On the Temporal Variations of Online Pricing in India: An Empirical Analysis

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I. Motivation

The presence of many sellers is known in the conventional economics literature to improve competition outcomes for normal perishable goods. As the number of sellers increase, final prices for the consumers start declining and in most situations, leads to an improvement in welfare.

This premise about effect of increased number of sellers in the market is tested most severely in the recent news reports and activism by sellers in the physical market place as well as its online counterpart. Over 2014-15, the big e-commerce entities (Flipkart, Amazon and Snapdeal) have engaged in a price war and large scale advertisement campaigns. The Economic Times reported that Flipkart, the largest Indian e-commerce site, posted a loss of INR 2,000 crore in FY 2015, an increase of INR 1,275 crore over the last year's losses[1]. This has been despite a trebling of sales by Flipkart over 2014-15. The main reason for the losses has been attributed by the report to price discounts offered by Flipkart, advertising campaigns as well as technology upgradation and costs of warehousing. The report states that 30-50 per cent of sales are a part of its losses due to high logistics cost and discounted pricing. The physical market place, as defined in the following paragraph, has been suffering from the price discount war among the e-tailers. The recent cases at the Competition Commission of India (case no. 17 of 2014 [Ahuja vs. Snapdeal.com and SanDisk Corporation] and case no. 80 of 2015 [Manglani vs. Flipkart and ADCTA vs. Flipkart, Amazon and Snapdeal]) highlight the increasing tension that the online selling strategies are creating for the physical market place. Most of the physical market place sellers allege predatory pricing, exclusive supply and distribution agreements and exclusion of certain sellers for some product categories by the three big e-commerce engines, as they find it hard now to compete against the low online prices.

To put the debate in the perspective of competition in retail, we should focus on the peculiarities of brick-and-mortar Indian markets for comparison against online sales. By the physical market place, we imply brick-and-mortar shops where the consumer has to travel physically for transactions. First, we need to have a clear idea of which physical market place to compare online prices against. Saha, Shrestha and Vasuprada (2015) consider the Nehru Place market as the appropriate comparator for personal computer goods purchases in New Delhi, after a detailed consumer survey. For any other good, it is not immediately clear which physical market should be accessed for comparing online and offline prices.

Second, e-commerce does not have a long history in India. Internationally, selling through the internet or e-commerce is not a new phenomenon, starting with some companies in the US and Western Europe using the internet between 1998 and 2000 to sell their products. However, the dotcom collapse in 2000 in the US led to immediate demise of many a nascent e-commerce start-up. Though the big internet businesses like Amazon and e-bay began in 1994, it was not until 2003 that Amazon in the US showed positive profits after almost a decade of operations. This lack of profitability has plagued the e-commerce business model, more so for India where

[1] http://articles.economictimes.indiatimes.com/2015-12-03/news/68741935_1_flipkart-and-snapdeal-flipkart-internet-mukesh-bansal

it accounts for only about 1 per cent of the overall retail market[2]. The e-commerce market in India also seems highly contestable, with a new entrant in the market every other day. Alongside is the unstable nature of competition in online business, with a new internet start-up declaring bankruptcy in regular intervals (the Indian arm of the online food ordering start-up Foodpanda recently laid off 500 employees and is discontinuing services in six Indian cities[3]). As per recent reports[4], in the first six months of 2013, some 136 e-commerce businesses exited operations.

For the three big online sellers which have piqued anti-competitive concerns in recent times in India, Flipkart launched operations in 2007, while Snapdeal started later in February 2010. Amazon, on the other hand, began its India operations in 2013. The latter began with a marketplace model, whereas Flipkart has changed its business strategy from an initial inventory-led model of online selling to a marketplace model, without the requirement of inventory. For further cost-cutting measures, Flipkart is considering a purely application-based business located on smartphones, rather than as a web-based entity.

Since its inception, the physical market place has had some form of interaction with internet-based commerce in India. There have been instances of physical market dealers selling to these online entities through the B2B segment[5]. In many instances, online and offline sales are done by the same entity that treats the two as a part of multi-channel marketing strategy. This presumably improves the possibility of price discrimination. This logic holds clearly in the B2C segment, with the last mile (the retail market) choosing among two separate marketing channels: online or offline with different pricing strategies for either. However, the recent discount war among e-tailers has led to suspicions among physical marketplace sellers about being replaced altogether by online sellers, as their survival (in times of ever-decreasing retail prices) is at risk.

From a competition perspective, the first question is whether we should treat e- commerce as part of the same market as the physical marketplace. In the competition cases that the CCI has recently concluded involving e-commerce vs. the physical market, it has ruled that online and offline sales do not constitute separate markets, rather they are different distribution channels of the same product. CCI has also declared that e-commerce provides an alternative mechanism for price discovery and is a more efficient mechanism for distribution (clearance of inventory or distributing newly launched products). Such a claim, if established for online sales, would automatically imply that consumers benefit.

[2] Report by Price Waterhouse Coopers (PWC), August 2014

[3] http://www.livemint.com/Companies/44bsSS8LYs7TY8wppoSbFO/Foodpanda-fires-more-than-500-employees-will-stop-own-deliv.html

[4] http://www.livemint.com/Consumer/vEJTorzdWCppvGSzuvWx4J/Amazons-Indian-online-marketplace-opens-today.html

[5] In a companion study on the nature of competition in personal computers at Nehru Place, Saha, Shrestha and Vasuprada (2016) find evidence of B2B sales of this kind among many traders at the physical Nehru Place market. In some instances, there were complaints that the online sellers would resell the product at a price below what they procured from at the physical market and in some cases, there were complaints of incorrect tax invoicing by the e-tailers. As a retaliation against deep discounts by the large e-tailers, many traders at Nehru Place has stopped their trading business with Flipkart, Amazon and Snapdeal.

The primary motivation of this paper is *to analyse the strength of both these arguments through an empirical analysis of the top three online retail players, viz. Flipkart, Amazon and Snapdeal.* Our null hypothesis treats the physical marketplace as separate from that of online sellers and we conduct a naïve Vector Autoregression (VAR) analysis of the stationary price series of preferred/advantage sellers on these three e-commerce entities for two products (mobile phones and laptops (notebooks, in our sample)).

We find that our null hypothesis is rejected in two cases (HP and Samsung), whereas the null cannot be rejected for Sony and Lenovo. Therefore, a claim that online and offline are part of the same market, but are different channels for marketing should first account for the nature of the product market. We cannot generalize our results by durability of the product, given our limited data. Presumably with a larger data set, more general results regarding nature of the product market and online vs. offline competition will emerge.

The anecdotal evidence in support of our research is that in the product categories of laptops and mobile phones, manufacturers are treating sales through online portals differently from that in the physical marketplace, Table 1a notes the number of launches of laptops (as on 27 July 2016) which have been made exclusively on the following online portals. These products are not available in the physical marketplace. Hence, it is not possible that online and offline sales are perfectly substitutable distribution alternatives for these product categories[6].

