

# “Gauging optimal selling prices from high-frequency sales data”

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<b>ARTICLE INFO</b>	Colin Ellis (2011). Gauging optimal selling prices from high-frequency sales data. <i>Innovative Marketing</i> , 7(1)
<b>RELEASED ON</b>	Friday, 25 March 2011
<b>JOURNAL</b>	"Innovative Marketing "
<b>FOUNDER</b>	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

0



NUMBER OF FIGURES

0



NUMBER OF TABLES

0

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## Gauging optimal selling prices from high-frequency sales data

### Abstract

While profit maximisation is clearly defined in theoretical models, in practice producers selling their goods and services can find it hard to measure the price sensitivity of customer demand. While marketing departments often rely on aggregated data to analyse the interlinkages between selling prices and sales volumes, this paper suggests a new approach that relies on disaggregated data across different stores and locations. By considering the whole distribution of selling patterns, a much richer picture of consumer demand can be uncovered, and a more accurate estimate of the price elasticity of demand. This technique therefore allows marketing professionals to take advantage of information that is already collected to maximise their firms' profits.

**Keywords:** price elasticity of demand, microdata, supermarket prices.

### Introduction

Economic theory states that, in order to maximise profits in competitive markets, producers should sell their goods and services at a price that reflects a markup over marginal cost. That markup, in turn, depends on the price elasticity of demand. Gauging this elasticity should therefore be a key concern for marketing departments in predicting and forecasting both demand and profits. Unfortunately, in practice the price elasticity of demand is not easy to observe, given the need to control for changes in tastes, incomes or expectations, and other factors that may affect demand other than the price. However, using high frequency data on supermarket sales and prices, there is a way to uncover consumers' underlying price elasticities, and hence for marketing departments to set the optimal price that maximises profits. This paper discusses how this technique works, and its potential drawbacks and benefits.

### 1. Profit maximisation and price setting: theory vs. practice

The starting point for much modern macroeconomic research is the theoretical microfoundations of the underlying model. In competitive markets, a standard assumption is that firms are monopolistically competitive, ie face downward sloping demand curves and a rising marginal cost of production. In the context of this simple framework, the firm maximises profits by setting price as a markup over marginal cost. With a simple constant elasticity of substitution production function with labour ( $N$ ) and capital ( $K$ ) as the two factors of production ( $Y$ ), where  $a$  represents labour-augmenting technical progress:

$$Y^S = \left[ \alpha K^{-\varrho} + (1 - \alpha)(Ne^a)^{-\varrho} \right]^{-1/\varrho} \quad (1)$$

and a simple constant elasticity demand curve:

$$Y^D = P^{-\varepsilon}, \quad (2)$$

where  $P$  denotes price, the profit-maximising condition (with respect to labour) delivers the well-known factor pricing equation:

$$p = w - \frac{1}{\sigma}(y - n) + \mu - \left( \frac{\sigma - 1}{\sigma} \right) a - \ln(1 - \alpha), \quad (3)$$

where  $W$  denotes wages, lower case denotes natural logarithms, and  $\sigma = 1/(1 + \varrho)$  is the elasticity of substitution between capital and labour in production. In this framework, the markup,  $\mu$  is a function of the elasticity of demand:

$$\mu = \ln \left( \frac{\varepsilon}{\varepsilon - 1} \right). \quad (4)$$

A common simplifying assumption is that of Cobb-Douglas production technology ( $\sigma = 1$ ), in which case (3) can be simplified to:

$$p = ulc + \mu - \ln(1 - \alpha), \quad (5)$$

where the profit-maximising price is now a markup over unit labour costs ( $ulc$ ), plus a constant term from the distribution parameter in the production function ( $\alpha$ )<sup>1</sup>.

It follows that, in markets where consumer demand is relatively price inelastic, i.e. sales volumes are relatively unresponsive to changes in price, producers will charge high markups over cost. In contrast, where demand is price elastic, consistent with fiercer competition, markups will be lower. Furthermore, the degree of competition can also affect producers' ability or willingness to change prices – for example, Mumtaz *et al* (2009) find that more competitive sectors may be less likely to pass on increases in cost via higher prices.

While this theoretical framework is relatively simple, in practice maximising profits is somewhat harder. Marginal cost can be relatively simple to calculate

<sup>1</sup> For a complete derivation of the profit-maximising conditions, see Ellis (2006).

within the confines of simple economic conditions – particularly under the assumption of Cobb-Douglas technology, for instance, as shown in equation (5) – but in the real world production technologies are often more complicated. Ellis and Price (2004) and Chirinko (2008), for instance, find that economic data strongly reject the Cobb-Douglas assumption. And Ellis (2006) demonstrates that if markups vary over time and technological process follows a stochastic trend (as opposed to a deterministic one), then the evolution of firms' costs may be very different from what common empirical techniques suggest. Various surveys of pricing behavior have suggested that, if anything, firms tend to focus on average rather than marginal cost, perhaps for that reason.

Even if firms do observe their own marginal cost, however, the price elasticity of demand for a particular product is not directly observable, preventing producers from maximising profits. While producers and retailers can observe changes in prices, and changes in sales volumes, it does not follow that one causes the other. This is partly because there are a number of variables that the firm does not observe, which also affect consumer demand. These include labour income, employment status, property income, tastes and preferences, and consumers' expectations about all of the above. If a firm cuts its price, and sales rise, then that could reflect the price cut – but the increase in sales could also be due to wage rises at local businesses, or a change in consumer preferences following bad news about a competitors' product.

How then can marketers study and forecast the elasticity of demand and hence optimal selling prices? Using high-frequency data from supermarkets, the rest of this paper discusses how marketing professionals can get an accurate picture of how consumers will respond to changes in price.

## 2. