# A Longitudinal Investigation of Price Dispersion and Price Adjustment in the Electronic Computer Commodity Market

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## ABSTRACT

Electronic markets facilitate price discovery by both buyers and sellers compared to traditional, physical markets. Consumers can search a number of e-stores themselves, or visit price comparison sites before buying. Most past research has focused on buyers, but sellers can make use of the same search tools, and more sophisticated "pricebots" to search out competitors' prices. Given this information, the electronic vendor can execute a number of different pricing strategies, including setting product prices as well as the frequency and amount of price changes. This paper presents five hypotheses about price dispersion in fixed price electronic markets and tests them with data from the computer commodity market. The results demonstrate considerable spatial and temporal price dispersion in this market. As buyer demand drops over time, the marketplace exhibits greater price dispersion. There is evidence that price dispersion is less for high priced items where there are significant gains from buyer search. We found through a simulation analysis that the computer commodity market exhibits synchronized price changes, not random changes. Finally, the data suggest that some vendors change their price strategies frequently to hide information from consumers.

# INTRODUCTION

Electronic markets increase the ease of price discovery and search for both buyers and sellers compared to physical markets. Motivated consumers can search a large number of e-stores and use price comparison sites to seek the lowest prices for an item. The Internet allows vendors to adjust prices frequently for a given product in order to elicit information about the consumer's demand curve. The stage is set then, for a struggle, between the buyer and seller: the buyer searches for lower prices, and the seller alters prices frequently to capture business. The high price seller tries to attract customers who do not want to search further, and the low price seller hopes that there is elasticity in demand and customers will search out its lower prices. The purpose of this paper is to explore price setting activity in electronic markets, in contrast to much past research which has looked at consumer rather than vendor behavior. *To what extent are sellers in electronic markets adopting a dynamic pricing strategy to capture consumer surplus?*

In contrast to the price convergence view where prices in the electronic commodity market will eventually converge at marginal costs (Bakos, 1997) or the monopoly price (Kauffman and Wood, 2000), the vast majority of existing empirical studies have shown that price dispersion exists spatially in the theoretically efficient electronic fixed-price commodity markets (Baily,1998; Brynjolfsson and Smith, 2000; Clemons, Hann and Hitt, 2002). Researchers argue that price dispersion should be considered the market equilibrium where high-quality vendors with brand recognitions charge higher prices for the same commodity than do low-quality vendors (Varian, 1999, Brynjolffson and Smith, 1999).

Despite numerous empirical studies, our understanding as to the persistence of price dispersion and the magnitude of price adjustment is limited because of the lack of research on the nature of price competition over time in the market. This study focuses on the electronic computer commodity market where the environment is highly competitive. Price dispersion is explored from three different perspectives, vendor, product, and time. We construct a model that explores how price dispersion varies across 14 vendors and 37 products, over 24 different time periods. In addition to vendor-specific price dispersion, we test whether prices of products for which consumers have higher gains to search converge more rapidly than prices with low gains to search. We also measure the actual magnitude of price adjustments and examine changes in price ranks among the vendors over a one-year time period. Finally, based on a carefully designed simulation, we test whether price changes are synchronized across online vendors.

The major contribution of the research is a better understanding of how online retailers establish and change prices. The research demonstrates that in one online market and for a specific group of vendors, there is significant price dispersion. We believe the nature of online markets encourages this dispersion. Consumers have the power to influence vendors in setting prices, but only if they take advantage of the reduced search costs of electronic markets.

# PAST RESEARCH

Recently, Bakos (1997) showed that electronic markets structurally favor buyers by reducing the search costs associated with product offerings and price information. He argues that as buyers become fully informed, largely due to low search costs, the electronic commodity market is likely to move towards the competitive price-taking equilibrium seen in the classical market model. Kauffman and Wood (2000) argue that competition by sellers in the electronic market is largely determined by the way market leaders behave. They can either compete or collude, depending on the industry situation under which they operate. Kauffman and Wood

(2000) suggest that prices are expected to converge at the monopoly price as a result of Stackelberg competition (1934)[1].

A number of empirical studies of electronic markets have shown that a substantial degree of price dispersion still exists spatially across various sellers despite significant reductions in buyer search costs (Brynjolfsson and Smith, 2000 ; Clemons et al., 2002; Bakos, Lucas, Oh, Simon, Viswanathan and Weber, 2000). Although both Brynjolfsson and Smith (2000) and Clemons et al. (2002) found significant price dispersion in the market, they provided different explanations for the source of price variability observed across sellers. Brynjolfsson and Smith (1999) argue that sellers with brand recognition such as Amazon.com are able to charge higher prices than smaller sellers with no market power, since consumers are willing to pay a premium for such an intangible utility. As a result of such "equalizing," price dispersion should be viewed as a reasonable equilibrium. On the other hand, Clemons et al.(2002) view the source of price dispersion differently. They claim that vendors' opportunistic pricing behavior, which seeks to extract extra profits from uninformed consumers by charging a price higher than the market price (Varian, 1980), accounts for the variability in prices.

## Search Costs, Competition and Price Dispersion in Fixed-Price e-Markets

Price dispersion may come from positive search costs, product differentiation, or collusion among sellers.

**Search Costs.** Traditionally, price dispersion has been considered the consequence of positive search costs. With positive search costs, one view maintains there is a unique equilibrium with all sellers charging the same monopoly price (Diamond, 1971), while the opposite view is that price differences are likely in equilibrium (Pratt, Wise & Zeckhauser, 1979;

[1] It should be noted that Kauffman and Wood (2000) also suggest that a Bertrand type of price competition occurs in a certain type of industry.

Butters, 1977). Diamond demonstrated that in the presence of positive search costs, in equilibrium no consumers would search, enabling firms to charge the monopoly price that maximizes their profit. The result is a Nash equilibrium since identical prices for the same goods do not induce consumers to search, while lack of search provides sellers with no incentive to reduce prices. On the other hand, Pratt et al. (1979) introduced a model where the all-at-monopoly price outcome might fail because some sellers defect downward to capture a larger fraction of the market. As a result, price dispersion is a stable equilibrium where low-priced vendors sell more with lower margins and high-priced vendors do the opposite.

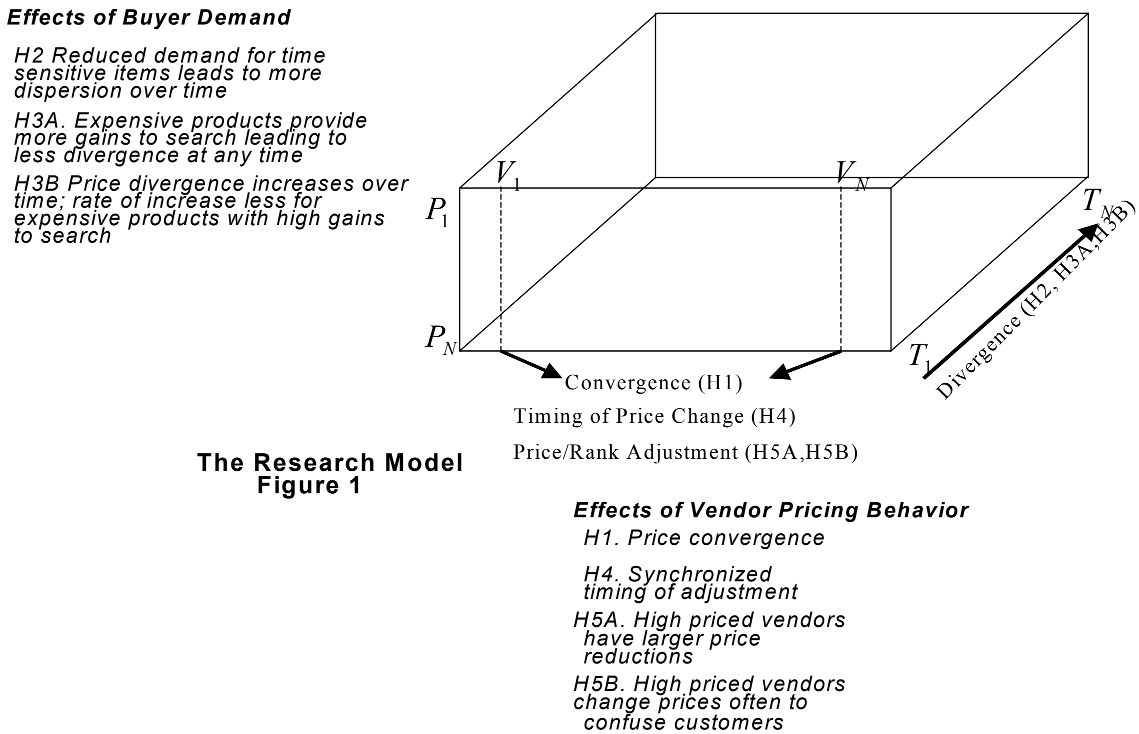
It has been suggested that the electronic fixed-price commodity market should come close to the perfectly competitive market where sellers charge undifferentiated prices at the marginal cost due to low search costs. Choudhury, Hartzel and Konsynski (1998) demonstrated that a Bertrand type of competition exists in certain industries such as the airline parts industry. However, the law of one price has received little empirical support. Search costs have been reduced dramatically in the electronic market, but they are still non-trivial and not close to zero. It also seems unrealistic to assume that marginal costs incurred by larger vendors are the same as those of smaller vendors, since the former usually take advantage of economies of scales and volume discounts (Reinganum, 1979).

**Product Differentiation.** The presence of product differentiation has been widely cited in the current literature as a source of price dispersion (Brynolfsson and Smith, 1999; Varian, 1999). Stigler (1961) notes that there may be no "absolute homogeneity" in a commodity because there is heterogeneity in the non-price characteristics of a transaction, such as the quality of service, brand recognition, etc. Researchers who advocate this view argue that on-line consumers are purchasing a bundle of the base commodity plus fulfillment characteristics that include both tangible and intangible factors such as timeliness, risk, security, reputation, and return policy. In this respect, online consumers are viewed as utility maximizers, not purchase price minimizers. As a result, the market equilibrium should be characterized by price dispersion where high-quality (or brand name) vendors can charge higher prices for the same goods than can low-quality counterparts.

**Tacit Collusion.** Recently, Kauffman and Wood (2000) suggest that tacit collusion, where vendors tend to collude rather than compete, in the form of "matching" competitors' prices, is present in the electronic market. Price "cheating" is technically more feasible in the electronic market due to software bots designed to ascertain rivals' prices. The idea of tacit collusion stems from asymmetric competition in the marketing literature, which denotes that larger firms with brand recognition do not compete the same way as smaller ones (Carpenter, Cooper, Hanssens, and Midgley, 1988). Under the tacit collusion situation, prices converge at the price currently offered by a market leader such as Amazon.com.[2] The tacit collusion perspective is interesting because it suggests an upward shift of the price convergence point close to the monopoly price. However, as evident in Kauffman and Wood (2000), tacit collusion is not always present in all markets, but rather depends on industry characteristics.

## Research Model and Hypotheses

Figure 1 describes the research model for this study. We test five main hypotheses about vendors and consumer in this market with prices from 14 vendors over a one-year period. As the figure shows, the vendors set prices partially in response to consumer demand using some strategy that is not revealed to buyers. The individual actions of sellers lead to price convergence or divergence in the market place.




**The Research Model**
**Figure 1**

In the following sections we develop hypotheses in detail. The first is that there is price convergence in the fixed price computer commodities market; if the test of this hypothesis leads to its rejection, we can continue to test the remaining hypotheses to gain insights into the nature of price dispersion. Hypotheses 2 and 3 explore how consumer demand and search might affect dispersion, while Hypotheses 4 and 5 examine vendor pricing strategies including synchronization of price changes, changes associated with high priced vendors, and strategies aimed at hiding information from consumers.

When the environment in which vendors operate is highly competitive and unstable, a market leader in that particular industry is likely to compete rather than collude. For example, in

[2] Brynjolfsson and Smith (1999) showed that Amazon (the big three in online book-selling industry) charge 8% higher than other competitors.

an industry where the market share currently owned by pure online vendors is small, such as the computer commodity industry,[3] the online market leader is likely to be forced to compete on price. We should remember that the vast majority of online vendors compete not only online, but also against offline rivals, many of which have high brand recognition.

If an industry deals with high-priced items such as laser printers or digital cameras, consumers are expected to be more search-oriented and price-conscious. This is a reasonable assumption because the gains from search increase as the price of the product goes up[4]. Consequently, intense price competition is expected in the highly competitive computer commodity market and, price dispersion among vendors is predicted to be insignificant, even after controlling for heterogeneity in non-price attributes.

*Hypothesis 1: Due to the highly competitive market environment, where offline vendors have significant market share and consumers are price-conscious, the online computer commodity market should exhibit intense price competition. As a result, the variability in prices across vendors is expected to be insignificant.*

The level of product demand for time-sensitive products such as computer commodities should decrease over time as new models become available in the market. According to Stigler (1961), the price dispersion of highly demanded (or frequently purchased) products is smaller than that of low demand (less frequently purchased) products due to a large number of requests for price-quotes and more frequent advertisements. As a product ages, the popularity of the product decreases, as does the level of demand. Consequently, price dispersion for a particular product across vendors is expected to increase over time.

[3] According to Computer Retailers Week, Buy.Com, the largest online computer retailer, had a revenue of $110M in 1998, which is approximately 2% of CompUSA ($5,750M), the largest offline computer store in U.S. The top 10 offline retailers collectively had a revenue of 24Billions during the same year.

[4] The Forrester research reports that there is a great disparity between the number of searches performed CD buyers and computer hardware buyers. Details will be provided later.

In addition, a longitudinal perspective on price dispersion across vendors provides an understanding of the extent to which price dispersion in the electronic market is associated with inflation. The positive relationship between price dispersion and inflation has been well documented in economics literature (Mills (1927), Parks (1978), and Parsley (1996)).

In contrast to product characteristics and inflation, the market evolution factor and consumers' search experience reduce price dispersion over time. The electronic market is rapidly growing, as is competition among sellers. Consumers tend to become more price-sensitive and improve their search skills on the Web over time (Ward and Lee, 1999), which might force sellers to be more price-competitive. If some sellers always offer the lowest prices and if consumers can learn over time to identify them, price dispersion will disappear as consumers will only shop at those low-priced sellers. Consequently, price dispersion might decrease over time due to increased price competition and improved buyers search skills (Morgan, Orzen and Sefton, 2001).