Table 1a: Exclusive laptop launches on Flipkart, Amazon and Snapdeal

Exclusive Laptop Launches as on 27 July, 2016		
Flipkart Exclusives	**Amazon Exclusives**	**Snapdeal Exclusives**
Micromax Ignite LPQ61 Pentium Quad Core - (4 GB/1 TB HDD/Windows 10) Notebook LPQ61408W	Refurbished Dell Vostro-14 3458 14.0-inch Laptop (Core i3-4005U/4GB/500GB/Integrated), Black	Notion Ink Cain Signature Black 32GB 3G 2-in-1 Laptop (Free Active Stylus & Mobile Office)
	Refurbished Dell Inspiron-11 3137 11.6-inch Laptop (Celeron 2955U/2GB/500GB/Integrated Graphics), Silver	Micromax Canvas Lapbook L1161 Laptop (Intel Quad Core Processor- 2GB RAM- 32 GB eMMC- 29.46 cm (11.6)- Windows 10) (Black)
	Refurbished Dell Inspiron-15 3542 15.6-inch Laptop (Core i3-4005U/4GB/500GB/2GB Graphics), Silver	Notion Ink Able 2-in-1 (3G- 4GB RAM- Full Day Battery) (AB14489AG)

Source: Compiled from the respective e-commerce websites on 27 July, 2016

[6] Exclusive launches of products online is happening very markedly with mobile phones in recent times. For instance, see the following links:
http://www.flipkart.com/mobiles/~mobileexclusives/pr?sid=tyy,4io&otracker=hp_header_nmenu_sub_Electronics_0_FK%20Exclusive%20Mobiles
https://www.amazon.in/Smartphones/b/ref=nav_shopall_sa_menu_mobile_smartphone?ie=UTF8&node=1805560031
http://www.snapdeal.com/offers/exclusive-launches

Second, we find some evidence of price dispersion for online sellers (some variation of prices across e-commerce sites for the exact product category description), as measured by the coefficient of variation in prices. This is indicative of a few things: (a) non-negligible search costs, which are present for online trading, (b) inventory smoothing costs, reflecting price differences across websites and (c) hidden costs which affect the different e-commerce sites differently. To the extent that we cannot rule out the presence of search costs by consumers (they may have become less than in the physical marketplace, but nonetheless, are not completely absent) our conclusion about the overall welfare effect of e-commerce is ambiguous. Search costs might have fallen with the e-commerce, but are not completely absent. In the light of aggressive online marketing strategies, multiple prices posted online (maximum, minimum and advantage seller's prices) coupled with losses in online transactions and thinning of alternatives in the physical market place through continuous exit of offline traders[7], the overall welfare effect of e-commerce is ambiguous. Furthering our enquiry about price dispersion online, we investigate the relationship between the maximum and minimum prices posted on the website of a particular e-commerce entity. We find that for most online trading in Flipkart, Amazon and Snapdeal, the preferred/ advantage seller is most often the minimum price seller. Given that consumers are price-sensitive (there exists empirical estimates of the extent of price sensitivity among Indian consumers), the specific role of the maximum price seller is suspect. For the same product and for the same day trade, a consumer should ideally be settling for the lowest cost seller: indicating that the highest cost seller should never be able to make a sale at that price. The exact role of the maximum price is therefore questionable: either it is a complicated way of finding out underlying willingness to pay by consumers or it is fictitious and meant to create a psychological feeling of low prices on offer (deceiving the consumer and confusing the process of price search online). There have been unsubstantiated complaints from the physical market place wholesale suppliers that these e-commerce sites force them to offer as low prices as possible, resulting in their margins being squeezed. In either case, an immediate conclusion that the mere presence of e-commerce reduces search costs for consumers and improves competition is not very clear cut given our results.

At this juncture, we should highlight the deficiencies in our analysis. First and foremost, we do not have access to actual trade data and hence, we cannot calculate any elasticity-based measures as literature investigating online pricing by e-Bay or Amazon have used. In the absence of any sales or sales rank data, we have to assume that actual trades happen at the preferred/ advantage seller's price. This is an approximation of the actual equilibrium price, which requires some measure of actual sales by the online sellers. E-commerce sites such as Flipkart, Amazon or Snapdeal simply list posted price, but not actual sales data.

Second, we consider only a limited profile of commodities (2 brands of laptops and 2 brands of mobile phones). The entire product basket sold by these e-commerce businesses is very large, from fashion apparel to electronic products. Our choice of products was driven by two factors: (i) choose the price series of the largest selling product online and (ii) contrast with the price series of a slightly more durable commodity. India has the highest penetration in mobile

[7] Saha, Shrestha and Vasuprada (2016) find evidence of exit in the physical market place of Nehru Place traders who are undiversified in services.

phone sales through e-commerce (41 per cent of all e-commerce sales in 2014 was through mobile phones[8]), higher than China (34 per cent) and United Kingdom (around 20 per cent). Flipkart has about 60 per cent of the e-commerce market in mobile phones, according to an interview of their Head of Commerce to the Economic Times Bureau[9]. A closely related but slightly more durable product is computer purchases (mostly Notebooks) sold online. Our conjecture is that the pattern of sales of goods online will depend on their underlying characteristic: durability being a principal feature. A durable good has a quality dimension that is likely to affect sales more than a less durable product. The issues of reliability and trust that plague online sales are likely to be larger for durable goods, and therefore, larger price volatility than non-durable goods. There is no clear pattern regarding this in our data, presumably because we have tracked only two of the popular brands of each of these products sold online. Additionally, e-commerce sells provide different pricing strategies for bundles of commodities purchased (laptops and mobiles/ laptops and accessories purchased together etc.). Unless we account for the pricing of all the commodity bundles offered through these e-commerce sites, our data will not be able to fully reflect the nature of pricing and underlying volatility appropriately. With a limited data, we establish a few initial claims about competition in pricing among internet-based businesses. More importantly, we feel that our methodology should serve as a template for future research and our results should be treated as preliminary outcomes with ceteris paribus conditions. As there is a major paucity of empirical evidence of online pricing and its volatility in India, our research is an exploratory step in this promising area of future research.

II. Data Description

For most consumers trying to purchase a commodity online, the prices on different websites are a key determining factor of the search costs they have to bear. These costs are in terms of the time spent looking for the least possible price both during a day as well as across time. Thus, for studying how prices on rival websites are causally linked to each other, we have collected prices for products belonging to the laptop and mobile phone categories. We have collected daily data at a fixed time interval (between 9:30 pm to 12 am) on two popular laptops and two mobile phones sold by Flipkart, Amazon and Snapdeal over the period from 17th June, 2015 till 30th October, 2015, which results in 136 days of data points.

To avoid potential product heterogeneity issues, we have retained the same detailed product description for each of these categories across each of the three e-commerce websites as shown in Table 1b. However, in the process, we lost data points for the HP laptop as it went out of stock on Flipkart within less than a month of our data collection period, to be precise from 10th August till the end of the data collection period.

Table 1b: Detailed product description of items tracked simultaneously on Flipkart, Amazon and Snapdeal

[8] http://tech.economictimes.indiatimes.com/news/internet/41-of-india-e-commerce-sales-is-from-mobile-mobile-wallet-usage-surging-meekers-2015-internet-trends/47452981

[9] http://economictimes.indiatimes.com/industry/services/retail/e-commerce-firms-like-flipkart-snapdeal-raked-in-thousands-of-crores-in-last-week-alone/articleshow/49445809.cms

Product Label	Detailed Description
Lenovo G50-80 80E501LRIN Notebook (laptop)	5th Gen, Ci5, 4GB, 1TB, Win8.1, 2GB Graph
HP 15-r204TX Notebook (K8U04PA) (laptop)	5th Gen, C i5, 4GB, 1TB, Win8.1, 2GB Graph
Samsung Galaxy Note 4 (mobile phone)	32GB, 3GB RAM, Black Colour
SONY Experia E4 (mobile phone)	Dual Sim, 8GB, Black Colour

The total data points for each product aggregating across e-tailers should ideally have been 408 (=3*136). However, on some days a product either went out of stock or there were technical difficulties in accessing the e-tailer's website which resulted in a lesser number of final our data points. The fact that search costs are significant is evident from table 2, which notes the price variation within (maximum, minimum and advantaged seller's price) and across websites for the same product.

Table 2 : Price variation within and across websites for same product for some dates

Lenovo									
Date	**min_len_f**	**max_len_f**	**a_len_f**	**min_len_s**	**max_len_s**	**a_len_s**	**min_len_a**	**max_len_a**	**a_len_a**
11.8.15	42490	47850	42490	42698	50361	44471	40873	48560	40873
2.9.15	43700	47850	43990	41115	50975	41115	45099	51816	46136
13.9.15	41350	47850	41350	51148	55000	51148	42500	50688	42500
Samsung									
Date	**min_sam_f**	**max_sam_f**	**a_sam_f**	**min_sam_s**	**max_sam_s**	**a_sam_s**	**min_sam_a**	**max_sam_a**	**a_sam_a**
20.6.15	41534	55399	44999	41900	64000	41900	42739	61699	49395
4.7.15	40523	55399	40523	41800	64000	41800	40250	58342.66	46039
29.8.15	40399	55399	40399	39899	78805	39899	41600	61500	41900

Source: Websites of Amazon, Flipkart and Snapdeal: ***min_len_i is the minimum price of Lenovo in the i^{th} website; max_len_i is the maximum price of Lenovo in the i^{th} website; a_len_i is the advantage/preferred seller price of Lenovo in the i^{th} website. Similar definitions apply to Samsung.***

Table 3 presents the summary of total number of observations across the three websites, along with the average price, standard deviation (std. dev.) and coefficient of variation (CV as defined by the per cent figure of standard deviation normalized by the mean).

