeneous with different search costs, there are incentives for a monopolist to use sale promotions to create "noise" in the search process in order to be able to charge higher prices to those buyers that are unable to search efficiently. This static model of price dispersion in equilibrium is built upon in Salop & Stiglitz (1977) in a more generalised framework where uninformed buyers (with positive search costs) suffer a higher price, and informed buyers (no search costs) get charged close to the competitive price (marginal cost). This model is certainly appealing in today's online market where the informed buyers would be those that utilise services such as Prisjakt or PriceRunner. These are good examples of the information clearinghouses that subsequent models use to explain price dispersion in equilibrium.

An early and commonly cited paper is that of Varian (1980). Varian argues that not only do we find the effects of *ex ante* heterogeneity amongst buyers where some are informed and some are not – similarly to Salop and Stiglitz (1977) he also raises the important point that if price dispersion is to persist in equilibrium, the uninformed buyers must not be able to learn about the distribution of prices over time (i.e. where to find the lowest price). This implies that sellers need to engage in some random price-setting behaviour, a theoretical foundation for Lach's (2002) finding that sellers move considerably within the intra-distribution of price rankings.

Other models have used the same intuition, but with a slightly different story, to produce similar outcomes. Shilony (1977) and Rosenthal (1980) show that instead of having buyers that are unwilling or unable to utilise the information clearinghouses to become informed, you can achieve price dispersion in equilibrium when there are buyers that for some reason are simply loyal to certain firms.

Baye and Morgan (2001) use a similar model to Varian (1980), with some crucial differences. They show that even in a framework with optimizing buyers (that utilise the clearinghouse) and optimizing sellers, price dispersion will be persistent in equilibrium due to fees charged by the clearinghouse for sellers to post their prices.

In one of the most recent contributions to the clearinghouse stream of research, Baye, Morgan and Scholten (2004a) encompass Shilony (1977), Rosenthal (1980), Varian (1980) and Baye and Morgan (2001) as special cases in a general clearinghouse model that is also successfully applied to empirical data in their corresponding study.

3. Empirics of Intra-Distribution Mobility

Although the foundation of our study rests on general theories of price dispersion in the cross-section, greater insights stand to be gained from delving deeper into the actual behaviour of the price setting firms. By studying the competitive relationships among firms, when and how they change price and thus place in the price ranking relative to other firms, or the *intra-distribution* in jargon, further conclusions can be drawn about what actually goes on inside the cross-sectional price dispersion.

Lach (2002) uses a dataset consisting of 31 products collected by the Israeli Central Bureau of Statistics between January 1993 and June 1994 which he then reduces to four products: one durable and three staple foodstuffs. As is common, Lach begins with an examination of the persistence of price dispersion that is evident in the markets for these goods. Even after controlling for visible and hidden product heterogeneity he finds that this considerable dispersion is persistent over time. His main finding, and contribution to our study, however, is that "The cross-sectional price dispersion is quite stable over time, but this stability masks an intensive process of stores' repositioning within this cross-sectional distribution" (Lach, 2002, p.443). He concludes that this is evidence for Varian's (1980) model where hit-and-run sales create "noise" that prevents uninformed buyers from learning the composition of the price distribution over time. As a side note, Lach's findings are supported by Baye, Morgan and Scholten (2004b) who study online markets for 36 products at the turn of the millennia. However, the methodology differs in the aspect that their study is carried out on the retailer level[2] and revolves mainly around the observation that the identity of the absolute low-priced firm changes over time.

Baylis and Perloff (2002) gather prices from US online retailers for two consumer electronics products, a digital camera and a flatbed scanner, during 14 weeks between October and December in 1999. Cross-sectional price dispersion is evident and stable over time in their dataset, in line with other studies from this period. Baylis and Perloff also consider Varian's (1980) model as a possible explanation for this price dispersion, but find no evidence of the mixed sales strategy Lach (2002) uncovers in his study. They explicitly state that "We do not observe firms collectively raising or lowering prices randomly over time or individual firms taking turns undercutting each other" (Baylis & Perloff, 2002, p. 307). Instead, they find a stable intra-distribution that persists over as long time periods as ten months, "high-priced firms remain high-priced over time, and low-priced firms remain low-priced over long periods" (Baylis & Perloff, 2002, p. 314). This leads them to favor the Salop and Stiglitz (1977) framework, where firms aim to capture different segments of the market, the *tourists* and the *natives.*

[2] The dataset consists of 36 popular products gathered from a price comparison site from November 1999 to May 2001. The specific retailers studied are kept constant over time, and thus the study suffers from life-cycle effects as products become obsolete and drop out of the sample over time – or worse for inference, stay in the sample without any actual transactions taking place.

These radically different results from two studies that study the same market mechanics give rise to a number of questions. Although there are arguable differences in studied markets (online vs. physical) and products (durables vs. staple goods), the contrast is startling. The conflicting results call for further research into this particular area of the price dispersion field, and further testing on data from a suitable environment.

One plausible way forward would be to look closer into the intra-distribution and examine what drives the mobility of individual firms within the cross-sectional price distribution. This is employed by Kauffman and Wood (2007) who use a comprehensive dataset gathered between February and March in 2000 to examine price change timing and behaviour in great empirical detail. They uncover that "The Internet allows many different pricing strategies, including reactive competitive pricing or tacit collusion […]. Firms tend to match competitor changes, and so prices tend to go both up and down – as opposed to just down" (Kauffman & Wood, 2007, p. 694-695). Their results provide support for Baylis and Perloff's (2002) study as the observed rapid matching of price offers limit the effectiveness of a Varian mixed sales strategy.

4. Data

Our dataset describes a set of six products with differing dates of introduction, and the retailers that offer them. The earliest product introduction is July 2, 2009, and observations on all six products continue on a daily basis until April 28, 2010.[3]

The products selected for the study are the Apple iPod Shuffle 2GB (portable music player), Canon EOS 7D[4] (DSLR camera), Corsair DDR3 2x2GB[5] (computer memory), HTC Hero (smartphone), Intel X25 80GB (internal computer hard drive) and PS3 Slim 120GB (gaming console). Popularity and an online market with a large number of active retailers is the basic requirement for product selection. We select products with different price level, price pattern, type of usage and complexity. Summary statistics of the data is provided in Table 1 and 2. In Table 1 we show the different price levels of the products, with mean prices ranging from a low of 659 SEK for the iPod to a high of 17 185 SEK for the Canon DSLR camera.

Table 1. Price Descriptives (SEK)

				Price			
Product	N. Prices	N. Price Changes	N. Weeks	Mean	Std. Dev.	Min	Max
Apple iPod Shuffle	15 961	780	34	659	89	425	995
Canon EOS 7D	17 170	2 651	36	17 185	1 398	12 907	24 526
Corsair DDR3	15 820	3 086	38	1 370	204	849	2 240
HTC Hero	14 966	758	43	5 130	688	3 490	8 228
Intel X25	22 377	4 933	42	2 386	255	1 792	3 887
PS3 Slim	15 376	2 515	36	3 565	473	2 400	7 999
Total	101 670	14 723					

All descriptives are for the entire periods. Number of prices is the number of price quotations each day summed up over the entire period. Since price levels change over the period, the range and standard deviation of prices should not be interpreted as measures of price dispersion. The level of price dispersion is instead shown in Table 3.

Studying price dispersion and the pricing of products, it is important that we secure that the products are physically homogenous. To start off with, we have defined the products to the greatest detail possible out of different versions regarding, for example, memory capacity. The first step to ensure homogenous products is handled by Prisjakt, by means of them conducting thorough and continuous control to ensure correct matching of price and product when indexing the prices on their site. As Prisjakt offer the possibility to list both the single product and the same product bundled with some extras, we have reviewed the product descriptions as submitted by the retailer for each price and removed those products that are not homogenous.

[3] In spring 2009 Prisjakt increased the scope of data to be saved and from that point and forward saves all information about historical price changes etc., instead of as previously dropping some of the historical information relating to discontinued offerings. An appropriate time period for data selection, to guarantee correct and complete data, is thus after this change.

[4] A DSLR camera, or Digital Single-Lens Reflex camera, is an advanced and relatively higher priced camera used mainly for enthusiast and professional photography. The product in our sample refers to the body of the camera and is not bundled with any camera lens.