Price dispersion is determined by multiple factors, each of which has a different impact. Product characteristics and inflation increase price dispersion across vendors over time, whereas market evolution and consumers' increased search skills have the opposite effect. Nonetheless, for time-sensitive products such as computer commodities, product characteristics are expected to have the most significant effect on price dispersion over a relatively short period of time, outweighing the market evolution effect.

*Hypothesis 2: As the demand for time-sensitive products drops over time, price dispersion across vendors increases.*

The nominal variability in prices is naturally larger in markets for expensive homogeneous goods than in those for inexpensive goods. As a result, the mean price of the product is positively related to the degree of price dispersion. The positive relationship between these two variables suggests that the amount of search performed by consumers depends on the price of the product.

Assuming the existence of price variability across sellers, consumers will visit more stores when purchasing expensive goods than when purchasing cheap goods in order to maximize their economic savings from search activities. The unit search cost for expensive products is smaller than that for inexpensive ones. In fact, for less expensive products the question concerning search is usually not how many stores to visit, but whether or not to search. Consequently, real price dispersion (price dispersion normalized over the price of the product) for expensive goods should be smaller than that for inexpensive products. In addition, as consumer search increases proportional to the price of the product, prices of products for which consumers have higher gains to search are expected to disperse less rapidly than prices with low gains to search.

> *Hypothesis 3A: Due to the potentially larger savings, consumers engage in more intense search when purchasing expensive products than inexpensive ones. Therefore, the amount of price dispersion is lower for expensive products than for inexpensive products.*

> *Hypothesis 3B: Price dispersion for a particular product is expected to increase across vendors over time according to hypothesis 2. The rate of price dispersion in products for which consumers have higher gains to search is expected to be less than the rate of dispersion for products with low gains to search over time.*

The timing of price adjustments among different vendors reflects the degree of competition in the market (Ball and Cecchetti, 1988). There has been an ongoing debate over the timing of price adjustment by different sellers. Simultaneous or synchronized adjustment is considered optimum in the Walrasian market. However, models grounded in Keynesian microeconomics postulate that "staggered" price setting, under which sellers change prices at different times, is the equilibrium outcome due to exogenous market frictions such as substantial menu costs and sellers' price search costs (Fishman, 1992; Ball and Cecchetti, 1988).

In our study, we consider three aspects of price adjustment in the electronic fixed-price market; 1) the degree of price change synchronization among various vendors to examine the impact of reduced menu costs and 2) the actual magnitude of price adjustment by different vendors and 3) changes in price ranks among vendors over time to see if vendors deliberately change prices to hide their price position in the market.

In the traditional market, the high costs associated with making price changes (known as menu costs[5]) and ascertaining rivals' prices have prevented sellers from synchronizing price changes. Prior studies have shown that online vendors make much smaller price adjustments, but they do so much more frequently than do offline stores (Brynolfsson and Smith, 2000). Menu costs result in significant economic consequences, influencing each seller's pricing strategies (Akerlof and Yellen, 1985; Blanchard and Kiyotaki, 1985). Economic theory posits that under small menu costs, price synchronization is the likely equilibrium as changes in consumer demand should affect the timing of price adjustments by all firms equally in the market (Lach and Tsiddon, 1996; Ball and Cecchetti, 1988). Sellers need to adjust prices promptly when there is an idiosyncratic shock in the market, such as high price reduction of computer memory chips. In an efficient market, where buyer search costs are low, any significant delays in adjusting prices results in a serious loss for sellers. In general, staggering is Pareto-inferior to synchronization under perfect information since it brings about a price-level inertia, which aggravates business cycles (Ball and Cecchetti, 1988). For the most part, staggered prices have been considered the result of market imperfection in the economics literature (Hall and Taylor, 1988; Okun, 1981).

[5] Menu costs range from the costs associated with printing new price lists to the subjective costs borne by firms from consumers unhappy with recurrent price change (Levy, Bergen, Dutta, and Venable, 1997; Rotermberg, 1982).

Market frictions such as costly information gathering or high menu costs cause sticky prices, which, in turn, contribute to price staggering. In addition to menu costs, high search costs associated with ascertaining competitors' prices have made it difficult for sellers to make effective price adjustments in the traditional market.

While the presence of price dispersion in electronic markets is well documented, little is known about whether or not sellers in the electronic market make price changes simultaneously. We expect that price adjustments in the electronic fixed-price market are synchronized due to the ease with which sellers can observe competitors' prices. Electronic markets also reduce menu costs to a minimum. By utilizing either proprietary *pricebots* or publicly available price comparison sites, sellers in the electronic fixed-price market can easily ascertain competitors' prices. Special price software agents continuously canvass the prices set by others and adjust their own prices accordingly. In this respect, price change happens simultaneously across the vendors within less than a few seconds. Consequently, in addition to insignificant menu costs, the low costs of ascertaining rivals' prices should promote timely price adjustments and synchronize price changes across various vendors in the highly competitive electronic computer commodity market.

> *Hypothesis 4: Due to minimum menu costs and the lower costs of ascertaining prices, the timing of price adjustments is synchronized in the highly competitive electronic computer commodity market.*

Economic theory suggests that high-priced vendors can stay in business because of a sufficiently large number of uninformed consumers who purchase products from their sites (Varian, 1980; Salop and Stiglitz, 1977). However, this equilibrium cannot be sustained if a significantly large number of uninformed consumers learn from their shopping experiences and increase their search skills. Some economists argue that the reason why the variation in prices persists is that sellers adjust prices randomly so that uninformed consumers cannot learn which seller offers the lowest prices (Varian, 1980). Price dispersion should eventually disappear in equilibrium if consumers can learn the distribution of prices over time.

Based on survey data from the GVU center at the Georgia Institute of Technology, Ward and Lee (2000) found that as consumers improve their search skills and become more experienced with the Internet, they tend to depend less on brand name products and become more price conscious. As the magnitude of competition intensifies over time, prices are expected to converge to the low-priced vendors' price in a highly competitive market (Kauffman and Wood, 2000). Medium- and high-priced vendors seem to have limited options. One option would be to follow the leader's strategy by lowering prices. As they face more price reduction pressures in order to compete with low-priced vendors, the size of price reductions by these vendors is expected to be greater than that of low-priced vendors. Through reductions, they can elicit demand from informed consumers (Salop and Stigliz, 1982).

*Hypothesis 5A: Due to increased price competition in the electronic market, there is significant difference among sellers with respect to the magnitude of price changes; the degree of price reduction by high-priced vendors is expected to be larger than that of low-priced vendors.*

Alternatively, high-priced vendors can deliberately change prices in a random fashion so that consumers cannot learn prices (Varian, 1980). The “intentional” fluctuation in price is aimed at extracting more revenue from uninformed consumers. Consequently, some vendors with higher prices are expected to exhibit bigger fluctuations in price ranks across different time periods to avoid price competition.