Table 3 : Summary statistics of daily data across all websites by product

Products	Observations	Mean	Std. Dev.	Coefficient of Variation
Lenovo	397	43402.11	1670.45	3.85
HP	211	43966.28	3122.11	7.10
Samsung	390	42364.86	2966.00	7.00
Sony	405	10197.08	892.14	8.75

Source: *Authors' own calculations*

Table 4 below lists the summary statistics along with the coefficient of variation (CV) by product and by individual e-tailer, highlighting the website for a given product with the highest

CV. Though we have evidence of positive CV, we do not find evidence of any pattern in the CV with respect to product category and hence any ranking in the CV of prices by durability. This, as discussed earlier, is likely to be due to the small product basket under survey for our analysis. The average price of Lenovo and HP Notebooks as well as the Samsung mobile phone is around INR 43,000, whereas the Sony mobile phone is cheaper at around INR 10,000.

Table 4: Summary statistics for each product in each e-tailer website

E-tailer	Observations	Mean	Std. Dev.	Coefficient of Variation (CV)
Lenovo				
Flipkart	133	43985.33	1922.28	4.37
Snapdeal	131	43255.64	1301.85	3.01
Amazon	133	42981.73	1577.96	3.67
HP				
Flipkart	54	42414.11	985.32	2.32
Snapdeal	128	44986.05	3367.02	7.48
Amazon	29	42411.79	2773.54	6.54
Samsung				
Flipkart	134	42040.86	3970.17	9.44
Snapdeal	133	42117.86	1826.38	4.34
Amazon	123	42466.21	4855.47	11.43
Sony				
Flipkart	136	10344.87	1005.21	9.72
Snapdeal	136	10221.72	896.74	8.77
Amazon	133	10045.17	738.49	7.35

Source: *Authors' own calculations*

III. Literature Review and Contribution to the Literature

With the advent of e-commerce as an alternate market and its inroads into providing a variety of consumer goods accessible online through a number of seller platforms, the nature of online pricing and competition has generated much interest. The reason for this increased interest is mainly because research has sought to access factors influencing price dispersion in physical markets (for instance, search and information costs) in the context of online markets. Salop and Stiglitz (1982) show that in the presence of asymmetric information and the search cost, the 'law of one price' may not hold. Without search cost, the single-price-equilibrium might still exist. In the presence of search costs, however, the equilibrium with price dispersion appears, when the underlying price distribution is known. If, additionally, the price distribution is not known as well as search costs are present, then it is possible that equilibrium does not exist. In fact, if the single price equilibrium, if it exists, is higher than that of competitive equilibrium. When information asymmetry and search cost are present together then it will inadvertently lead to a market structure with monopoly power.

Pan et. al (2001) is an attempt at empirically understanding the factors that influence price dispersion across various product markets. To begin with, the study summarizes the main causes of price dispersion as given in theoretical literature. These are temporary price rigidity faced by some sellers due to the menu costs, price discrimination according to the type of consumer, consumer loyalty to a particular brand and qualitative advantages that are derived by purchasing from a particular seller. The first two causes are not particularly relevant for online markets since prices can be changed anytime and a consumer's utility cannot possi9.bly be disclosed. Further, their study divides causes of online price dispersion into features of online retailers and characteristics of the market. The former comprises ease of buying and comparing on the website, reliable customer service, detailed information about the product, price charged for shipping, and pricing strategy of a particular seller. While the latter which directly vary with price dispersion are the number of competitors in that segment, the efforts that a consumer puts in searching for lower prices and the online popularity of a product. To study the effects of these causes on online price dispersion, the authors first use factor analysis to determine the significant features of e-tailers and cluster analysis to divide the 105 e-tailers in their dataset according to the services that they provide to customers. Next, to find the causal factors of price dispersion, the authors calculate different measures of price dispersion at the product level as the successive dependent variables with variables representing the features of e-tailers and market characteristics as the independent variables. All the variables representing e-tailers features are significant in explaining price dispersion while of the variables representing market characteristics; the number of competitors, average price and product popularity are significant.

Gupta and Qasem (2002) maintain that in the presence of asymmetric information and the price dispersion, the search cost becomes significant leading to inefficiency in the market. The opportunity cost of search increase with each additional unit of time spent on search. Hence, the search continues to the point when marginal benefit of search reaches to marginal cost of search. Apart from efficiency loss, the search cost may harm quality seller. The search cost can be reduced by “semantic web” development. More websites can be included and the search cost decreases significantly with development of “semantic web technology”. Defining a framework based on search cost and search premium theory, Walter et. al (2006) classify variables affecting online pricing into consumer information search factors (cross-site search, onsite search) and consumer information evaluation factors (variety of products offered, type of product description and product demonstration). The importance of each of these factors is different in the different markets they take into consideration.

Instead of using prices displayed on the e-tailer’s website, Ghose and Yao (2011) use data on actual prices at which a transaction materialised from the Federal Supply Service of the US Federal government. This dataset is extremely rich since it contains data on product cost, order cycle time, own price elasticity and transaction quantity. Based on these four variables, the authors formulate four hypotheses in which product cost and transaction quantity are directed related to price dispersion while order cycle time and own price elasticity are inversely related. Their results find the online markets have a lesser degree of price dispersion than physical markets but since the price dispersion is less than one percent the authors attribute this result to the actual transaction prices that they use as against posted prices used by previous studies.

In order to factor in the fact that retailers may not be functioning in just one retail space, Friberg (2001) divides them into three categories: retailers that operate only in a physical market space, retailers that sell online, or "e-tailers" and retailers that cater to both physical and virtual markets. To study the pricing strategies in ecommerce, Friberg (2001) first proves a proposition theoretically and then find empirical support by analysing the books and music CDs markets in Sweden. Their key proposition depends on the underlying market structure. In the first scenario outlined there exist two independent sellers (an e-tailer and a brick-and-mortar shop) and in the second, we have a monopoly retailer catering to both physical and virtual markets. The authors prove that the monopoly retailer in the second scenario will charge a higher price online than the e-tailer in the first scenario, so that business in their "brick- and- mortar" establishment is not affected adversely.

In the context of this literature on price dispersion online and potential competition effects of e-commerce, our contribution is largely methodological. We devise a novel method of testing for whether or not to treat online and offline as separate markets across product categories (more vs. less durable goods sold online), as well as incorporate controls for time-specific effects (weekend sales effects and festival days effect). We additionally measure price dispersion online through coefficient of variation (as reported in Section II) and note the nature of relationship among maximum, minimum and advantage seller prices (as reported in Section I). For Indian e-commerce, the methodology for using VAR analysis for e-commerce prices has not been attempted.

IV. Methodology for analyzing co-movement in online prices

For this part of the analysis, we focus only the advantage/ preferred seller's price for all e-tailers. As is standard with time series modelling, we first test for the stationarity of the time series of the advantaged seller's price on all three websites. We use the Augmented Dickey-Fuller test to judge stationarity, which is a one-tailed test with the null hypothesis that there is a unit root in the data. Excepting the price series for HP and Sony for each individual e-tailer, the remaining were stationary. We also test for stationarity for the price of each of the products on all three e-tailers as a group using the Levin, Lin and Chu (2002) t*-statistic test, which assumes a common autoregressive parameter for all series. As for the individual price series, HP and Sony price series are non-stationary when we consider Flipkart, Amazon and Snapdeal businesses as a group. Lenovo and Samsung price series are stationary for the group stationarity test.

Next, as our time series is not long enough to conclude any long-term co-integrating relations, we do not consider the VECM (Vector Error Correction Method), which works with non-stationary price series with co-integrating constraints. Instead, we settle for the standard unrestricted Vector Autoregression analysis (VAR) for understanding the joint evolution of the prices in any particular e-tailer's website as a function of competing prices from the two other major e-tailers. We use the first differenced stationary price series for HP and Sony and the other price series at levels for our analysis.

The technique of VAR was introduced in empirical macroeconomics by Sims (1980). The purpose was to study the joint time series of a group of variables without imposing strong structural assumptions. We do the same as a first pass in our research. Other than an exogenous constant term, the only explanators of the price series of any particular e-tailer is assumed to its owned lagged price as well as current and lagged prices of its competitors (after testing for suitable lag lengths given our sample size). We have not introduced any other controls, as we are interested in observing the extent to which we can treat the online market as separate/distinct from the brick-and-mortar markets.

The standard VAR representation takes the form of a system of *n* equations in *m* variables, each of which is linearly explained by *l* lags of itself and the other *(m-1)* variables along with an error term. In our case, the naïve VAR representation takes the following form:

$$p_t(i|x) = c + \sum_{n=1}^{l} \beta_{iin} p_{t-n}(i|x) + \sum_{n=1}^{l} \beta_{ijn} p_{t-n}\,(j|x) + \sum_{n=1}^{l} \beta_{ikn} p_{t-n}\,(k|x) + \epsilon_t(i|x)\ \forall t,$$

$$p_t(j|x) = c + \sum_{n=1}^{l} \beta_{jjn} p_{t-n}(j|x) + \sum_{n=1}^{l} \beta_{ijn} p_{t-n}\,(i|x) + \sum_{n=1}^{l} \beta_{kjn} p_{t-n}\,(k|x) + \epsilon_t(j|x)\ \forall t,$$

$$p_t(k|x) = c + \sum_{n=1}^{l} \beta_{kkn} p_{t-n}(k|x) + \sum_{n=1}^{l} \beta_{ikn} p_{t-n}\,(i|x) + \sum_{n=1}^{l} \beta_{jkn} p_{t-n}\,(j|x) + \epsilon_t(i|x)\ \forall t,$$

$$x = product\ category$$

$$\{i, j, k\} = identity\ of\ e - tailer$$

$$\beta_{rsn} = co - efficients\ to\ be\ estimated\ for\ price\ effects\ between\ any\ pair\ of\ e - tailers\ r\ and\ s$$

For a given product (mobile or laptop), we have two product categories X={(Sony, Samsung), (HP, Lenovo)} respectively. For each of these four product categories, we are looking for the evolution of their respective prices on each of the e-tailers {i=Flipkart, j=Amazon and k=Snapdeal}, using past prices of competing e-tailers and a constant term as predictors. In this specification, we do not test for any structural breaks in the data, nor for any seasonality. We later extend our analysis to include time-specific effects. In theory, the Ordinary Least Squares (OLS) estimates of the coefficients of the regressors in the system of VAR equations should have asymptotically efficient properties, as right hand side of the equations contain no contemporaneous terms as explanators. However, residual autocorrelation enters through the error terms in the equations.

Note that in a typical VAR representation, the error terms $\epsilon_t(r|x)\ \forall t, r = \{i, j, k\}$ representing "unpredictable innovation" in the price series of any e-tailer for a given product are likely to be autocorrelated. This is presumably due to some co-movement in e-tailer prices. Note that there are the total error term can be decomposed into two parts: (i) one part that is un-attributable to any change in the past values of own and competitor prices and (ii) one part that is attributable to current changes in the price of the competitors, which is not directly entering any of the equations of the VAR system, but enters indirectly through the error term.

If we find no evidence of autocorrelation among the residuals of the VAR system we are estimating, we can place confidence in the Best Linear Unbiased Estimate property of the OLS estimates of the coefficients $\boldsymbol{\beta}$. Else we require restrictions on the VAR and use other estimation procedures. For instance, with non-stationary price series which are co-integrated of the same order (same degree of non-stationarity), researchers improve upon the VAR with the VECM (Vector Error Correction Model), by imposing long term relationships among the variables as restrictions in the VAR model.

Instead, we use the basic VAR for causality and forecasting of prices. Regarding the former, we use the pairwise Granger causality tests for identifying the nature and direction of causality in online pricing of the e-tailers under examination. For the latter, we study the impulse response functions of the VAR model.

The principle of Granger causality test rests on a two-way test of the hypothesis that if x causes y **and** y does not cause x, then there is a uni-directional causality running from x to y i.e., the x series causally explains the evolution of the y series, while the y series cannot explain the dynamics of the x series. In our case, the existence of one-directional pairwise causality for any product between any two e-tailers will help us identify the nature of price competition online. Bi-directional causality implies x Granger causes y and y also Granger causes x, whereas no Granger causality implies the lack of causal linkages between x and y.

Impulse response functions are central to understanding the transmission of shocks to any one of the error terms of the VAR system on the prices of the e-tailers for any product. Note that any single equation in the VAR, such as:

$$p_t(i|x) = c + \sum_{n=1}^{l} \beta_{iin} p_{t-n}(i|x) + \sum_{n=1}^{l} \beta_{ijn} p_{t-n}\,(j|x) + \sum_{n=1}^{l} \beta_{ikn} p_{t-n}\,(k|x) + \epsilon_t(i|x)\ \forall t,$$

can be written as:

$$p_t(i|x) = \Psi\ \epsilon_t(i|x)\ \forall t,$$

where Ψ is the coefficient matrix for the contemporaneous error term. This translation expresses the price of a product on any e-tailer purely as a function of the error terms (as a Moving Average time series process).

Now, the impulse response of a contemporaneous shock to the error term in period t has an impact on the current and future prices of the e-tailer's product and dies out after some time, depending on the strength of transmission of the shock from the error term to prices, as shown in the following equation below:

$$\frac{\partial p_{t+l}(i|x)}{\partial \epsilon_t} = \Psi_l$$

This partial derivative helps us predict the future path of prices, as shocks impact the system of VAR equations.

V. Discussion of Results

The results of our econometric exercises are organized in three Appendices following the paper: Appendix A for HP laptops, Appendix B for Sony mobile phones, Appendix C for Lenovo laptops and Appendix D for Samsung mobile phones.

Section 1 of all the Appendices contains the stationarity results as discussed in the methodology section. Section 2 of all the Appendices contains the VAR estimation results. For Appendix A, table 3A selects the appropriate lag of length 1 for VAR estimation for the HP price series according to all the three information criteria (Akaike, Schwarz and Hannan-Quinn information criteria are minimized at lag length 1). Table 4A presents the coefficient estimates for the VAR model as presented in the last section. Our results indicate that lagged (stationary) prices (at date 't-1') for HP on Amazon significantly and negatively affects HP current prices (date 't') for Amazon itself, Flipkart and Snapdeal. On the other hand, one-period lagged HP prices on Flipkart significantly and positively affects prices of on all the three e-tailers. Interestingly, lagged HP prices on Snapdeal only significantly negatively affects current prices on Snapdeal alone; its effect on Amazon and Flipkart prices are insignificant. The constant is statistically insignificant. The model fit is not very good, though the VAR is stable (table 5A), and residual autocorrelation is significant only from the third lag of prices of all e-tailers (table 6A). *The fact that other factors (**prices at the physical market place**) might be driving the price dynamics for the VAR for HP is further strengthened by the rejection of the null hypothesis that error terms are multivariate normal in table 7A*. We cannot conduct any further causality analysis, as with non-stationarity at levels, we need to impose co-integrating restraints in the VECM formulation, which we avoid for our data.

Section 2 of Appendix B highlights the VAR analysis for Sony mobile phones. The appropriate lag selection criterion for the stationary Sony price series is 9 lags. This being too many to report, we show in table 3B the normality of the residual error terms, indicating that our OLS estimates of the coefficients in a regression with Sony prices across e-tailers will be consistent and unbiased. The test for residual autocorrelation does not apply for 9 lags (table 4B). The impulse response functions for the Sony price series in Table 5B shows only significant effect of shocks to the price for a particular e-tailer for the own price of the e-tailer. The impulse of a current period shock is initially negative, but it dies out in about 6 periods for all e-tailers. In section 3 of Appendix B, we observe a significant (at 3 per cent) time-specific negative effect (weekend sales as shown by the coefficient of -51.7 for the dummy variable dum1 which takes value 1 for the weekend alone, and is zero otherwise)[10]. This is true for the sales of Sony

[10] For the time specific effects on Sony prices, we keep only one period lagged Sony price as control, rather than 9 period lags as controls.

mobiles only on Snapdeal, and not for the other e–tailers in table 6B. A non-linear term of the weekend dummy, interacted with the lagged price on Snapdeal for Sony is insignificant.

Section 2 of Appendix C showcases the VAR results for Lenovo. Table 3C demonstrates that one lag is the correct lag specification for Lenovo VAR modelling as all the three information criteria are minimized at one lag. Table 4C shows the coefficient estimates: (i) the lagged prices of Lenovo on Amazon positively and significantly affects the current price of Lenovo on Amazon and Flipkart alone, (ii) the lagged prices of Lenovo on Flipkart positively and significantly affects the current price of Lenovo on Flipkart and Snapdeal alone, (iii) the lagged prices of Lenovo on Snapdeal only positively and significantly affects its own current price. Other than for Amazon Lenovo prices, the coefficient of the constant is significant and positive. The R^2 values are not very high though. Table 5C shows the graphs for the impulse response functions for the Lenovo prices: here the responses are significantly larger than for the Sony price series. For sure, a shock to Lenovo's prices for any e-tailer has a negative effect on its own prices, and the shock dies out very slowly (lasting for at least 10 periods). The impulse response function for all other cross-prices is insignificant. Table 6C shows that the Lenovo VAR is stable. Most interestingly, table 7C shows that the residuals of the VAR are jointly normal (giving us confidence in the good properties of the estimates of coefficients in table 4C). However, there might be some residual autocorrelation in the price series, as the null hypothesis of no autocorrelation in Table 8C is rejected at 5 per cent level of significance, though not at 1 per cent. Table 9C reports the Granger causality results: there are two clear one-directional relationships. Clearly, Amazon Lenovo prices Granger cause Flipkart and Snapdeal prices. There is a weak bi-directional relationship: Flipkart prices significantly Granger causes Snapdeal prices, but Snapdeal prices also seem to Granger cause Flipkart prices (significant only at 11 per cent).

Section 3 of Appendix C shows the time-specific effects: weekend and festive days' effect (13-17 October 2015) which are significant across most e-tailers only for Lenovo prices. While there is a significant positive weekend effect on Amazon, the weekend effect is significantly negative for Snapdeal Lenovo sales. For Flipkart, the weekend effect is significantly positive at 8 per cent level of significance. The non-linear term of the weekend dummy interacted with the lagged prices on Amazon and Flipkart are also significant (at 9 per cent for the latter), but negative. It is significant and positive for Snapdeal. *An explanation for this trend for the negative weekend effect on sales of Lenovo and Sony only on Snapdeal is that consumers are shopping more from competitor websites of Amazon and Flipkart, which have positive significant weekend effects at least for Lenovo. This is the effect of within-e-tailer competition driving prices down in the weekend for Snapdeal sales.* Significant and positive effect on Lenovo sales prices are observed for only Amazon, where the dummy variable dum2 takes value 1 only from 13^{th} to 17^{th} October and is zero otherwise. The interaction of the dummy with past prices on Amazon has a significant negative coefficient. These festival day effects are not significant for any other e-tailer and any other product category.

The AIC and HQ criteria select 9 lags as appropriate for the VAR model for Samsung. However, we tested that the VAR for Samsung is unstable, hence we did not analyse it further.

It is likely that for Samsung mobile phones, physical market place prices would make a difference in the VAR model.

In summary, we observe the following:

i. For at least one laptop (Lenovo), current prices on Amazon have a causal effect on Flipkart and Snapdeal prices. Whereas Flipkart seems to be able to influence Snapdeal price, the latter has an influence only on its own price.
ii. The nature of the impulse response functions (as observed for Sony and Lenovo) is that shocks to own price alone have a significant downward influence in the price of the product, shocks to other prices do not seem to influence the impulse response of prices for any e-tailer for these products.
iii. Weekend effects are typically negative for Snapdeal, indicating a shift towards its competitors for purchases during this interval when consumers have more shopping time.
iv. The festival period effect is significantly positive only for Amazon (Lenovo) sales, though Flipkart had a mega-sales announcement during this period.
v. The naïve VAR without controls for Sony and Lenovo provides consistent OLS estimates, reducing the requirement of controlling for physical market prices.
vi. The naïve VAR for HP and Samsung prices without controls is likely to improve with the inclusion of controls from the physical market place.

Overall, *we do not see evidence of different pricing effect on durable vs. non-durable goods in the advantage seller's price for any e-tailer*. Noting the caveats about the small basket of products over which we conduct the analysis, our results are to be interpreted as indicative of what we are likely to find once the product basket covers the entire range of products sold by the e-tailer.

VI. Conclusion

The purpose of our paper is to demonstrate a methodology for understanding the nature of competition between online and offline business as reflected in final posted prices. Even with limited data, competitive strength of the different e-tailers emerges quite clearly. Lenovo sales indicate Amazon prices having a clear first mover advantage in pricing (it causally influences competitor prices), whereas Snapdeal prices has no influence on competitors. Amazon also seems to enjoy some consumer loyalty (positive festival price effect on Lenovo) and Snapdeal appears to be the weakest competitor among the three (negative weekend sales effect for Lenovo and Sony). Flipkart, despite its Big Billion Day sales offer during the festival period, faces stiff competition from Amazon and is intermediate in its influence on competitor pricing (Lenovo Flipkart prices causally influence Snapdeal prices, but not Amazon).

Our method is useful for understanding competition dynamics between online and offline retail, with minimal data requirements. We depend only on daily price data from online sellers. After an appropriate consumer survey indicating the correct physical market comparator, the naïve

VAR can be extended with physical market prices to determine the extent of competition pressure. We do not require actual sales data (which is difficult to collect from the retail level: be it online or offline), as the advantage seller's price is modelled as a function of its past prices. While this rests on the assumption that actual trade occurs at the advantage seller's price, the control for past prices is most likely to incorporate actual sales information to which the current prices are seen to react. For sure, access to actual sales data will help us calculate some more metrics based on elasticities and we can cross-check our results. Given the paucity of such, we feel our analysis provides a simpler template to understand the dynamics of competition between online and offline sales at the retail level.

The penetration of e-commerce in retail trade India is at a nascent stage (with less than 1 per cent share of all retail trade). However, its explosive growth in terms of sales and even more spectacular losses and turbulence (through continuous entry and exit of small e-commerce firms) has given enough reason to investigate this distribution channel for its effects on economic welfare and competition outcomes. While our econometric exercises are limited to four products from two categories with different degrees of durability with posted price observations over 136 days, our methodology can be implemented for studying the entire product basket offered by any e-tailer and contrasted with physical market prices to understand the twin issues of price dispersion (search costs online) and substitutability between online and offline sales. It is a part of our future research plans to extend this research along these lines.

References

Friberg, R., M. Ganslandt, and M. Sandström. 2001. "Pricing Strategies in E-Commerce: Bricks vs. Clicks." IUI working paper.

Ghose, A. and Y.Yao. 2011. "Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets." *Information Systems Research* 22 (2). INFORMS: 269–88.

Gupta, T. and A. Qasem. 2002. "Reduction of Price Dispersion through Semantic E-Commerce: A Position Paper." In *Proceedings of the Semantic Web Workshop*, 1–2.

Hamilton, J. D. 1994. *Time Series Analysis*. Princeton university press, Princeton.

Levin, A., C.-F. Lin, and C.-S. J. Chu. 2002. "Unit root tests in panel data: Asymptotic and finite-sample properties." *Journal of Econometrics* 108: 1–24.

Pan, X., B. T. Ratchford, and V. Shankar. 2001. "Why Aren't the Prices of the Same Item the Same at Me. Com and You. Com?: Drivers of Price Dispersion Among E-Tailers." *Drivers of Price Dispersion Among E-Tailers (November 2001). University of Maryland Department of Marketing*.

Salop, S., and J.E.Stiglitz. 1982. "The Theory of Sales: A Simple Model of Equilibrium Price Dispersion with Identical Agents." *The American Economic Review*. JSTOR, 1121–30.