[5] The exact product name is "Corsair XMS3 DDR3 PC12800/1600MHz CL9 2x2GB"

However, we have for example considered different colours of the same product to be homogenous traits. To achieve a single listing from each retailer each day, despite allowing for such differences, we have singled out the lowest price as the one to include. Price listings from the retailers "Blocket.se" and "Tradera.com" have been removed as they offer used products.

For these products and their specific periods, we have observations of all price changes made by every retailer offering the product (the date, the new price or a note of discontinuation, and corresponding retailer product description). If a retailer changes price more than once on a given day, the observation in our dataset is the price offered at the time of Prisjakt's final update that day. We are thus not able to conduct our analysis on an intra-day level. From our list of price changes and discontinuations we recreate the distribution of all prices offered each day throughout the period, by carrying data forward between observations.

Our dataset of daily observations also includes the rating of the retailer's services as submitted by Prisjakt's users, and the number of ratings that have been posted the last twelve months. These ratings are the users' subjective judgement of the customer satisfaction level in connection with a transaction. The retailers are graded on a scale from one to ten, and the rating can be complemented with a text comment. In order to not give few reviews of a retailer too much weight, Prisjakt use a formula to calculate the rating that is actually quoted on the site, and this is the measure we have chosen to use. Equation (1) shows the exact formula used by Prisjakt, based only on ratings submitted in the last twelve months.

$$Weighted\ Rating = Average\ Rating + \frac{5 - Average\ Rating}{N.Ratings + 1} \tag{1}$$

In Table 2, we show descriptives for the retailers offering the products. Most retailers offer the products a predominant part of the time. This can be seen from the tendency of the mean number of retailers and mean weeks in sample to be closer to their corresponding maximums rather than minimums. With a mean number of retailers around 70, it is evident that these are active markets for each product.

Table 2. Retailer Descriptives

	N. Retailers			Weeks in Sample		
Product	Mean	Min	Max	Mean	Min	Max
Apple iPod Shuffle	72	1	87	30	5	34
Canon EOS 7D	74	7	91	32	3	36
Corsair DDR3	66	5	80	37	1	38
HTC Hero	54	2	68	34	1	43
Intel X25	85	10	109	33	1	42
PS3 Slim	64	6	78	29	1	36

The low minimum number of retailers is a result of starting to observe the products immediately as a retailer lists the product for sale. Some retailers are quicker than others to begin marketing new products, and some even start to take orders before first delivery.

The prices are gathered by Prisjakt in two distinct ways. For roughly half of the retailers they are automatically communicated to Prisjakt through built-in systems in the retailer's web-pages, and for the other half they are gathered by Prisjakt through automatic scanning of the retailers' sites. Regardless of technique, the prices are updated on average more than three times a day. The price quotations are thus factual and up to date, making concerns about the accuracy of the data, as in some other studies, of little concern. It is free of charge for a retailer to merely list prices and Prisjakt actively seek to list all retailers that are present in the markets they cover. Additionally, they do so independently of whether or not the retailer requests it by utilizing the latter of the two techniques. Prisjakt's market position and the exposure and many potential leads this generates, as well as their own efforts to list all retailers, make us confident that the vast majority of the Internet retailers for our set of products, and an even larger fraction of total sales, are captured in our dataset.

Prices including postage and packaging are only disclosed by some retailers in our dataset, and as a consequence of this we use prices excluding these charges. Thus, in most cases, the prices do not reflect the final cost to the end customer. These costs may have an effect on the decision of the consumer and they might be used strategically by retailers to obfuscate the real cost, as Ellison and Ellison (2009) explores. Also, individual differences in shipping costs cannot be captured in a general listing; distance to the customer, total weight and tiered shipping costs in relation to purchase price all affect individual customers final cost. This is an inherent problem when gathering prices from comparison sites such as Prisjakt. However we consider the benefits in form of access to an extensive range of product and retailer characteristics, as well as the accuracy and sheer scale of the dataset to outweigh these issues.

The problem of not knowing whether there are transactions actually taking place on all price quotations is often raised in studies of prices dispersion. As we cannot observe actual transactions, nor if the product is held in stock by all retailers at a certain time, this issue is present in our dataset as well. Baye, Morgan and Scholten (2004a) validate the price quotations in their dataset with the fact that it is costly to post prices at the price comparison site that is their source, and that prices thus can be expected to lead to transactions since it would otherwise be irrational to pay to list them. The fact that it is not costly to list prices on Prisjakt might in this light be seen as a disadvantage leading to that some prices may not be representative of the actual market situation and that some prices might be "dead" (not kept up to date). On the other hand, as stated, an advantage is that there is a greater probability that the whole market is captured. One possibility, as also used by Cabral and Hortaçsu (2006) in their study on eBay, is to proxy for the amount of sales with the number of user reviews. As it is voluntary to post such a review, the absolute number of reviews will obviously not reflect the absolute number of sales, but most often a scholar is more interested in the relative sales of different retailers to be able to control for this.

5. Price Dispersion and Price Changes

We find clear evidence of persistent price dispersion in our dataset. The average level of price dispersion for each of our products is shown in Table 3. Selected measures can also be seen graphically in Figure 1. This is of importance to us as we study the movement and behaviour of the market participants within this range.

5.1 Prevalent and Persistent Price Dispersion

With a mean price that is on average 33.1-61.4% higher than the lowest price, our dataset once again confirms the persistent price dispersion in online markets. This means that an uninformed consumer, who randomly selects a retailer and purchases one of the products, will pay a price that is on average 46.4% higher than an informed consumer purchasing at the lowest price. At a casual glance, the results from our dataset also shows evidence of the previously found relationship between absolute price level and level of price dispersion, with lower levels of price dispersion for more expensive products (Gatti & Kattuman, 2003; Lach, 2002). We can, for example, see this by contrasting the Canon camera with the Apple iPod. Note that these measures are calculated on raw prices, not after controlling for factors that have previously been found to be significant in explaining parts of price dispersion. See for example Brown and Goolsbee (2002) and Lach (2002). Although we acknowledge the obvious benefits of controlling for known sources of price dispersion, such as hidden product heterogeneity, when studying and comparing the level of price dispersion, it is not necessary for the purpose of this study.

Table 3. Price Dispersion (Mean over Sample Period)

			Percentage Difference			
Product	Coef. of Var (%)	Perc. Gap	Mean/ Low	75th/ 25th	95th/ 5th	2nd High/ 2nd Low
Apple iPod Shuffle	13.4	3.4	55.0	19.8	54.5	63.9
Canon EOS 7D	7.3	1.5	33.1	8.8	24.7	32.8
Corsair DDR3	11.0	3.2	61.4	13.4	44.1	58.9
HTC Hero	9.9	1.4	47.0	14.2	36.1	40.6
Intel X25	10.2	1.4	33.2	14.3	36.5	52.8
PS3 Slim	12.5	2.8	48.5	16.6	44.0	52.9
Mean	10.7	2.3	46.4	14.5	40.0	50.3

All measures of prices dispersion are computed each day and then averaged over the entire period. Percentage gap is defined as the difference between the second lowest and the lowest price, over the lowest price, as introduced by Baye, Morgan and Scholten (2004a).

5.2 Discussion on Dispersion and Changes

In order to facilitate the reader's understanding and interpretation of our findings, as well as provide evidence of the existing price dispersion in our dataset we provide casual thoughts on the price development of our six products below.