*Hypothesis 5B: High priced vendors will resist price competition by deliberately changing their price strategies in order to prevent consumers from learning their “true” prices.*

# REARCH DESIGN

## Description of Data

Retail prices for 37 homogeneous computer components offered by fourteen electronic fixed-price vendors were periodically gathered and analyzed to quantify the degree of price dispersion and price adjustment over time. We employed a stratified sampling method through which fourteen vendors were chosen from CNET.com's (www.shopper.com) list of 100 popular computer products. The bi-weekly data, gathered over a period of twelve months, provided price quotations of a particular product for a total of 24 different time periods.  The products sold at the beginning of data collection were exactly the same as those sold at the end - the identical product IDs; no version upgrades were used as substitutes since their functionalities and features are different. Due to the relatively short lifecycle of computer products, we removed products whose price was not quoted by at least 11 vendors. Data on shipping and handling (S&H) charges were also gathered to precisely measure the total costs that a consumer would have to pay at each site. Since some online vendors are known to manipulate their total prices with shipping charges, it is important to include these costs. New York City (Zip Code 10012) was used as the default destination city to calculate the S&H fees.

## Data Sampling

To reduce any sampling error, this study employed a stratified sampling method instead of simple random sampling. Forty-three computer commodity retailers from CNET.com were pooled and grouped into three different price groups (low-, medium-, and high-priced vendors) based on a preliminary test using the top 20 ranked on CNET's popularity ratings at the time of our preliminary data collection. Initially, we gathered 60 vendors from the CNET list, and excluded 17 that did not carry at least 15 out of the 20 items chosen. We considered the eliminated vendors unrepresentative of the active online retailers at the time of our study.

We divided the remaining 43 vendors into three groups based on the average price of the 15 products available from all 43 vendors. More specifically, 14 vendors that were approximately in the top 33 percentile of all 43 vendors were categorized as high-priced. The next 33 percentile we classed as medium-priced, and the final group we considered to be low-priced[6]. Finally, we selected fifteen by choosing five from each of the three different price groups. During the data collection period, one of the vendors in the sample merged with the largest vendor in the sample and so we eliminated the merged vendor from the dataset.

### Price Scanning Software Agent (PCSA)

We developed a proprietary software agent (PCSA) which automatically scanned and gathered numerous target prices directly from a vendor's Web-server. The PCSA was designed to simulate the price query action of actual consumers who send a price request on a specific product to the seller's local search engines. We used product IDs as search strings, since they uniquely identified products and allowed consumers to easily find the current market price for a given product. The PCSA captured various prices from the vendors' server, and then transmitted them to a linked MS Access database, which stored all the price information. The database contains several fields such as unit price, S&H charges, tax, the URL from which the price was extracted, and a time stamp.

## DATA ANALYSIS AND RESULTS

### Price convergence in the electronic computer commodity market (H1)

[6] Due to the inequality, fifteen, instead of fourteen, vendors were classified as low-priced vendors. The average price of the 15 products offered by the 15th vendor was closer to the low-priced group.

To understand the degree of price competition in the electronic computer retailing market, we used a regression model to analyze price differences among the 14 different vendors. The regressors in the model are all dummy variables representing the identity of vendors, products and time coefficients for each product. P1(Product1, $\alpha_1$) and V1 (Vendor 1, $\beta_1$) were used as the default product and vendor respectively in the model. Log transformed prices were used as the dependent variable vector while products $(\alpha_s)$, vendors $(\beta_s)$ and the time periods $(\gamma\ )$ represent the independent variables in the model. The dependent variable was log transformed since use of nominal price data violates homoskedasticity where the variance of error terms depends on independent variables (Borenstein, 1989). Equation 1 is the simplified regression representation explaining the basic structure of the full model. Note that $\alpha$ coefficients indicate price difference for identical products among 37 products while $\gamma$ coefficients represent the possible price change of a particular product over a one-year time period. The $\beta$ coefficients show the vendor effect, testing the underlying hypothesis with regard to the price convergence in the context of the electronic fixed-price market.

$$1)\quad \mathit{Log}\ \mathrm{P}_{\mathrm{ijt}} = \mu + \sum_{\mathrm{i}=1}^{37} \alpha_{\mathrm{i}} \mathit{Product}_i + \sum_{j=1}^{14} \beta_j \mathit{Vendor}_j + \sum_{i=1}^{37} \gamma_i t \mathrm{Time}_{\mathrm{i}} + \varepsilon_{ijt}\ , \qquad \mathit{Var}\ \varepsilon_{ijt} = \delta_{ij}^{\ 2}$$

where $i$ =number of products, $j$ =number of vendors, $t$ =number of time periods.

In spite of log-transformation, the error term exhibited heteroscedasticity at the 5% significance level ($F$ = 5.78, $p<0.05$). Heteroscedasticity indicates that the standard errors of the regression coefficients are not estimated correctly and as a result, the t-statistics might be misleading (White, 1980). To remedy the problem presented in our data, we used White's Heteroskedasticity Consistent Covariance correction method (White, 1980). This method reduces the standard errors, while not affecting the way in which coefficients are estimated. As a result of the Heteroskedasticity Consistent Covariance correction, the size of the t-statistics for the coefficients was reduced, but the reduction did not affect the significance of the coefficients at the 5% level.

Results show that the complete model in equation 2 accounts for 98.9% of the variability in the target variables ( $R^2 = 0.99, R^2_{adjusted} = 0.99$ ). Also, an $F$-test indicates a strong overall significance of the regression model at the 0.05 significance level ( $F_{86,12027} = 13988, p < 0.01$ ). The individual $t$-statistics for the vendors ( $\beta_1,...,\beta_{14}$ ) are all statistically significant at the 0.05 level, suggesting sizeable price differences among the 14 vendors (See equation 2). Consistent with existing studies, we find that online vendors charge substantially heterogeneous prices for identical products, even in the highly competitive electronic computer commodity market. Interestingly, in contrast to the online book-selling industry, the two lowest vendors (V1 and V2) had the greatest brand recognition. Thus it would appear that heterogeneity in non-price attributes such as brand recognition is not responsible for price dispersion in this market.

The data suggest that we should reject Hypothesis 1 and proceed with testing Hypotheses 2-5 to provide insights into the nature of price dispersion in the fixed price computer commodities market.

$$2)\ Log(Price) = \alpha_1 P_1 + ... + \alpha_{37} P_{37} + 2.2 - \underset{(t\,=\,-5.7)}{0.008\beta_2} + \underset{(t\,=\,8.7)}{0.014\beta_3} + \underset{(t\,=\,24.4)}{0.033\beta_4} + \underset{(t\,=\,220.3)}{0.027\beta_5}$$

$$+ \underset{(t\,=\,9.2)}{0.013\beta_6} + \underset{(t\,=\,14.4)}{0.023\beta_7} + \underset{(t\,=\,12.2)}{0.015\beta_8} + \underset{(t\,=\,29.8)}{0.043\beta_9} + \underset{(t\,=\,11.0)}{0.016\beta_{10}}$$

$$+ \underset{(t\,=\,13.4)}{0.021\beta_{11}} + \underset{(t\,=\,20.0)}{0.027\beta_{12}} + \underset{(t\,=\,13.7)}{0.018\beta_{13}} + \underset{(t\,=\,12.6)}{0.016\beta_{14}}$$

$$+ \gamma_1 T_{1,...,24} + .... + \gamma_{37} T_{1..24} + \varepsilon$$

$$R^2 = 0.99,\ F_{86,12027} = 13988, p < 0.001$$

## Changes in spatial price dispersion over time (H2)

To identify how price dispersion across vendors changed *over time*, we considered each product *i* independently to isolate its effect on price dispersion. We computed 24 standard deviations of prices across the 14 vendors, for each time period ( $SD_{t=1},...,SD_{t=24}$ ) for each product *i (i= 1,…,37).* Then we used the SDs as the dependent variable in a regression on time. We ran 37 regressions and calculated the same number of *t* values for the purpose of testing the significance of coefficients ( $\beta$ s).

The magnitude of price dispersion across 14 vendors changed over a one-year time period for each of the 37 products, on average, falling between 0.05 and 0.2. It appears that spatial price dispersion has increased over time. The *t*-values of 27 out of 37 regressions are significant at the 0.05 level (See the column, One Year (T1-T24) in Appendix A). Seventy three percent (= 27/37) is high enough to provide evidence that the variability in price for a given homogeneous product across various vendors changed significantly over time ($t=9.9$, $p<0.01$). Appendix A summarizes the t-values for all 37 products, indicating the statistical significance of changes in price dispersion over time. In particular, the majority of the positive increase in price dispersion occurred during the last 6 months (22 out of 37 or 60%). The percentage was much lower during the first half (13 out of 37 or 35%). A total of 25 out of the 27 products (93%) have a significant periodic trend in price dispersion shown by positive signs for the coefficients.

We assumed that demand for the products chosen in this study decreased over time for two reasons; 1) all 37 products ranked among the CNET's 100 most popular products at the time of data sampling, but none ranked in the top100 after 3 months, and 2) the availability of the products significantly decreased as time progressed. Assuming that demand for time sensitive products decreases over time, this result suggests that price dispersion increases as a result of the decreased demand over time.

**Impact of Inflation on Price Dispersion**

We tested whether the increased price dispersion observed had resulted from the inflation during the periods we conducted the study.[7] We performed a time series analysis to control for the non-stationarity in the data using the consumer price index (CPI) from Bureau of Labor Statistics (http://www.bls.gov/cpi) as a measure of inflation. Based on the Durbin Watson test, the residual errors were found to be significantly correlated, which violates the assumption of a linear regression model. We employed a first differencing method to correct for the autocorrelation problem (Equation 4).

*For product i*,

$$4)\ Dispersion_{i,t} - Dispersion_{i,t-1} = \alpha + \beta\,(Inflation_t - Inflation_{t-1}) + \varepsilon$$

The results indicate that only 4 out of 37 products (10%) were significantly associated with inflation. This result suggests that the increased price dispersion over time did not result from inflation during the periods, but from reduced demand for the product. However, it should be noted that a one-year time period might not be sufficient for studying the effects of inflation.

## The relationship between product price and price dispersion (H3A)

We examined the relationship between the two variables, price dispersion, measured by the standard deviation of prices, and the mean price, measured by the average of fourteen quoted prices, via regression analysis. The result shows a strong positive relationship between the mean of the *nominal price* and standard deviation of prices using a least squares fit of the logarithm of estimated standard deviations to estimated means. The fitted model suggests that a doubling of the estimated mean price increases the SD by 75 percent ($2^{0.81} = 1.75$). The $R^2$ for the fit was high (82%) and the t-statistics for the $\beta$ was statistically significant ($t$=62.7, $p$<0.01).

$$Ln\ SD = -1.412 + 0.81\ Ln\ \mu, \quad R^2 = 0.816$$
$$(t = 62.7)$$

However, when price dispersion is normalized by the price of the product (SD/price), the degree of *real* price dispersion is significantly negatively associated with the price of the product ($r = -0.5, p = 0.002$). This finding suggests that as the product price increases, real price dispersion decreases. Sellers have to set the price close to the average market price for expensive products and cannot deviate much from the mean because consumers search more intensively when purchasing higher priced-items compared with low-priced ones.

## The effect of product price on price dispersion over time (H3B)

We predict that the price of the product affects the degree to which prices are dispersed over time; prices of expensive products for which consumers have higher gains to search are expected to disperse less rapidly than prices with low gains to search over time. The dependent variable was coded as 1 if price dispersion increased over time, 0 if no changes, and –1 if dispersion decreased over time. The price of the product was used as the independent variable. We found no significant impact of product price on the changes in price dispersion over time ($t$ =0.8, $p$=0.38).

## A test of price change synchronization in the electronic fixed-price market (H4)

Testing the fourth hypothesis on price change synchronization requires estimating the dependency in the timing of price changes for 37 commodity products across 14 online fixed-price vendors. Because we sampled multiple products, the use of a time series of the percentage

[7] The inflation rate increased by 3% during the one-year period.

of firms that changed prices averaged over products is problematic for verifying price synchronization. For example, perfect price staggering (50% price changes) can occur when averaging out two perfect price synchronizations (0% and 100%)[8].

We used a Monte-Carlo simulation to generate uniformly distributed random numbers (Von Neumann, 1946; Rubenstein, 1981). In the simulation, each product *i* is considered separately to test whether there is high dependency among vendors with regard to the timing of price changes. Simulation techniques have been widely used in Economics and Operations Research to test the randomness of events (L'Ecuyer, 1990). In our study, each product's status of price adjustment from the previous period was coded as a categorical variable, 1 for price change, 0 for price unchanged.[9] A 14 X 23 matrix (Figure 2) with dummy variables results for each product *i*. Our simulation statistically examines the 'randomness' of the timing of price adjustments by comparing the standard deviation of the actual data for each product with that of simulation-generated values.

We computed column and row totals indicating the total number of price changes per each vendor and per time respectively**.** Then, the vendor with the biggest number of changes was identified and moved into the first column to be used as the benchmark. For each of the 37 products, the column totals were obtained and used in the simulation. The simulation program we wrote randomly generates the row totals given the fixed number of column totals, since the objective here is to test the randomness of price change across the 14 vendors. It is important to note that the sum of the column totals have to be the same as the sum of the row totals. The simulation randomly generates data with the bounds of the empirical data that we use to compute standard deviations. Then, we compared the standard deviations of the simulation-generated data

[8] This scenario is possible due to the differences in product characteristics

with that of the actual empirical data. For each product *i,* we performed 1000 simulation runs to check the significance of the deviation at the 0.001 level**.**

For each product *i,*

Vendor

| | | V(1), | V(2), | | ... | ... | | V(13), | V(14) | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | R(2) | | | | | | | | | $\sum_{j=1}^{14} R_2 V_j$ |
| | R(3) | | | | | | | | | $\sum_{j=1}^{14} R_3 V_j$ |
| | | | | | | | | | | |
| | | | | | | | | | | |
| Period | | | | | | | | | | |
| | | | | | | | | | | |
| | R(23) | | | | | | | | | $\sum_{j=1}^{14} R_{23} V_j$ |
| | R(24) | | | | | | | | | $\sum_{j=1}^{14} R_{24} V_j$ |
| | Total | $\sum_{i=2}^{24} R_i V_1$ | $\sum_{i=2}^{24} R_i V_2$ | | | | | $\sum_{i=2}^{24} R_i V_{13}$ | $\sum_{i=2}^{24} R_i V_{14}$ | $\sum_{j=1}^{14} \sum_{i=2}^{24} R_i V_j$ |

Figure 2: A 14X23 Matrix; a row total represents the number of vendors who changed price during the 24 time periods.