Saha, D., R.N. Shrestha and T.M.Vasuprada (2016). "Competing with Virtual Entities: A case study of retail computer purchases in India." Proceedings of the Indian Retail Conference 2016, Ambedkar University, New Delhi, published by Emerald Insight.

Sims, C.A. 1980. “Macroeconomics and Reality.” *Econometrica: Journal of the Econometric Society*. JSTOR, 1–48.

Walter, Z., A. Gupta, and B.-C Su. 2006. “The Sources of on-Line Price Dispersion across Product Types: An Integrative View of on-Line Search Costs and Price Premiums.” *International Journal of Electronic Commerce* 11 (1). Taylor & Francis: 37–62.

Appendix A: Results for HP

Section 1A: Test for stationary for HP

Table 1A: HP price series on Snapdeal non-stationary

Null Hypothesis: A_HP_S has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

	t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-1.208389	0.6694
Test critical values:	1% level	-3.485586	
	5% level	-2.885654	
	10% level	-2.579708	

Table 2A: HP price series on Amazon, Flipkart and Snapdeal as a group non-stationary

Group unit root test: Summary
Series: A_HP_A, A_HP_F, A_HP_S
Sample: 6/17/2015 10/30/2015
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.37801	0.6473	3	187
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.86435	0.8063	3	187
ADF - Fisher Chi-square	5.87788	0.4370	3	187
PP - Fisher Chi-square	8.16628	0.2262	3	197

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Section 2A: VAR results for HP

Table 3A: Lag selection criteria

Lag	AIC	SC	HQ
0	48.87460	48.99582	48.82971
1	46.04184*	46.52674*	45.86231*

* indicates lag order selection by the criterion:
AIC: Akaike information criterion
SC: Schwarz Criterion
HQ: Hannan-Quinn information criterion

Table 4A:Estimation of coefficients for HP Price series

Vector Autoregression Estimates
Sample (adjusted): 7/03/2015 8/09/2015
Included observations: 12 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(A_HP_A)	D(A_HP_F)	D(A_HP_S)
D(A_HP_A(-1))	-1.01	-0.77	-0.65

	(0.12)	(0.05)	(0.17)
	[-8.79067]	[-15.3867]	[-3.88275]
D(A_HP_F(-1))	1.40	1.03	1.36
	(0.27)	(0.12)	(0.39)
	[5.26750]	[8.82570]	[3.48647]
D(A_HP_S(-1))	-0.09	-0.05	-0.62
	(0.17)	(0.08)	(0.25)
	[-0.51269]	[-0.67964]	[-2.45174]
C	-333.42	-76.43	-415.46
	(210.49)	(91.84)	(307.53)
	[-1.58405]	[-0.83225]	[-1.35093]
R-squared	0.91	0.97	0.70
Adj. R-squared	0.87	0.96	0.59
Sum sq. resids	3092034.09	588596.13	6600647.27
S.E. equation	621.69	271.25	908.34
F-statistic	26.12	80.77	6.26
Log likelihood	-91.78	-81.83	-96.33
Akaike AIC	15.96	14.31	16.72
Schwarz SC	16.13	14.47	16.88
Mean dependent	335.17	416.67	148.75
S.D. dependent	1741.95	1293.93	1417.41
Log likelihood		-264.25	
Akaike information criterion		46.04	
Schwarz criterion		46.53	

Table 5A: VAR Stable for HP Price series

Roots of Characteristic Polynomial
Endogenous variables: A_HP_A A_HP_F A_HP_S
Exogenous variables: C
Lag specification: 1 1

Root	Modulus
0.94	0.94

0.67	0.67
0.23	0.23

No root lies outside the unit circle.
VAR satisfies the stability condition.

Table 6A: No autocorrelation in VAR for HP Price series

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: no residual autocorrelations up to lag h
Sample: 6/17/2015 10/30/2015
Included observations: 12

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	Df
1	13.87	NA*	15.13	NA*	NA*
2	20.02	NA*	22.51	NA*	NA*
3	26.66	0.00	31.36	0.00	9

*The test is valid only for lags larger than the VAR lag order.
df: degrees of freedom for (approximate) chi-square distribution

Table 7: Test for normality of the residuals

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 6/17/2015 10/30/2015
Included observations: 12

Component	Skewness	Chi-sq	Df	Prob.

1	0.07	0.01	1	0.92
2	0.04	0.00	1	0.95
3	-0.46	0.42	1	0.52
Joint		0.44	3	0.93

Component	Kurtosis	Chi-sq	Df	Prob.
1	1.90	0.60	1	0.44
2	2.20	0.32	1	0.57
3	2.52	0.11	1	0.73
Joint		1.04	3	0.79

Component	Jarque-Bera	df	Prob.
1	0.62	2	0.74
2	0.33	2	0.85
3	0.54	2	0.76
Joint	1.48	6	0.96

Appendix B: Results for Sony

Section 1B: Test for stationary

Table 1B: Sony price series on Snapdeal non-stationary

Null Hypothesis: A_SONY_S has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.140405	0.9677
Test critical values:	1% level	-3.480038	
	5% level	-2.883239	
	10% level	-2.578420	

*MacKinnon (1996) one-sided p-values.

Table 2B: Sony price series on Amazon, Flipkart and Snapdeal as a group non-stationary

Group unit root test: Summary
Series: A_SONY_A, A_SONY_F, A_SONY_S
Sample: 6/17/2015 10/30/2015
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.51885	0.6981	3	400
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.23489	0.8916	3	400
ADF - Fisher Chi-square	2.40316	0.8791	3	400
PP - Fisher Chi-square	3.76224	0.7088	3	403

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Section 2B: VAR results for Sony

Table 3B: Normality of the residuals for the VAR of Sony price series

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 6/17/2015 10/30/2015
Included observations: 129

Component	Skewness	Chi-sq	Df	Prob.
1	0.560118	6.745244	1	0.0094
2	0.491449	5.192729	1	0.0227
3	-0.615945	8.156851	1	0.0043
Joint		20.09482	3	0.0002

Component	Kurtosis	Chi-sq	Df	Prob.
1	7.215433	95.51309	1	0.0000
2	7.611758	114.3172	1	0.0000
3	11.72727	409.3886	1	0.0000
Joint		619.2188	3	0.0000

Component	Jarque-Bera	df	Prob.
1	102.2583	2	0.0000
2	119.5099	2	0.0000
3	417.5454	2	0.0000
Joint	639.3137	6	0.0000

Note that all the lag selection criteria selected 9 lags for all the e-tailer prices for Sony price series.

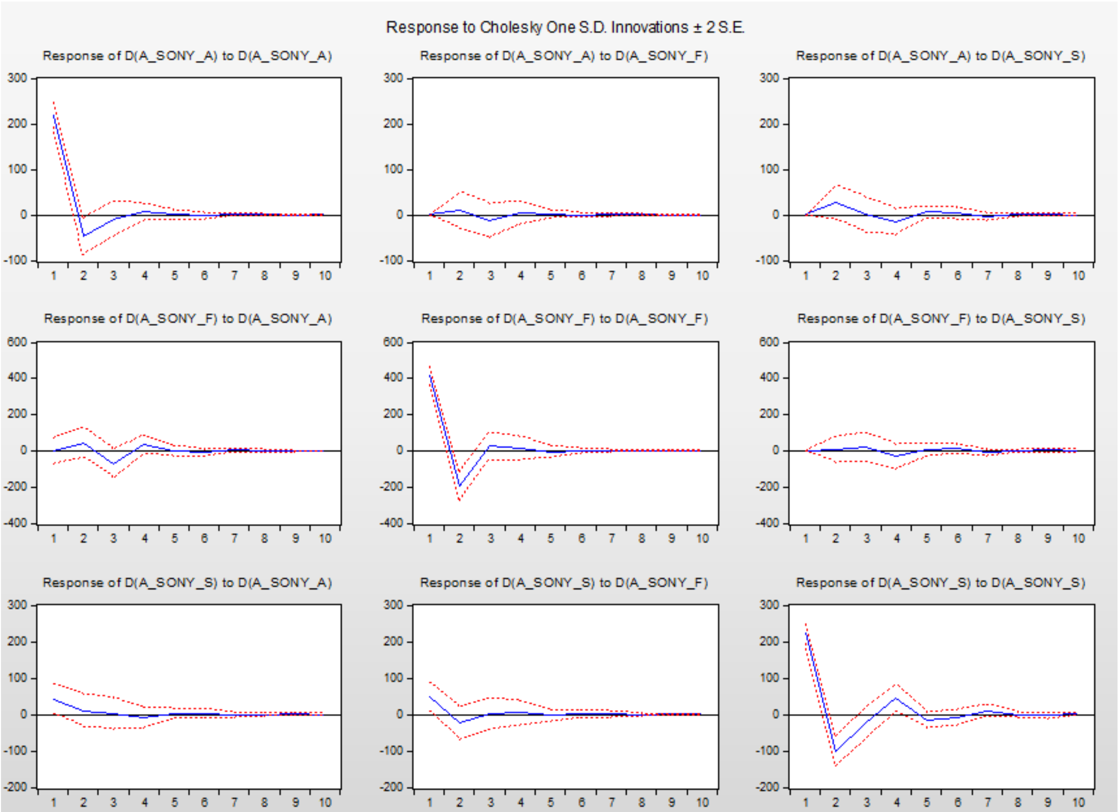
Table 4B: Autocorrelation test for the residuals