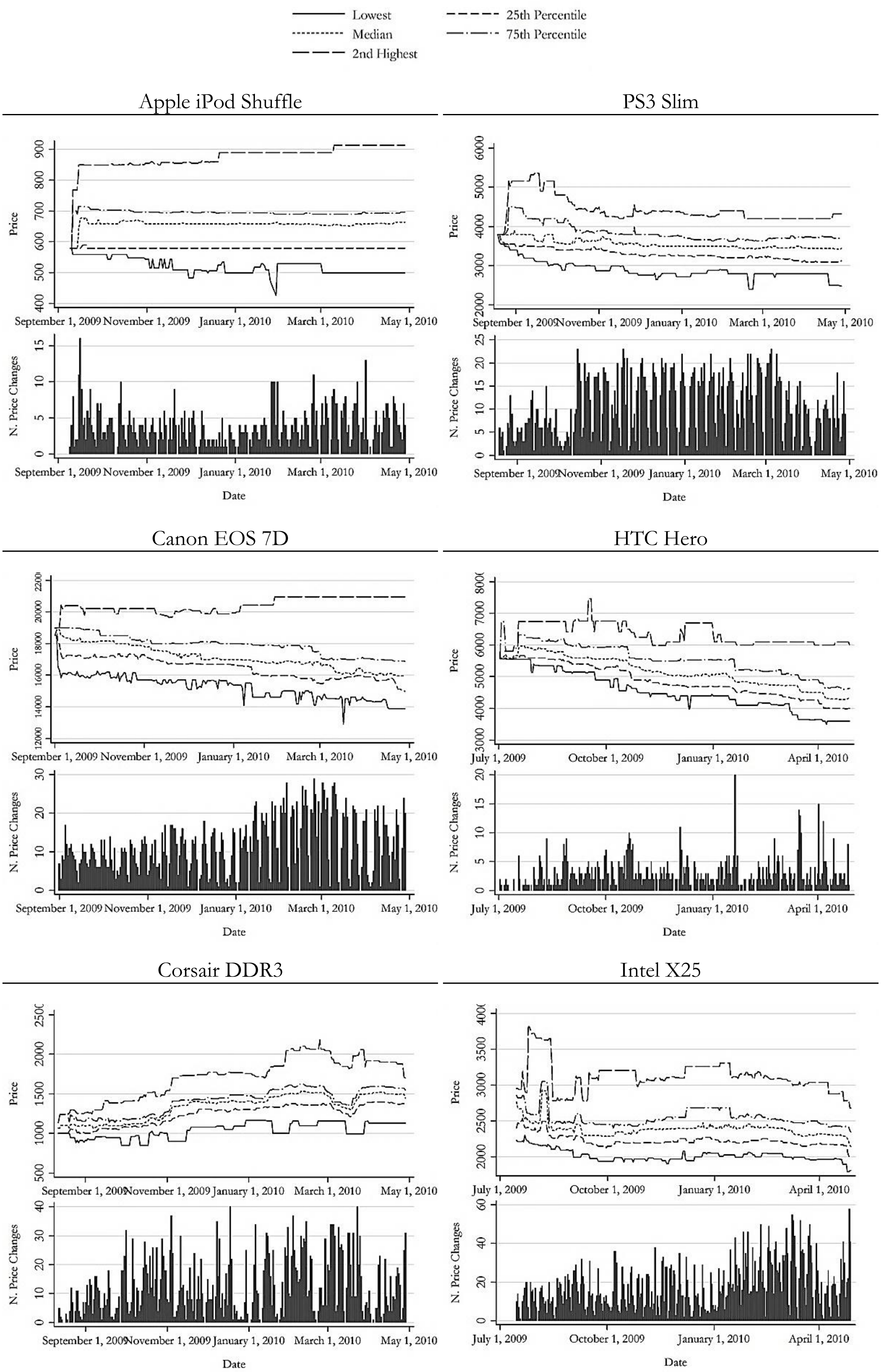
Figure 1 shows the price development from the products' entry to the market, the first time a store lists the price, until the last observation made on April 28, 2010, including the number of price changes made by retailers that are marketing the product at each given point in time. Out of the six products we have grouped three pairs side-by-side that, broadly speaking, have similar price developments.

We believe the stable prices of the portable music player and the gaming console are to a large extent results of clear pricing strategies from the manufacturers rather than the retailers. Our take regarding the portable music player is that the manufacturer Apple set an introduction price they intend to stick to for most, if not the whole, of the product life until they introduce a replacement. As a large retailer of their own products, they are able to exert control over the margin of the retailers and put pressure on them to enforce their pricing strategy. Regarding the gaming console, we believe that the stable prices are a result of the inherent market structure. The market is controlled by a few dominant actors and characterized by infrequent product introductions and long product life-cycles. Gaming consoles are often initially sold at a loss to increase sales and beat the competition in number of units on the market, with the profit then earned on the games sold for the consoles. It is thus important to have a large, locked-in, market for the manufacturers. This pricing strategy put pricing choices for the consoles under pressure and is very much dependent on the other consoles on the market, with little space for individual retailers to develop distinguished pricing schemes.

Declining prices, exhibited by the DSLR camera and the smartphone, is widely expected from consumer electronics as a result of continuous product developments and introductions from both the manufacturers of these specific products and their competitors.

The rising prices of the computer memory and hard drive stand out from the rest. As these products only function as part of a larger computer system, they may often be sold as bundles consisting of a number of components and thus retailers are less constrained when setting the price of the individual component. A price decline in one component might be used to increase the price of another, keeping the basket price at roughly the same level.

Figure 1. Price Development and Price Changes



All observations underlying the figures are on a daily basis and over the entire periods. Second highest price is displayed instead of highest to mitigate the effect of temporary outliers.

6. Results

6.1 Price Changes Spread Evenly across the Price Distribution

Contrary to the intuition provided by the dominating clearinghouse framework, we show in Table 4 below that on average more than 50% of all price changes take place in the upper half of the price distribution. At a product level, the two least dispersed products, the Canon EOS 7D and the HTC Hero, exhibit the price changing behaviour predicted by clearinghouse models with the bulk of the changes happening in the first quartile. However, in the two most active product markets, the Corsair DDR3 and the Intel X25, where the median retailer changes price 1.4 times a week, changes happen least often in the first quartile of the price distribution. Of the price changes in these product markets, 59% and 58% respectively occur in the upper half of the distribution. These two products exhibit the highest number of actual price changes, numbering in their thousands together and showing upon an intense activity within the intra-distribution.

The currently dominating clearinghouse models state that some firms capture the informed customers that purchase at the lowest price offered at the bottom of the price distribution where there is intense price competition, and that other firms post higher prices in hopes of capturing the uninformed customers. Accordingly, there is an incentive for low price firms to change their prices in response to competitor movements whilst the higher priced firms would post a price and then wait for customers to purchase from them at random. We examine the causes of the seemingly pointless repositioning of firms in the upper part of the price distribution.

Table 4. N. Price Changes per Retailer and Week

Product	Coef. of Var (%)	N. Price Changes	Changes per Week	Distribution Q1	Q2	Q3	Q4
Apple iPod Shuffle	13.4	780	0.1	21%	27%	17%	35%
Canon EOS 7D	7.3	2,651	0.5	43%	23%	19%	15%
Corsair DDR3	11.0	3,086	1.4	15%	27%	31%	28%
HTC Hero	9.9	758	0.3	41%	18%	22%	19%
Intel X25	10.2	4,933	1.4	21%	21%	29%	29%
PS3 Slim	12.5	2,515	0.4	12%	19%	39%	30%
Grand Mean	10.7	14,723	0.7	23%	22%	28%	26%

Changes per week is computed as the number of changes per week the median retailer does. Another alternative is to compute the average number of price changes per retailer and week across the whole dataset. This causes an upward bias however as there are a number of retailers that change prices very frequently relative to the whole population. The distribution is the number of changes made in each quartile over total number of price changes made, with quartiles redefined daily.

6.2 Local Intra-Distribution Mobility

Varian's (1980) model of mixed sales, in which firms use "hit-and-run" price promotion strategies to prevent uninformed customers from learning the identity of the low priced firms over time, predict price changes happening across the price distribution. For these promotions to be an effective tool, the jumps across the distribution need to be of a considerable magnitude and happen at random intervals.

To study the range of movements across the intra-distribution we construct one step transition matrices that estimate the probability that a firm moves from one decile to another between specified time periods. In Figure 2 overleaf we show that there is a tendency to the diagonal and that the firms with the lowest prices in a time period have a high relative probability to hold their position. The probability to stay in the first decile ranges from 66% for the HTC Hero to 98% for the Apple iPod, given a time interval equal to the median time between price changes of the retailers marketing each product. Firms jumping more than two deciles in a given time period are scarce. Thus, intra-distribution mobility is local and consumers have a good chance of learning where to find the lowest price over time. These findings reject Varian's model in this setting and show that the price changes primarily do not hail from firms that use random pricing strategies to capture informed and uninformed customers, as we would then see considerable changes in the identities of the lowest priced firms.