To illustrate numerically how we computed the simulation-generated SDs, we first obtained the 14 column totals for product *i*, let's say product 7 (14, 7, 12, 11, 7, 6, 2, 8, 4, 7, 11, 5, 6, 5)[10]. These numbers represent the actual column totals ($\sum_{i=2}^{24} R_i V_1, \sum_{i=2}^{24} R_i V_2, ..., \sum_{i=2}^{24} R_i V_{14}$) for each vendor respectively. In addition, we also computed the actual row totals ($\sum_{j=1}^{14} R_2 V_j, \sum_{j=1}^{14} R_3 V_j, ..., \sum_{j=1}^{14} R_{24} V_j$) for product 7 (3, 2, 4, 4, 3, 13, 5, 2, 3, 3,1, 9, 13, 10, 4, 4,2,5,0,

[9] Price unchanged includes price change less than 1% (Ross and Krausz, 1986)

2, 7, 3,3), respectively. Recall that each row corresponds to a time period and we are computing the standard deviation of the row totals. The computed SD of the actual row totals is 3.53.

The next step is to generate the simulated row totals by using the program we developed. To do so, we identified the vendor with the biggest column totals from the actual empirical data. In this case, Vendor 1 has the highest column totals and thus was used as the benchmark. Given the fixed number of the sum of the column totals ($\sum_{j=1}^{14} \sum_{i=2}^{24} R_i V_j$ = 105), the simulation program performs 1,000 runs, generating entries for the individual cells in the matrix and then computing 1,000 SDs (1.85, 1.81, 1.70, 2.21, 1.65, 2.45[11], …) based on the random row numbers. Finally, we compared 3.53 (actual SD) with that of 1,000 simulated generated SDs to test the price synchronization hypothesis in the electronic fixed-price market.

We compared the standard deviation of the actual data for each product with that of the simulation-generated values[12] to determine the "randomness" of the price changes among the 14 vendors. More specifically, for every one of the 37 products, we compared the standard deviation (row totals) of 1,000 simulation runs with that of the observed data. If the vendors operate randomly, then the row totals should fluctuate around a central value and result in a moderate standard deviation. If however, the vendors "collude" or at least tend to reduce prices at the same times (and therefore also tend to raise prices simultaneously), then the row totals will move away from their central value and approach either 0 or 14, resulting in a larger standard deviation. Thus, a large standard deviation for the row totals suggests that the vendors are not operating independently.

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[10] These numbers indicate the number of vendors that adjusted prices in the subsequent period.
[11] These are the first 6 simulation generated SDs for product 7.
[12] The simulation run computed an SD based on the procedures introduced earlier. See Appendix B for technical details.

In every case, the value of the SD in the actual data exceeded all 1,000 simulated values, suggesting that the results are significant with simulation p-values below 0.001. . Moreover, the simulated SDs do not approach the SD from the actual data. This result clearly supports price change synchronization, indicating that there is dependence among the 14 vendors in the sample with regard to the timing of price changes.

This result was very surprising. Not one simulation result out of 1,000 for 37 different products produced a standard deviation as large as that for the actual data. How could this happen? We examined the row totals in the actual data. Recall that a row total represents the number of vendors who changed price during a given time period. The actual data shows two extremes in terms of the price changes; either many vendors changed prices or many vendors held prices. Specifically, the row totals representing the number of vendors who changed price during a given time period were commonly within a range of 0 to 4 (out of 14) and occasionally between 12 to 14 (out of 14). The numbers 5 through 8 very rarely occurred as row totals. These clearly defy the randomness of the price changes among the vendors, suggesting that vendors use very similar timing for price adjustments.

## The magnitude of price changes among online vendors (H5A)

We expect that high-priced vendors are affected most severely by reduced search costs in the electronic fixed-price market, as a result of which their price reductions should be larger than those of low-priced vendors. We compared the actual magnitude of price change by vendor and time, averaged over products (Appendix B). We also correlated the amount of periodic price adjustments among the vendors. The non-parametric Chi-Square test confirmed the lack of differences in the mean of price adjustments across the 14 vendors

($\chi^2 = 11.9 < \chi^2_{0.05, df=13} = 35.2$). We ran a linear regression to determine if there was a significant relationship between the average magnitude of price adjustment per period and the overall average price for each vendor. The result shows an insignificant relationship ($p$=0.57). Consequently, based on our results, hypothesis 5A was rejected. There appears to be no significant evidence to say that vendors vary in the magnitude of price adjustments over time, at least during the one-year period we studied. The results indicate that we should reject the prediction that high-price vendors cut prices more aggressively than do low-priced vendors.

## Changes in Price ranks over time (H5B)

We performed a Friedman test to determine if there was a significant difference in price ranking changes among the 14 vendors over the 24 periods. The Chi-Square value (195.7) with 13 degrees of freedom greatly exceeds the critical value of $\chi^2_{0.05,df=13} = 35.2$ , showing that there is difference among the 14 vendors in rankings. In a correlation analysis of ranks among 14 vendors between different time periods, we found the ranks between time i and subsequent period i+2 highly correlated within a month. However, the correlations become statistically insignificant after approximately11-12 periods (or 6 months)[13]. This result suggests that consumers can predict a vendor's price position no more than 5-6 months ahead in any given month. In general consumers cannot learn about sellers' positions because rankings changed over time. The 5-6 month price prediction is similar to the findings of Lach (2002), who studied the rank changes in offline markets such as the refrigerator, coffee and flour markets.

We assumed the top, mid and bottom 33 percentiles as the low, medium, and high-priced vendors and tested whether there was a significant difference among the three groups with respect to the amount of fluctuation in price ranks. The result shows that high-price vendors have

[13] According to Siegel and Castellan (1988), a correlation coefficient above 0.5 should be considered statistically significant when the sample size (the number of sellers) is 14. The critical value decreases as the sample size increases (e.g. 0.32 is a critical value when the sample size is 38)

more fluctuations in price ranks (*t*=2.3, *p*=0.04). In particular, significant ranking changes were observed between the first and last 6 month-periods. Approximately 50% of the vendors changed their positions in the price ranks during the time period. Interestingly, however, the two lowest vendors with brand recognition maintained their price leadership throughout the year. Overall, vendors frequently change their pricing strategies, we believe to prevent consumers from learning their true prices.

# DISCUSSION

Consistent with prior studies, Bertrand competition (1883), where all vendors offer a uniform price, did not hold in the highly competitive electronic computer commodity market. However, heterogeneity in vendors' characteristics such as brand recognition, do not seem to have been the source of the price dispersion observed in our study. In contrast to the online book-selling industry where market leaders with brand recognition, such as Amazon, charge higher prices than smaller counterparts, low-priced vendors provided consumers with higher quality of service in the computer retail industry.

The two best well-known vendors (V1 and V2), who were the number one and two online computer retailers in terms of revenues according to Computer Retailer Weeks' top 100 computer retailers US, offered the lowest prices in the market. These two vendors were considered the 'Amazon and BN.com' in the online computer retailing industry at the time of this study. In addition to providing low prices, these vendors appear to offer good customer service. The low-priced vendors provided, on average, 97 hours of customer service support per week, while the rest offered only 48 hours (www.shopper.com/cmpny). In addition, vendors with low prices charged only 5% of sales price for restocking fees, while the rest charged, on average, 12%. Low-priced vendors all offered online tracking systems, while only half of the rest provided that service. There were no significant differences in the availability of products and secure online transactions, and the number of payment/delivery methods available.