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: no residual autocorrelations up to lag h
Sample: 6/17/2015 10/30/2015
Included observations: 129

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.385039	NA*	0.388047	NA*	NA*
2	2.832102	NA*	2.873647	NA*	NA*
3	13.68410	0.1340	13.98403	0.1229	9

*The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Table 5B: Impulse Response Function for Sony



Section 3B: Seasonality test for Sony prices

Table 6B: Significant weekend effects on Sony Snapdeal prices

Dependent Variable: D(A_SONY_S)
Method: Least Squares
Sample (adjusted): 6/19/2015 10/30/2015
Included observations: 131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(A_SONY_S(-1))	-0.220355	0.221544	-0.994631	0.3219
D(A_SONY_A)	0.154768	0.093225	1.660152	0.0994
D(A_SONY_A(-1))	0.095896	0.092504	1.036671	0.3019
D(A_SONY_F)	0.083439	0.049819	1.674837	0.0965
D(A_SONY_F(-1))	0.032486	0.049359	0.658149	0.5117
DUM1	-51.70655	24.77643	-2.086925	0.0389
DUM1*D(A_SONY_S(-1))	-0.164328	0.239564	-0.685944	0.4940

R-squared	0.176170	Mean dependent var	-27.17557
Adjusted R-squared	0.136307	S.D. dependent var	251.6840
S.E. of regression	233.9027	Akaike info criterion	13.79964
Sum squared resid	6784101.	Schwarz criterion	13.95328
Log likelihood	-896.8766	Hannan-Quinn criter.	13.86207
Durbin-Watson stat	2.221866		

Appendix C: Results for Lenovo
Section 1C: Test for stationary

Table 1C: Lenovo price series on Flipkart stationary

Null Hypothesis: A_LEN_F has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.569583	0.0077
Test critical values:	1% level	-3.482453	
	5% level	-2.884291	
	10% level	-2.578981	

*MacKinnon (1996) one-sided p-values.

Table 2C: Lenovo price series on Amazon, Flipkart and Snapdeal as a group stationary

Group unit root test: Summary
Series: A_LEN_A, A_LEN_F, A_LEN_S
Sample: 6/17/2015 10/30/2015
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.85455	0.0000	3	381
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.52515	0.0000	3	381
ADF - Fisher Chi-square	59.4793	0.0000	3	381
PP - Fisher Chi-square	70.3524	0.0000	3	384

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Section 2C: VAR results for Lenovo

Table 3C: Lag Selection Criteria

Lag	AIC	SC	HQ
0	52.43614	52.52612	52.47219
1	51.42841*	51.78833*	51.57261*
2	51.48200	52.11185	51.73434
3	51.65957	52.55936	52.02006
4	51.63650	52.80623	52.10513
5	51.70790	53.14757	52.28468
6	51.76362	53.47322	52.44853
7	51.71239	53.69193	52.50545
8	51.79984	54.04932	52.70105
9	51.87522	54.39464	52.88458
10	51.86786	54.65721	52.98536

Definitions as in Table 3A

Table 4C: Estimation of Coefficients

Vector Autoregression Estimates
Sample (adjusted): 6/18/2015 10/30/2015
Included observations: 120 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	A_LEN_A	A_LEN_F	A_LEN_S
A_LEN_A(-1)	0.75	0.29	0.00
	(0.07)	(0.11)	(0.08)
	[10.9956]	[2.68935]	[0.00279]
A_LEN_F(-1)	0.06	0.54	0.19
	(0.05)	(0.08)	(0.06)
	[1.12110]	[6.90402]	[3.09660]
A_LEN_S(-1)	-0.06	0.12	0.32
	(0.07)	(0.11)	(0.09)
	[-0.83365]	[1.14106]	[3.78678]
C	10772.33	2428.25	20795.72
	(3558.95)	(5594.91)	(4428.40)
	[3.02683]	[0.43401]	[4.69599]
R-squared	0.60	0.46	0.21
Adj. R-squared	0.59	0.45	0.19
Sum sq. resids	96623372.14	238794443.56	149600076.83
S.E. equation	912.67	1434.77	1135.63
F-statistic	57.89	33.19	10.36
Log likelihood	-986.20	-1040.49	-1012.43
Akaike AIC	16.50	17.41	16.94
Schwarz SC	16.60	17.50	17.03
Mean dependent	42867.32	43968.78	43215.59
S.D. dependent	1423.91	1931.14	1262.54
Log likelihood		-3033.66	
Akaike information criterion		50.76	
Schwarz criterion		51.04	

Table 5C: Impulse response function for Lenovo price series

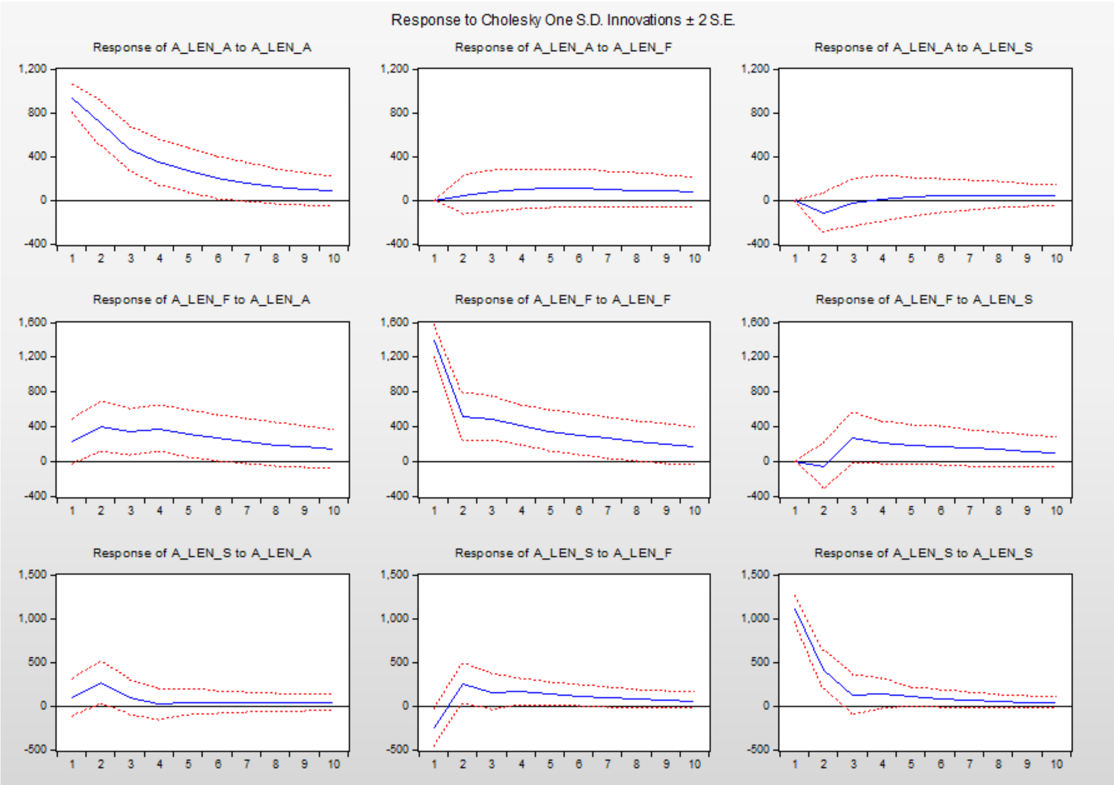


Table 6C: Stability of the VAR specification for Lenovo

Roots of Characteristic Polynomial
Endogenous variables: A_LEN_A A_LEN_F
A_LEN_S
Exogenous variables: C
Lag specification: 1 1

Root	Modulus
0.795761	0.795761
0.598233	0.598233
0.220727	0.220727

No root lies outside the unit circle.
VAR satisfies the stability condition.