When using transition matrices the length of intervals measured will have a large effect on the result, as we show in Appendix 1. Using too short time periods imply that firms are more static in their behaviour and too long that they are moving further than they actually are. We propose that the median time between price changes in a certain product market is a fair measure. This horizon captures the inherent differences between the product markets and avoids over- or understating mobility by not assigning weights to time periods that on average do not display any movement.

Lach (2002) also uses percentage of time spent in each quartile of the price distribution as a measure of intra-distribution mobility. He finds that firms spend approximately equal time in each quartile and concludes that there is strong support for Varian's model in his data. Figure 3 on page 20 shows that the firms in our sample mainly spend time in one or two quartiles, with the Apple iPod Shuffle retailers exhibiting the most static behaviour and the Canon EOS 7D retailers increased movement across the distribution. Lach studies relatively inexpensive food staples in physical markets and thus the differences in our dataset make direct comparison difficult. We conclude that support for Varian's model of random sales is limited in an online setting and seemingly more applicable to physical markets.

Figure 2. One Step Transition Matrices (Median Time Between Price Changes Horizon)

HTC Hero

23 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
83	q10	0.63	0.22	0.12	0.02		0.01				
61	q20	0.23	0.33	0.25	0.16	0.02	0.02				
69	q30	0.10	0.17	0.25	0.30	0.13	0.03	0.01			
63	q40	0.03	0.14	0.11	0.37	0.30	0.03			0.02	
66	q50	0.05	0.03	0.15	0.05	0.29	0.36	0.08			
70	q60		0.01	0.04	0.09	0.10	0.39	0.27	0.07	0.03	
70	q70		0.01	0.01	0.01	0.07	0.13	0.40	0.24	0.09	0.03
62	q80			0.02	0.02	0.05	0.06	0.16	0.48	0.19	0.02
68	q90			0.06	0.01	0.01		0.03	0.15	0.51	0.22
59	q100	0.03					0.03	0.03	0.05	0.14	0.71

Canon EOS 7D

14 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
134	q10	0.66	0.20	0.08	0.02		0.02				
125	q20	0.20	0.56	0.15	0.05	0.02	0.02				
130	q30	0.05	0.07	0.40	0.29	0.09	0.05		0.02		0.02
129	q40	0.06	0.09	0.12	0.40	0.22	0.09	0.03			
113	q50	0.04	0.05	0.14	0.11	0.37	0.19	0.08			
137	q60		0.02	0.04	0.07	0.08	0.46	0.26	0.05		
123	q70			0.02	0.07	0.09	0.11	0.42	0.26	0.02	
118	q80					0.04	0.11	0.11	0.54	0.18	
124	q90						0.02	0.06	0.13	0.72	0.08
118	q100			0.03					0.02	0.05	0.90

Intel X25

5 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
486	q10	0.80	0.14	0.03							
430	q20	0.15	0.62	0.17	0.02	0.02					
444	q30	0.04	0.14	0.59	0.14	0.04	0.02				
450	q40		0.03	0.15	0.62	0.14	0.02	0.01			
435	q50	0.02	0.01	0.02	0.13	0.58	0.18	0.03	0.02	0.01	
454	q60			0.02	0.04	0.15	0.58	0.17	0.02	0.02	
503	q70				0.01	0.02	0.15	0.54	0.21	0.05	
443	q80			0.01		0.01	0.02	0.22	0.53	0.18	0.01
374	q90			0.01		0.02	0.03	0.05	0.20	0.58	0.11
408	q100							0.01	0.02	0.09	0.85

Apple iPod Shuffle

64 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
443	q10	0.98	0.01								
295	q20	0.02	0.92	0.05							
348	q30	0.01	0.03	0.96							
334	q40				0.96	0.02					
362	q50				0.03	0.94	0.02				
375	q60					0.02	0.96				
333	q70						0.02	0.96			
337	q80							0.01	0.98		
364	q90									0.99	
325	q100										0.99

Corsair DDR3

5 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
370	q10	0.79	0.12	0.03	0.02	0.02		0.01			
334	q20	0.17	0.58	0.16	0.04	0.02		0.01			
351	q30	0.02	0.17	0.52	0.18	0.05	0.05				
334	q40	0.02	0.05	0.23	0.47	0.16	0.04	0.02			
346	q50		0.02	0.05	0.18	0.49	0.14	0.08	0.01		
376	q60			0.02	0.03	0.19	0.52	0.11	0.09	0.02	
333	q70	0.01			0.02	0.03	0.18	0.52	0.17	0.05	
293	q80					0.02	0.08	0.22	0.50	0.17	
324	q90		0.02			0.01	0.03	0.04	0.14	0.65	0.09
301	q100									0.08	0.90

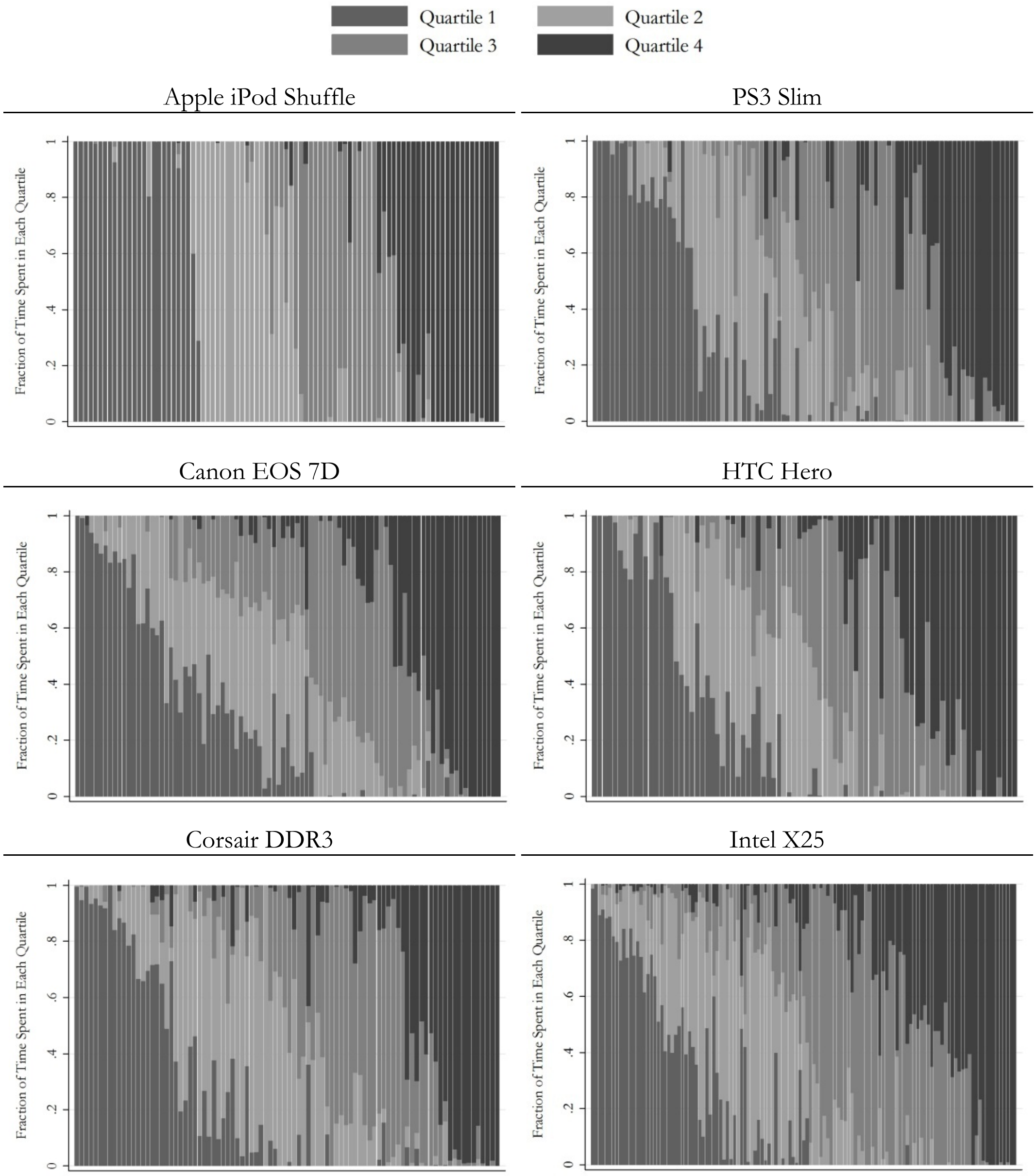
PS3 Slim

17 Day Horizon

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
92	q10	0.68	0.26	0.03	0.02						
78	q20	0.15	0.47	0.29	0.03	0.05					
73	q30	0.05	0.08	0.44	0.33		0.07	0.03			
83	q40	0.07	0.04	0.10	0.51	0.20	0.01	0.01	0.04	0.02	
76	q50		0.03	0.07	0.09	0.55	0.22	0.03		0.01	
80	q60		0.01	0.04	0.06	0.08	0.55	0.24	0.03		
74	q70	0.01				0.05	0.16	0.55	0.18	0.04	
77	q80	0.01	0.01	0.01	0.03	0.03		0.09	0.56	0.23	0.03
78	q90		0.03	0.03			0.01	0.03	0.10	0.64	0.17
72	q100					0.01		0.03	0.06	0.08	0.82

The matrices display the probability that a retailer that was situated in one of the deciles on the Y-axis of the price distribution in time t=1 is situated in the decile on the X-axis in time t=2. Probabilities of less than 0.01 have been omitted from the matrices.

Figure 3. Percentage of Time Spent in Each Cross-Sectional Quartile of the Price Distribution



Each bar shows a retailer that sold the product during the sample period. The quartile positions are computed on a daily basis to account for the differences in number of retailers over the period. Percentage of time spent is defined as days spent in each quartile over total number of days the retailer offers the product. Sorted over the normalized mean rank position of the retailer from low to high, i.e. the average cheapest retailers on the left.

6.3 Higher Rated Firms Change Price Less Frequently

Enquiring further into the identities of the firms that change prices frequently across the price distribution we find that firms rated higher by Prisjakt's users, a proxy of customer satisfaction, carry out fewer price changes. To estimate the relationship between seller characteristics and price changes we run an OLS regression across all firms in our dataset. Shown in Table 5, we regress the average number of price changes that a retailer carries out each week on the retailer's average position in the price distribution, the number of ratings it has received from Prisjakt's users and the weighted value of these ratings, as well as product dummies to account for differences between the products in our sample. The significant results from the regressions are as follows:

Price Distribution Rank, the average position a retailer holds in the price distribution. The coefficient is positive and significant at a 10% level. The economic interpretation is that the 50^{th} retailer in our normalized distribution of 100 will change price 0.2 times more often per week than the lowest priced retailer.

Retailer Rating, the weighted rating a firm has received from Prisjakt's users which we consider a proxy for the satisfaction level a firm delivers to its customers. The coefficient is negative and significant at a 0.1% level. A retailer with 10 "stars" will change price 0.9 times less often per week than a bottom-rated one.

This stylized fact can clearly be seen in the snapshot of our data that we show in Figure 4 overleaf. We show an excerpt from March 2010 of all the price changes of the Canon EOS 7D sorted by firm rating. The magnitudes of the changes have been omitted to simplify graphical interpretation. Among the firms with ratings lower than seven there are clear clusters of price changes, seemingly without exogenous shocks to the system as there are few price changes among the other retailers. Following Kauffman and Wood (2007) we use a Vector Autoregression framework to analyse this seemingly tacit collusion further.

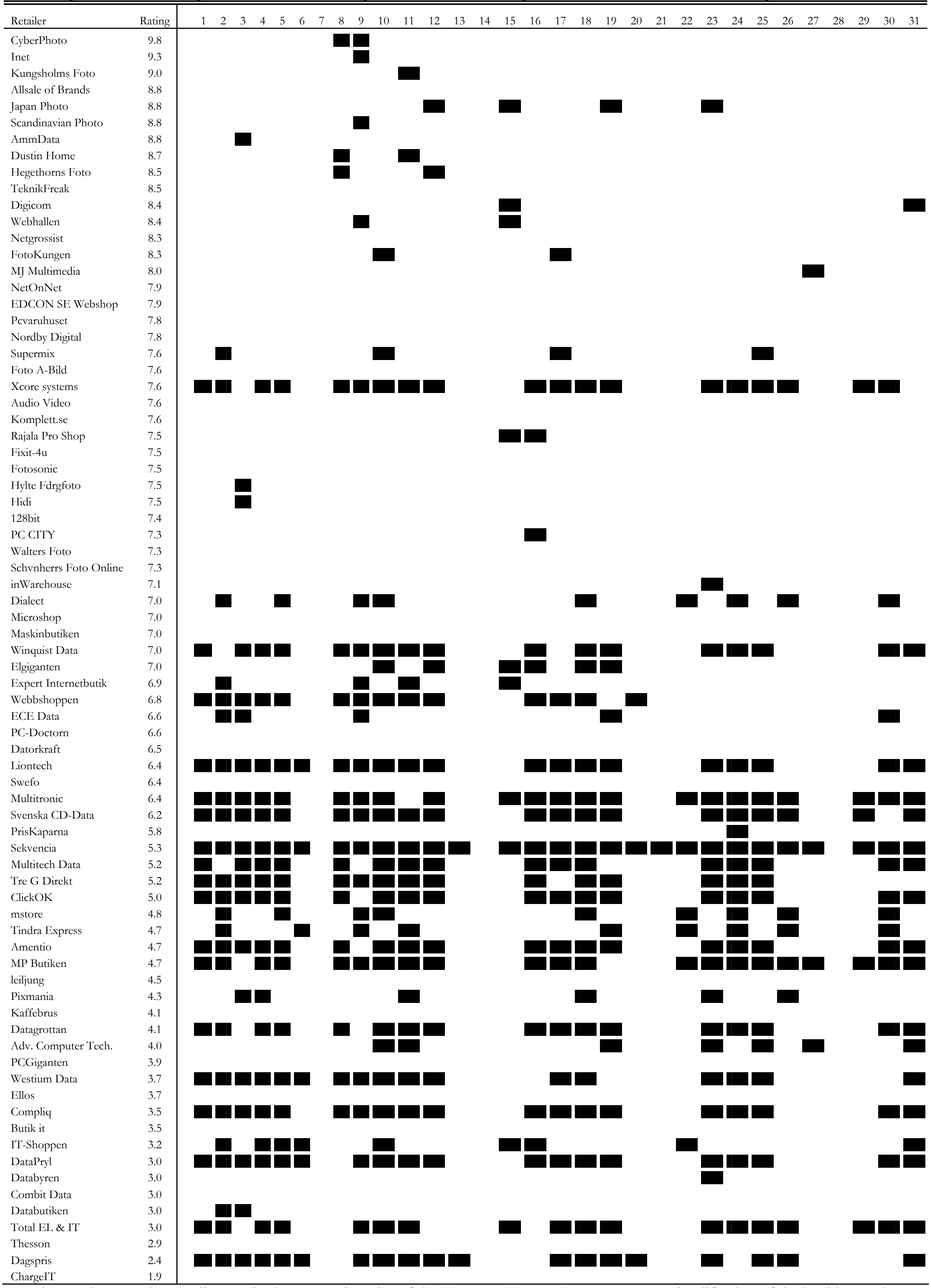
Table 5. OLS Regression of Weekly Number of Retailer Price Changes on Price Distribution Rank, Retailer Rating, Number of Retailer Ratings and Product Dummies

Number of Weekly Retailer Price Changes, Weekly	Coefficient	Robust Std. Err.	t
Price Distribution Rank	0.004	0.002	1.660*
Retailer Rating	-0.088	0.027	-3.300***
N. Retailer Ratings	-0.001	0.001	-0.750
Intercept	1.500	0.264	5.690***
Product Dummies	Yes		
Number of Observations	445		
R-squared	0.166		

* significant at 10%; ** significant at 5%; *** significant at 1%

Weekly number of retailer price changes is calculated through computing the number of price changes a retailer does each week, and then average this over all the weeks the retailer is present. Price distribution rank is defined as the normalized rank of a retailer's position in the price distribution each day, to account for the differing number of retailers offering the product over the period, and then averaged over the entire period the retailer is present. Retailer rating is the subjective rating by Prisjakt's users, as defined previously. Number of ratings is observed each day as the total number of ratings over the last twelve months, of which we use the average over the period. Retailers that reoccur across several products are kept in the sample as they are still exhibiting individual price setting behaviours in each market.

Figure 4. Clustering of Daily Price Changes by Retailer Rating of the Canon EOS 7D Through March 2010



Days in March 2010 when retailers made changes to the price of the Canon EOS 7D DSLR camera. For simplification of the intuition we have omitted the magnitude of the changes. Sorted on the rating of the retailer by Prisjakt's users.

6.4 Herd Behaviour

Table 6. Summary of Retailer Characteristics from VAR

HTC Hero, PS3 Slim, Apple iPod Shuffle					
Mean	Count	N. Changes	Avg. Rank	N. Ratings	Rating
Follower	119	0.68	49	26	6.1
Non-follower	28	0.50	40	31	6.8

Follower is defined as a firm that responds to competitor price changes within a two-day lag, significant at the 5% level, as fitted by a vector autoregression on all firms retailing the product. Firms that have been dropped due to collinearity are treated as followers. The characteristic measures, rank, number of ratings and rating, are averages on all three products.

Using a Vector Autoregression (VAR) framework shown in Equation (2) overleaf, as proposed by Kauffman and Wood (2007), we show in Table 6 that there are two distinct groups of retailers; those that follow price changes of other retailers, the *followers*, and those who do not, the *non-followers*. We define a follower as a retailer that respond to price changes within a two day window of a competitor price change, significant at a 5% level.

Out of the 137 retailers we examine through the VAR framework, 119 of the retailers exhibit a clear *follower* behaviour and react to competitor price changes within two days. 28 of the retailers seem to ignore the price setting behaviour of other firms, or take it into consideration in ways that are not captured within a two day window. A strong feature of the VAR analysis is that the *followers* follow both price reductions, as implied by Bertrand competition – but contrary to this also the price increases that are evident during the life cycle of the Apple iPod Shuffle. This gives further support to the notion that price dispersion is an equilibrium phenomena also in the product markets in our sample, as no race to the bottom is evident.

The two groups exhibit characteristics consistent with the findings in our other analyses, and the connection between rating and a *follower* price changing behaviour shown graphically in Figure 4 in the previous section is also present in Table 6. On average, the *followers* carry out more price changes, are relatively more expensive, have fewer ratings and achieve lower levels of customer satisfaction as opposed to the *non-followers*.

As shown in Table 6, firms in the upper levels of the price distribution are likely to belong to the *followers* that move in a seemingly tacit collusive way. When many of the *followers* compete in the same space, a price change does not only affect one specific firm and those above it in the distribution – but creates substantial ripple effects that echo throughout the price distribution. This amplification tells a compelling story to as why we observe an abundant number of price changes in the upper quartiles of the price distribution, and an explanation to why the intra-distribution mobility is frequent but local.

The VAR as used by Kauffman and Wood is specified with the following equation:

$$ln(\Delta price_{jt} + 1) = \sum_{l=0}^{L}\sum_{c=1}^{J} \gamma_{jc}\, ln(\Delta price_{c,t-l} + 1) + \varepsilon_{jt} \qquad (2)$$

In Equation (2), $\Delta price_{j\,t}$ is the percentage price change of *retailer j*'s price at *time t* and $\gamma_{j\,c}$ is the coefficient capturing the effect of *retailer c*'s price change in *time t-l* where *l* is the chosen lag time. The logarithm of the price change is used to adjust for heteroskedasticity. Generally speaking, the VAR regress all retailers' price changes on lags of all other retailers' price changes.

In our specification we choose to allow for two lags as we measure the immediate response to competitor action, and the sheer number of price changes make inference difficult with more lags. To allow a sufficient number of retailers to enter the market, the VAR includes the latter two thirds of the sample time period for each product. To achieve complete time series we exclude firms that are not present throughout this period. Firms are also dropped due to high collinearity as a prerequisite to use the VAR framework. An excerpt of the VAR for HTC Hero is shown in table 7 below. The complete VARs for all three products are found in Appendix 3.

Table 7. Vector Autoregression on Price Changes Between Retailers

HTC Hero						
			Descriptives, Not Included in VAR			
Retailer	R-sq	P>chi2	N. Changes	Avg. Rank	N. Ratings	Rating
inWarehouse	0.05	1.00	0.4	19	28	7.0
Mobillagret	0.12	1.00	0.1	40	6	8.9
Tell Your Friends	0.14	1.00	0.2	58	0	
Komplett.se	0.25	1.00	0.5	17	103	7.6
PrisKaparna	0.29	1.00	0.2	41	2	7.3
Katshing	0.34	0.95	0.7	15	30	8.6
Expert internetbutik	0.46	0.11	0.2	31	17	6.9
CyberPhoto	0.80	0.00	0.3	36	35	9.7
Elgiganten	0.69	0.00	0.6	12	72	6.9
Webhallen	0.98	0.00	0.2	40	171	8.3
Misco	0.66	0.00	0.3	55	61	8.3
DataPryl	0.64	0.00	0.2	78	1	3.0
Dialect	0.59	0.00	0.3	84	3	7.0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
DinMobil	Dropped		0.0	80	0	.

The Vector Autoregression includes the latter two thirds of the time period to allow retailers to enter the market. To achieve complete time series we exclude firms that are not present throughout this period. Firms are dropped due to high collinearity as a prerequisite to use the VAR framework.

7. Conclusion and Discussion

In this thesis we examine price changes and intra-distribution mobility within the price distributions observed in the online markets for six popular consumer electronic products.

Contrary to common intuition, more than half of all price changes observed in our dataset take place in the upper half of the price distribution, where there is no casual reason for price competition. We find that online retailers can be divided into two broad categories, *followers*, that immediately respond to competitor price changes, and *non-followers*, that set their prices independently of competitor action. The ripple effects caused by the *follower* behaviour is a compelling explanation to the large number of price changes in the upper levels of the price distribution, as a single price change will echo throughout the distribution.

A quantitative analysis of the retailer behaviour does not tell us about the nature of the relationship between the *followers*. Based on the differences in characteristics the two groups of retailers exhibit and a qualitative evaluation of the firms included, we give a few suggestion of the causality behind the relationship as a basis for further research. We propose that the *follower* firms either monitor the prices set by the competition closely using technology such as the one provided by Prisjakt, or follow a highly similar set of "business rules" that govern their price setting behaviour. An example of the latter is firms that act as independent storefronts for distributors and set their prices at a fixed margin to the distributor who feeds prices into their system. Arguably, this is a way for firms to reduce the managerial costs of strategic price setting and run a low involvement business.

This low involvement type of retailing has further implications for the uninformed consumers acting in online markets. Not only does a consumer that purchases a product from a random retailer overpay on average, but she is likely to purchase from a firm that others have found lacking in terms of service or quality. We conclude that there is still a large group of high-priced, low-service retailers that prey on uninformed consumers.

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Appendix

A1 Effects on Transition Matrices from Different Horizons

Table A1.1. One Step Transition Matrix (One-Day Horizon)

		HTC Hero									
#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
1721	q10	0.93	0.06								
1416	q20	0.05	0.87	0.07							
1487	q30		0.03	0.88	0.07						
1459	q40	0.01	0.01	0.03	0.88	0.07					
1446	q50				0.03	0.89	0.06				
1528	q60					0.03	0.89	0.06			
1484	q70						0.04	0.89	0.06		
1454	q80							0.04	0.90	0.05	
1545	q90								0.03	0.93	0.03
1343	q100									0.02	0.96

Table A1.2. One Step Transition Matrix (One-Week horizon)

		HTC Hero									
#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
238	q10	0.75	0.20	0.03	0.02						
205	q20	0.16	0.55	0.26	0.02						
206	q30	0.07	0.07	0.54	0.26	0.04	0.01				
208	q40	0.04	0.07	0.07	0.53	0.24	0.02	0.02			
198	q50	0.01	0.05	0.06	0.08	0.53	0.24	0.03		0.01	
215	q60		0.01	0.02	0.05	0.11	0.58	0.18	0.02		
211	q70				0.03	0.03	0.12	0.62	0.16	0.02	
207	q80					0.01	0.02	0.13	0.69	0.13	
214	q90					0.01			0.10	0.74	0.12
186	q100						0.02		0.02	0.10	0.84

Table A1.3. One Step Transition Matrix (Median Change 23 Day Horizon)

		HTC Hero									
#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
83	q10	0.63	0.22	0.12	0.02		0.01				
61	q20	0.23	0.33	0.25	0.16	0.02	0.02				
69	q30	0.10	0.17	0.25	0.30	0.13	0.03	0.01			
63	q40	0.03	0.14	0.11	0.37	0.30	0.03			0.02	
66	q50	0.05	0.03	0.15	0.05	0.29	0.36	0.08			
70	q60		0.01	0.04	0.09	0.10	0.39	0.27	0.07	0.03	
70	q70		0.01	0.01	0.01	0.07	0.13	0.40	0.24	0.09	0.03
62	q80			0.02	0.02	0.05	0.06	0.16	0.48	0.19	0.02
68	q90			0.06	0.01	0.01		0.03	0.15	0.51	0.22
59	q100	0.03					0.03	0.03	0.05	0.14	0.71

The matrices display the probability that a retailer that was situated in one of the deciles on the Y-axis of the price distribution in time t=1 is situated in the decile on the X-axis in time t=2. Probabilities of less than 0.01 have been omitted from the matrices.