As a result, the belief that vendors with brand recognition are able to set higher prices because of heterogeneity in non-price attributes (Varian 1980, 1999; Brynolffson and Smith, 1999) was not supported in this industry.

In general, computer products are more expensive than books and, as a result, price sensitivity is expected to be greater in the computer retail market than in the book market. In addition, computer commodities are more time-sensitive than books due to short life cycles. The gains from search naturally increase as the price of the product increases. Therefore, consumers purchasing computer products are more inclined to engage in search activities than those purchasing books online. According to Forresters' survey of online consumers, respondents purchasing computer products search approximately three times more than those buying books online (McQuivey and Wakeman, 1999). As a result, vendors in the computer retail industry face more severe price competition than those in the online book industry.

The online computer retailing industry seems offers more intense competition externally with offline establishments with high brand recognition, such as CompUSA and Best Buy. The market share of online versus offline vendors in the computer retailing industry was considerably lower compared to that in the book selling industry at the time of this study. The majority of computer products are technically more sophisticated than books. Moreover, shipping and handling charges for some computer products such as monitors and printers are expensive, which confers a cost-advantage on offline vendors. Difficulties assessing the quality of the product, for example, monitor resolution or print quality, and the effort to return products, provide consumers with high incentives to purchase offline. We suspect that the ongoing low prices by branded online computer retailers are likely to have resulted from this intensive competition with offline retailers.

Based on our simulation, we found strong evidence that there is indeed dependence among online vendors with regard to the timing of price change. We attribute this phenomenon to minimum menu costs, deployment of pricebots and the use of price comparison agents as sources of ascertaining competitors' prices.

We did not find any significant difference in the magnitude of price changes among different vendors. We predicted that high-priced vendors face more severe price reduction pressure over time in the highly competitive market and, as a result, the amount of price adjustment by high-priced vendors was expected to be larger than that by low-priced vendors. This prediction was not supported statistically. In fact, although not statistically significant, high-priced vendors generally had a relatively smaller amount of price reduction compared to that of low-priced vendors while exhibiting highly volatile periodic price changes.

The ranking analysis offers an interesting insight into the pricing strategies of vendors in different price groups. The ranks for the two low-priced vendors were consistently high over a one-year time period. However, about a half of the vendors in the sample changed their positions.  In addition, the result suggests that the more expensive the vendor, the larger is the fluctuation in price ranks to prevent consumers from learning pricing strategies. Do vendors deliberately change prices randomly in order to makes it difficult for consumers to learn about their true pricing strategies? The price ranks remained constant for any given month up to approximately 6 month (T12), but not thereafter. Consistent with the results reported in Lach (2000), the majority of vendors we studied tend to take advantage of the "short memory" of the market.

## CONCLUSION

The highly competitive computer commodity market faces substantial competition from both established offline vendors and other component manufactures online. Under these conditions, pure online vendors are forced to compete on price. Of the 14 vendors we studied, only 7 have survived as of May 2002, two years after the study was conducted. Interestingly, four out of five high-priced vendors no longer exist, but all four low-priced vendors are still operating. Although it is difficult to argue that pricing was the sole reason why high-priced vendors left the market, we speculate that high prices made a significant contribution to their market exit.

When buyers fail to take advantage of reduced search, sellers have no reasons to react to a changed market environment. Consequently, the extent to which consumers utilize technology, become more price-conscious, and make rational purchase decisions will determine whether or not electronic markets become perfectly competitive as theory predicts. If consumers do not become activists in electronic markets, vendors will continue to differentiate their products and services, discriminate against consumers, and disguise their "true" prices through frequent price adjustments. Future pricing in e-commerce may well depend on whether buyers or sellers make the most use of search technology for price discovery.

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**Appendix A**: Price Dispersion of 37 products over 24 time periods

| **Product** | **Average Price** ($) | **One Year (T1- T24)** | | **First 6Month (T1-T12)** | | **Last 6Month (T13-T24)** | |
|---|---|---|---|---|---|---|---|
| | | t-stats | p-value | t-stats | p-value | t-stats | p-value |
| P1 | 152.26 | **6.88** | .00 | **4.36** | .00 | 1.40 | .19 |
| P2 | 164.88 | .35 | .73 | **2.29** | .04 | -.23 | .81 |
| P3 | 334.37 | **3.80** | .00 | 1.41 | .18 | **3.39** | .00 |
| P4 | 332.59 | **6.40** | .00 | **2.65** | .02 | 1.61 | .13 |
| P5 | 95.2 | **9.00** | .00 | 1.31 | .21 | **10.86** | .00 |
| P6 | 124.92 | **2.21** | .03 | 1.29 | .22 | .50 | .62 |
| P7 | 380.27 | **5.31** | .00 | .49 | .63 | .30 | .76 |
| P8 | 85.29 | **7.44** | .00 | 1.24 | .24 | **6.19** | .00 |
| P9 | 391.24 | **2.80** | .01 | -.97 | .35 | **2.52** | .03 |
| P10 | 49.59 | **2.33** | .02 | **4.90** | .00 | .58 | .57 |
| P11 | 175.19 | 1.54 | .13 | **5.21** | .00 | **-3.88** | .00 |
| P12 | 354.59 | **4.89** | .00 | 1.23 | .24 | **2.44** | .03 |
| P13 | 326.21 | **8.47** | .00 | 1.00 | .33 | **3.50** | .00 |
| P14 | 27 | -.20 | .83 | 1.22 | .25 | **2.61** | .02 |
| P15 | 782.95 | **8.21** | .00 | **3.48** | .00 | 1.61 | .13 |
| P16 | 101.12 | -1.20 | .24 | **-3.17** | .01 | **2.99** | .01 |
| P17 | 52.42 | **2.83** | .01 | 1.25 | .23 | 1.57 | .14 |
| P18 | 124.72 | **4.20** | .00 | 1.16 | .26 | 1.08 | .30 |
| P19 | 537.05 | **6.62** | .00 | 1.96 | .07 | **4.70** | .00 |
| P20 | 575.47 | **8.61** | .00 | **2.19** | .05 | **2.41** | .03 |
| P21 | 82.2 | **-3.58** | .00 | -1.51 | .16 | -.14 | .89 |
| P22 | 152.38 | **3.57** | .00 | 1.48 | .16 | 2.06 | .06 |
| P23 | 212.97 | **3.93** | .00 | **3.15** | .01 | **3.63** | .00 |
| P24 | 24.64 | 1.78 | .08 | 1.94 | .08 | **2.96** | .01 |
| P25 | 520.93 | .14 | .88 | -.98 | .35 | 1.57 | .14 |
| P26 | 683.89 | **7.56** | .00 | **2.39** | .03 | **4.80** | .00 |
| P27 | 453.26 | **-3.69** | .00 | **-3.52** | .00 | **3.76** | .00 |
| P28 | 922.61 | 1.71 | .10 | .61 | .55 | **2.48** | .03 |
| P29 | 120.48 | **3.55** | .00 | -.49 | .63 | .22 | .82 |
| P30 | 439 | **7.94** | .00 | .87 | .40 | **4.08** | .00 |
| P31 | 52.06 | .72 | .47 | 2.02 | .07 | **-2.67** | .02 |
| P32 | 71.88 | **5.99** | .00 | **2.20** | .05 | **2.64** | .02 |
| P33 | 33.23 | 1.00 | .32 | .54 | .59 | -.94 | .36 |
| P34 | 1184.19 | **4.32** | .00 | .55 | .59 | **4.21** | .00 |
| P35 | 462.03 | **5.66** | .00 | .77 | .45 | **2.64** | .02 |
| P36 | 321.53 | **4.50** | .00 | **5.33** | .00 | 1.32 | .21 |
| P37 | 281.91 | 1.97 | .06 | -.27 | .78 | **2.90** | .01 |