Table 7C: Test of Normality for residuals for Lenovo

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 6/17/2015 10/30/2015
Included observations: 120

Component	Skewness	Chi-sq	Df	Prob.
1	1.359069	36.94136	1	0.0000
2	0.878067	15.42004	1	0.0001
3	1.969443	77.57415	1	0.0000
Joint		129.9355	3	0.0000

Component	Kurtosis	Chi-sq	Df	Prob.
1	9.160734	189.7732	1	0.0000
2	7.263705	90.89592	1	0.0000
3	13.87673	591.5167	1	0.0000
Joint		872.1858	3	0.0000

Component	Jarque-Bera	df	Prob.
1	226.7146	2	0.0000
2	106.3160	2	0.0000
3	669.0909	2	0.0000
Joint	1002.121	6	0.0000

Table 8C: Test for autocorrelation for the residuals for Lenovo

VAR Residual Portmanteau Tests for Autocorrelations
Null Hypothesis: no residual autocorrelations up to lag h
Sample: 6/17/2015 10/30/2015
Included observations: 120

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	8.697916	NA*	8.771008	NA*	NA*
2	16.65712	0.0544	16.86511	0.0509	9

*The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Table 9C: Granger Causality Test for Lenovo

Pairwise Granger Causality Tests
Sample: 6/17/2015 10/30/2015
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
A_LEN_F does not Granger Cause A_LEN_A	126.00	1.33	0.25
A_LEN_A does not Granger Cause A_LEN_F		9.79	0.00
A_LEN_S does not Granger Cause A_LEN_A	123.00	0.50	0.48
A_LEN_A does not Granger Cause A_LEN_S		3.56	0.06
A_LEN_S does not Granger Cause A_LEN_F	122.00	2.56	0.11
A_LEN_F does not Granger Cause A_LEN_S		13.73	0.00

Section 3B: Seasonality tests for Lenovo prices

Table 10C: Significant weekend effects on Lenovo Snapdeal prices

Dependent Variable: A_LEN_S
Method: Least Squares
Sample (adjusted): 6/18/2015 10/30/2015
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
A_LEN_S(-1)	0.112459	0.065648	1.713048	0.0895
A_LEN_F	-0.160972	0.053747	-2.994967	0.0034
A_LEN_F(-1)	0.232692	0.053213	4.372828	0.0000
A_LEN_A	0.065838	0.084472	0.779416	0.4374
A_LEN_A(-1)	-0.070040	0.086574	-0.809015	0.4202
DUM1	-39626.31	3878.591	-10.21667	0.0000
DUM1*A_LEN_S	0.914510	0.089780	10.18613	0.0000

R-squared	0.612187	Mean dependent var	43215.59
Adjusted R-squared	0.587948	S.D. dependent var	1262.541
S.E. of regression	810.4408	Akaike info criterion	16.29737
Sum squared resid	73563202	Schwarz criterion	16.48321
Log likelihood	-969.8424	Hannan-Quinn criter.	16.37284
Durbin-Watson stat	2.150478		

Table 11C: Significant weekend effects on Lenovo Flipkart prices

Dependent Variable: A_LEN_F
Method: Least Squares
Sample (adjusted): 6/18/2015 10/30/2015
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
A_LEN_F(-1)	0.720924	0.114382	6.302747	0.0000
A_LEN_S	-0.296458	0.112443	-2.636510	0.0096
A_LEN_S(-1)	0.214722	0.101166	2.122458	0.0360
A_LEN_A	0.305287	0.139984	2.180879	0.0313
A_LEN_A(-1)	0.059432	0.146891	0.404601	0.6865
DUM1	9412.026	5417.637	1.737294	0.0851
DUM1*A_LEN_F(-1)	-0.208889	0.123259	-1.694717	0.0929

R-squared	0.519597	Mean dependent var	43968.78
Adjusted R-squared	0.494089	S.D. dependent var	1931.138
S.E. of regression	1373.568	Akaike info criterion	17.34477
Sum squared resid	2.13E+08	Schwarz criterion	17.50738
Log likelihood	-1033.686	Hannan-Quinn criter.	17.41081
Durbin-Watson stat	2.344968		

Table 12C: Significant weekend effects on Lenovo Amazon prices

Dependent Variable: A_LEN_A
Method: Least Squares
Sample (adjusted): 6/18/2015 10/30/2015
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
A_LEN_A(-1)	0.928931	0.091733	10.12648	0.0000
A_LEN_F	0.138972	0.058981	2.356211	0.0202
A_LEN_F(-1)	-0.050031	0.061941	-0.807719	0.4209
A_LEN_S	0.091332	0.072202	1.264947	0.2085
A_LEN_S(-1)	-0.109830	0.070974	-1.547462	0.1245
DUM1	10357.73	3884.790	2.666226	0.0088
DUM1*A_LEN_A(-1)	-0.243131	0.090910	-2.674421	0.0086

R-squared	0.627356	Mean dependent var	42867.32
Adjusted R-squared	0.607570	S.D. dependent var	1423.915
S.E. of regression	892.0007	Akaike info criterion	16.48137
Sum squared resid	89910172	Schwarz criterion	16.64398
Log likelihood	-981.8824	Hannan-Quinn criter.	16.54741
Durbin-Watson stat	2.150299		

Table 13C: Significant Festival Days effects (13-17 October 2015) on Lenovo Amazon prices

Dependent Variable: A_LEN_A
Method: Least Squares
Sample (adjusted): 6/18/2015 10/30/2015
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
A_LEN_A(-1)	0.752621	0.067052	11.22446	0.0000
A_LEN_S	0.158434	0.065679	2.412253	0.0175
A_LEN_S(-1)	-0.031950	0.063906	-0.499960	0.6181
A_LEN_F	0.148092	0.056582	2.617281	0.0101
A_LEN_F(-1)	-0.031742	0.060211	-0.527183	0.5991
DUM2	54634.00	16582.06	3.294765	0.0013
DUM2*A_LEN_A(-1)	-1.195102	0.369470	-3.234638	0.0016

R-squared	0.651092	Mean dependent var	42867.32
Adjusted R-squared	0.632566	S.D. dependent var	1423.915
S.E. of regression	863.1252	Akaike info criterion	16.41556
Sum squared resid	84183319	Schwarz criterion	16.57816
Log likelihood	-977.9336	Hannan-Quinn criter.	16.48159
Durbin-Watson stat	2.121280		

Appendix D: Results for Samsung
Section 1D: Test for stationary

Table 1D : Samsung price series on Flipkart stationary

Null Hypothesis: A_SAM_F has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.733491	0.0000
Test critical values:	1% level	-3.479281	
	5% level	-2.882910	
	10% level	-2.578244	

*MacKinnon (1996) one-sided p-values.

Table 2D: Samsung price series on Amazon, Flipkart, Snapdeal as a group stationary

Group unit root test: Summary
Series: A_SAM_A, A_SAM_F, A_SAM_S
Sample: 6/17/2015 10/30/2015
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 5
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.20664	0.0000	3	357
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-11.2842	0.0000	3	357
ADF - Fisher Chi-square	122.802	0.0000	3	357
PP - Fisher Chi-square	139.752	0.0000	3	379

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.