A2 Weekly Transition Matrices

Table A2. One Step Transition Matrix (One-Week Horizon)

HTC Hero

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
238	q10	0.75	0.20	0.03	0.02						
205	q20	0.16	0.55	0.26	0.02						
206	q30	0.07	0.07	0.54	0.26	0.04	0.01				
208	q40	0.04	0.07	0.07	0.53	0.24	0.02	0.02			
198	q50	0.01	0.05	0.06	0.08	0.53	0.24	0.03		0.01	
215	q60		0.01	0.02	0.05	0.11	0.58	0.18	0.02		
211	q70				0.03	0.03	0.12	0.62	0.16	0.02	
207	q80					0.01	0.02	0.13	0.69	0.13	
214	q90					0.01			0.10	0.74	0.12
186	q100						0.02		0.02	0.10	0.84

Canon EOS 7D

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
265	q10	0.74	0.20	0.03		0.01	0.01				
247	q20	0.16	0.63	0.12	0.05	0.01	0.02				
253	q30	0.04	0.08	0.57	0.22	0.03	0.04				
271	q40	0.03	0.03	0.11	0.58	0.21	0.01	0.01			
214	q50	0.05	0.02	0.08	0.10	0.44	0.25	0.05			
261	q60	0.01	0.02	0.05	0.02	0.10	0.56	0.23	0.01		
253	q70				0.04	0.05	0.09	0.58	0.21	0.02	
238	q80					0.03	0.05	0.11	0.67	0.12	
240	q90						0.03	0.02	0.09	0.79	0.06
234	q100			0.02					0.01	0.04	0.92

Intel X25

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
344	q10	0.78	0.16	0.03				0.01			
299	q20	0.18	0.58	0.18	0.03	0.01	0.01				
312	q30	0.04	0.16	0.56	0.18	0.02	0.02				
319	q40	0.02	0.03	0.16	0.56	0.18		0.02	0.01		
306	q50	0.02	0.02	0.04	0.16	0.51	0.21	0.04			
312	q60			0.01	0.03	0.19	0.52	0.19	0.03	0.02	
343	q70		0.01			0.04	0.15	0.51	0.22	0.05	
322	q80			0.02			0.02	0.16	0.54	0.23	
268	q90		0.01		0.01	0.02	0.04	0.05	0.19	0.54	0.13
286	q100			0.02				0.04	0.02	0.08	0.83

Apple iPod Shuffle

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
344	q10	0.93	0.06	0.01							
279	q20	0.05	0.87	0.08							
162	q30	0.03	0.09	0.85	0.02						
245	q40			0.02	0.88	0.07	0.02				
261	q50				0.07	0.85	0.06				
261	q60					0.07	0.84	0.07	0.01		
249	q70					0.02	0.08	0.87	0.03		
240	q80							0.04	0.89	0.04	0.01
255	q90								0.04	0.95	0.01
234	q100									0.02	0.98

Corsair DDR3

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
245	q10	0.71	0.15	0.05	0.04	0.02	0.01	0.01			
219	q20	0.24	0.47	0.17	0.06	0.03				0.01	
225	q30	0.04	0.22	0.44	0.19	0.04	0.03	0.01	0.02		
226	q40	0.01	0.08	0.21	0.37	0.21	0.10	0.01			
209	q50		0.03	0.08	0.24	0.42	0.16	0.04	0.03		
265	q60	0.02	0.02	0.03	0.04	0.14	0.48	0.22	0.05		
220	q70				0.02	0.03	0.25	0.48	0.16	0.05	
190	q80				0.02	0.03	0.05	0.17	0.50	0.21	0.01
211	q90			0.01	0.01	0.02	0.03	0.03	0.18	0.58	0.12
200	q100						0.01	0.02		0.09	0.87

PS3 Slim

#		q10	q20	q30	q40	q50	q60	q70	q80	q90	q100
256	q10	0.77	0.17	0.04	0.02						
194	q20	0.11	0.66	0.21	0.01						
218	q30	0.04	0.07	0.67	0.17	0.02		0.01			
204	q40	0.05		0.07	0.67	0.16		0.02			
221	q50	0.02	0.01	0.01	0.08	0.67	0.16	0.03	0.02		
206	q60	0.01			0.02	0.10	0.65	0.19			
204	q70				0.01	0.03	0.15	0.63	0.16		
215	q80					0.02		0.10	0.69	0.16	0.01
207	q90			0.02					0.10	0.76	0.09
193	q100			0.01			0.01	0.02	0.01	0.07	0.88

The matrices display the probability that a retailer that was situated in one of the deciles on the Y-axis of the price distribution in time t=1 is situated in the decile on the X-axis in time t=2. Probabilities of less than 0.01 have been omitted from the matrices.

A3 Vector Autoregressions

Table A3.1. Vector Autoregression on Price Changes Between Retailers

HTC Hero						
			Descriptive, Not Included in VAR			
Retailer	R-sq	P>chi2	N. Changes	Avg. Rank	N. Ratings	Rating
inWarehouse	0.05	1.00	0.4	19	28	7.0
Mobillagret	0.12	1.00	0.1	40	6	8.9
Tell Your Friends	0.14	1.00	0.2	58	0	
Komplett.se	0.25	1.00	0.5	17	103	7.6
PrisKaparna	0.29	1.00	0.2	41	2	7.3
Katshing	0.34	0.95	0.7	15	30	8.6
Expert Internetbutik	0.46	0.11	0.2	31	17	6.9
CyberPhoto	0.80	0.00	0.3	36	35	9.7
Elgiganten	0.69	0.00	0.6	12	72	6.9
Webhallen	0.98	0.00	0.2	40	171	8.3
Misco	0.66	0.00	0.3	55	61	8.3
DataPryl	0.64	0.00	0.2	78	1	3.0
Dialect	0.59	0.00	0.3	84	3	7.0
Pixmania	0.63	0.00	1.7	14	101	4.3
CDON	0.98	0.00	0.4	35	93	6.4
Dustin Home	0.60	0.00	0.3	32	215	8.8
IT-Shoppen	0.63	0.00	0.7	29	1	3.2
Megastore	0.63	0.00	0.1	45	25	6.3
Fixit-4u	0.98	0.00	0.1	91	1	7.5
ClickOK	0.96	0.00	0.6	40	33	5.0
PC CITY	0.98	0.00	0.5	10	64	7.3
Skansor	0.97	0.00	0.5	53	1	3.0
Liontech	0.99	0.00	0.1	71	3	6.4
Dagspris	0.62	0.00	2.6	90	2	2.4
Tre G Direkt	0.99	0.00	0.5	85	2	5.2
AmmData	0.74	0.00	0.4	74	10	8.7
Multitech Data	0.99	0.00	1.1	72	14	5.6
MP Butiken	0.92	0.00	1.4	63	0	4.7
Ekervalls	0.96	0.00	0.2	34	1	7.6
Telenorbutiken	0.83	0.00	0.1	65	8	3.3
Phone4u of Sweden	0.92	0.00	0.4	13	2	8.2
Telia Webbutik	0.84	0.00	0.2	44	6	2.0
Hidi	0.70	0.00	0.5	83	1	7.5
NoYes	0.87	0.00	0.5	5	33	9.4
Netbay	1.00	.	0.1	46	0	
MobilGiganten	1.00	.	0.2	21	9	4
Scandinavian Photo	Dropped		0.1	64	10	8.7
The PhoneHouse	Dropped		0.2	45	12	3.6
Megapart	Dropped		0.1	84	2	5.4
Datagrottan	Dropped		0.1	68	5	4.1
DAEK Data	Dropped		0.0	93	3	4.9
Nymobil	Dropped		0.1	52	2	6.6
Tele2 webbutik	Dropped		0.1	21	3	6.2
DinMobil	Dropped		0.0	80	0	

The Vector Autoregression includes the latter two thirds of the time period to allow retailers to enter the market. To achieve complete time series we exclude firms that are not present throughout this period. Firms are dropped due to high collinearity as a prerequisite to use the VAR framework.