Appendix B: Magnitude of Price Change by Vendor Averaged over Product

| | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | V10 | V11 | V12 | V13 | V14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| t = 2 | -1.30% | -2.53% | -1.19% | -4.93% | 0.08% | -1.73% | 0.06% | 0.00% | -0.62% | -1.32% | -0.34% | -2.97% | -1.11% | -1.76% |
| t = 3 | -3.69% | 0.15% | 0.08% | 3.72% | -3.48% | 1.78% | -0.33% | -1.20% | 0.00% | 0.00% | -2.03% | -0.17% | -4.77% | 0.00% |
| t = 4 | -0.42% | 2.04% | 0.09% | 0.71% | -1.20% | -4.26% | -1.45% | 0.26% | -0.27% | -2.14% | -0.95% | -0.56% | -0.91% | -0.74% |
| t = 5 | 2.12% | 0.09% | -0.72% | -3.25% | -0.01% | -0.56% | -0.56% | -2.90% | 0.31% | 0.19% | -5.13% | 0.00% | -0.14% | 0.00% |
| t = 6 | -0.92% | 0.48% | 0.30% | -6.49% | -0.01% | -1.39% | -1.23% | -2.32% | -0.49% | -0.77% | -1.84% | 0.00% | -0.43% | -0.68% |
| t = 7 | -0.58% | -0.60% | -1.40% | 6.28% | 11.21% | 1.17% | 0.17% | -0.04% | 0.14% | 0.34% | 0.22% | 0.00% | 0.14% | -0.38% |
| t = 8 | 1.78% | 1.34% | 1.84% | -6.16% | -8.10% | -1.19% | -3.17% | -0.17% | 0.01% | 3.45% | -3.57% | -1.22% | 0.00% | -0.69% |
| t = 9 | 0.38% | -0.74% | 1.51% | 7.31% | -1.78% | -0.37% | 0.00% | -0.16% | 0.00% | 0.20% | -0.07% | 0.00% | -0.88% | -0.15% |
| t = 10 | 1.30% | -0.18% | 0.51% | 5.40% | 0.00% | -0.06% | 0.11% | -2.11% | -0.88% | -0.24% | -2.01% | -0.97% | -0.88% | -0.78% |
| t = 11 | 1.07% | -0.71% | -0.84% | -0.46% | -0.84% | 0.65% | 1.93% | -0.83% | -0.55% | 0.03% | 4.93% | 0.00% | 0.00% | 0.12% |
| t = 12 | -2.04% | -0.80% | -1.65% | -2.09% | -0.36% | -1.59% | 0.33% | 0.62% | -1.53% | -0.54% | 1.67% | -2.24% | -2.18% | -1.28% |
| t = 13 | -9.64% | -0.28% | -7.77% | -8.90% | -9.08% | -11.79% | -6.28% | -9.58% | -6.79% | -5.50% | -9.91% | -6.17% | -8.48% | -9.76% |
| t = 14 | 9.17% | 1.01% | 19.06% | 8.72% | 8.88% | 9.93% | 21.87% | 7.53% | 17.13% | 2.76% | 14.14% | -3.20% | 8.34% | 7.93% |
| t = 15 | 4.25% | -3.94% | -2.11% | -1.93% | 0.00% | 0.60% | -3.18% | -1.93% | 0.39% | -5.00% | -2.63% | 1.09% | 1.90% | -0.66% |
| t = 16 | -5.72% | 2.64% | -0.98% | 1.19% | 0.00% | -1.45% | 0.32% | 0.07% | 4.68% | 2.41% | 0.75% | -0.96% | -2.38% | -0.15% |
| t = 17 | -8.51% | -0.03% | -1.20% | 0.69% | -0.72% | -0.03% | 0.22% | -0.43% | 0.00% | -1.04% | -0.11% | -0.62% | 0.00% | -0.81% |
| t = 18 | 8.81% | 2.37% | 0.87% | -1.19% | 4.04% | -0.52% | -0.92% | 3.98% | 0.00% | 0.63% | 0.27% | -0.66% | -0.95% | -1.50% |
| t = 19 | 1.06% | -1.82% | -0.07% | 0.00% | 0.02% | -0.39% | 0.33% | -0.52% | 0.00% | 0.46% | -0.06% | 0.31% | -0.93% | 0.00% |
| t = 20 | -1.93% | -2.73% | -0.93% | -1.17% | 0.00% | -0.97% | -1.09% | -0.24% | 0.00% | -0.45% | 2.48% | -0.28% | -1.23% | -1.18% |
| t = 21 | 1.43% | 0.63% | -0.20% | -0.01% | -2.16% | 0.93% | 47.10% | -0.29% | -1.10% | -0.02% | -0.15% | -1.20% | 0.00% | 0.35% |
| t = 22 | -2.22% | -0.90% | -1.37% | -0.18% | -0.41% | -0.24% | 0.19% | -0.66% | 0.00% | -0.12% | -2.17% | 0.00% | -0.82% | 0.64% |
| t = 23 | 1.23% | -0.34% | 0.04% | -0.73% | 2.45% | -0.29% | -23.86% | -0.73% | 0.00% | -1.46% | -0.73% | -0.73% | -0.67% | -1.17% |
| t = 24 | -0.20% | -1.98% | -0.60% | 0.91% | 0.00% | 0.17% | 0.00% | 0.43% | 0.00% | -0.89% | -1.64% | 10.80% | 0.00% | 0.30% |
| | | | | | | | | | | | | | | |
| AVERAGE | -0.20% | -0.30% | 0.14% | -0.11% | -0.06% | -0.50% | 1.33% | -0.49% | 0.45% | -0.39% | -0.39% | -0.42% | -0.71% | -0.54% |
| STDEV | 4.38% | 1.62% | 4.51% | 4.37% | 4.25% | 3.50% | 12.24% | 2.90% | 4.06% | 2.01% | 4.24% | 2.88% | 2.82% | 2.74% |
| MAX DECREASE | -9.64% | -3.94% | -7.77% | -8.90% | -9.08% | -11.79% | -23.86% | -9.58% | -6.79% | -5.50% | -9.91% | -6.17% | -8.48% | -9.76% |
| MAX INCREASE | 9.17% | 2.64% | 19.06% | 8.72% | 11.21% | 9.93% | 47.10% | 7.53% | 17.13% | 3.45% | 14.14% | 10.80% | 8.34% | 7.93% |