Table A3.2. Vector Autoregression on Price Changes Between Retailers

PS3 Slim						
			Descriptive, Not Included in VAR			
Retailer	R-sq	P>chi2	N. Changes	Avg. Rank	N. Ratings	Rating
Multisale	0.21	1.00	0.2	16	9	7.5
Spelbutiken se	0.27	1.00	0.5	34	58	6.4
Hidi	0.28	1.00	1.3	92	1	7.5
ONOFF Onlineshop	0.31	1.00	0.3	46	21	4.8
Komplett.se	0.45	0.22	0.3	18	100	7.6
Combit Data	0.45	0.20	0.3	48	0	3.0
Console.se	0.53	0.00	0.1	51	9	6.8
Thorn	0.82	0.00	0.3	92	0	
SIBA	0.99	0.00	0.4	34	45	5.6
inWarehouse	1.00	0.00	0.2	22	29	7.1
Elgiganten	0.68	0.00	0.8	11	73	6.9
Webhallen	0.95	0.00	0.2	16	173	8.4
DataPryl	0.93	0.00	3.2	70	0	3.0
Mediacenter	0.90	0.00	3.2	80	1	7.0
Pixmania	0.87	0.00	1.1	7	105	4.3
CDON	0.97	0.00	0.2	18	94	6.4
Sekvencia	0.57	0.00	3.1	13	72	5.0
Databyren	0.98	0.00	0.2	64	1	3.0
Datagrottan	0.83	0.00	4.2	61	4	4.1
Vsterlens Fvretagstjdnst	1.00	0.00	0.1	44	1	7.5
ClickOK	0.67	0.00	2.1	44	31	5.0
PC CITY	0.71	0.00	0.8	11	66	7.3
Radars	0.99	0.00	0.5	36	15	8.6
Skansor	1.00	0.00	0.4	48	1	3.0
Westium Data	0.77	0.00	1.5	88	2	3.7
Databutiken	0.82	0.00	2.8	70	1	3.0
Liontech	0.95	0.00	2.9	62	3	6.3
ECE Data	0.85	0.00	3.4	60	2	6.8
Dagspris	0.96	0.00	3.7	87	3	2.4
Tre G Direkt	0.87	0.00	3.5	75	2	5.2
Billigakonsoler	0.90	0.00	0.2	17	4	4.9
AmmData	0.82	0.00	1.9	58	10	8.8
Datorkraft	0.58	0.00	2.6	58	1	6.5
MP Butiken	0.98	0.00	3.9	32	0	4.7
Media Network	0.81	0.00	2.7	95	0	
ElektronikBiten	0.85	0.00	0.2	11	2	7.9
Faceplate	0.92	0.00	0.2	27	2	8.2
Hallbdcks	Dropped		0.1	50	14	7.4
Discshop	Dropped		0.1	70	31	7.7
Audio Video	Dropped		0.1	45	6	7.6
GAME Onlineshop	Dropped		0.1	41	12	7.9
Tvspeloteket	Dropped		0.0	85	1	3.0
Alina Systems	Dropped		0.1	39	35	9.2
Ellos	Dropped		0.0	92	6	4.1
Expert Internetbutik	Dropped		0.0	44	17	6.9
Wesellcd	Dropped		0.0	24	7	7.4
PS3kungen	Dropped		0.0	17	5	8.9
Discshop Kids	Dropped		0.1	70	0	

Table A3.3. Vector Autoregression on Price Changes Between Retailers

Apple iPod						
			Descriptive, Not Included in VAR			
Retailer	R-sq	P>chi2	N. Changes	Avg. Rank	N. Ratings	Rating
Elgiganten	0.02	1.00	0.1	7	73	6.9
Datorfixarna	1.00	1.00	0.1	70	2	6.9
Datorkraft	0.05	1.00	0.1	38	2	8.5
Audio Video	0.19	1.00	0.1	13	6	7.5
Webbshoppen	0.23	0.99	0.2	67	32	6.8
Misco	0.24	0.98	0.6	43	66	8.2
Pixmania	0.25	0.95	0.6	7	106	4.3
Kontorslandet	0.28	0.83	2.3	52	0	4.7
AmmData	0.28	0.79	0.3	84	1	7.5
Complete Solutions	0.29	0.74	0.5	63	9	8.8
ClickOK	0.31	0.58	0.5	71	32	5.0
Sekvencia	0.35	0.13	2.5	20	70	5.3
PC-Doctorn	0.36	0.12	1.7	95	2	2.4
Fyndbvrsen	0.40	0.01	0.2	4	88	9.0
Tre G Direkt	0.40	0.01	0.3	68	16	5.2
PC CITY	0.41	0.00	0.2	6	68	7.3
DataPryl	0.43	0.00	1.5	81	0	3.0
SIBA	0.44	0.00	0.1	9	44	5.6
NetOnNet	0.95	0.00	0.1	18	105	7.7
Dataparadiset	1.00	0.00	0.0	62	1	7.5
ComputerCity	0.45	0.00	0.2	8	6	7.2
Webhallen	0.97	0.00	0.0	17	181	8.4
Dialect	0.74	0.00	0.3	61	3	7.0
CDON	0.90	0.00	0.5	25	101	6.3
Dustin Home	0.59	0.00	0.1	15	216	8.7
IT-Shoppen	0.69	0.00	0.1	8	1	3.2
Multitronic	0.60	0.00	3.8	93	12	6.3
Skansor	0.85	0.00	0.1	72	1	3.0
Databutiken	0.51	0.00	1.0	66	3	6.5
Liontech	0.46	0.00	0.3	53	2	6.6
ECE Data	0.45	0.00	0.2	52	12	6.6
Dagspris	0.66	0.00	0.1	59	2	5.2
ndbutiken se	0.49	0.00	2.5	32	26	4.7
128bit	0.46	0.00	0.9	85	1	6.5
Amentio	1.00	0.00	0.0	18	11	7.8
WWWorkshop	0.77	0.00	0.3	89	0	4.7

The table continues on the next page.

Apple iPod

Retailer	R-sq	P>chi2	N. Changes	Avg. Rank	N. Ratings	Rating
ONOFF Onlineshop	Dropped		0.1	11	21	4.8
Komplett.se	Dropped		0.0	19	96	7.6
inWarehouse	Dropped		0.0	19	28	7.1
Hallbdcks	Dropped		0.0	13	14	7.3
Mycom	Dropped		0.1	36	11	5.6
Inet	Dropped		0.0	19	136	9.3
TDJ Data	Dropped		0.0	71	1	7.0
Proxdata	Dropped		0.0	49	1	3.0
Datagrottan	Dropped		0.0	67	4	4.1
Macoteket	Dropped		0.0	20	4	5.1
Megastore	Dropped		0.0	42	25	6.1
Xcore systems	Dropped		0.0	87	5	8.3
Combit Data	Dropped		0.0	81	0	3.0
Radars	Dropped		0.3	4	15	8.6
Multitech Data	Dropped		0.1	49	0	
MP Butiken	Dropped		0.0	49	0	
United Computer Systems	Dropped		0.0	45	0	
Media Network	Dropped		0.1	62	1	7.3
Elektronikbutiken com	Dropped		0.0	99	0	
PCGiganten	Dropped		0.0	77	0	
Multisale	Dropped		0.0	84	0	
mstore	Dropped		0.1	91	0	
Tindra Express	Dropped		0.0	96	0	
Hidi	Dropped		0.0	40	3	5.3
Profsoffice	Dropped		0.0	17	1	5.2
TeknikFreak	Dropped		0.0	57	0	
PCPunkten	Dropped		0.1	92	0	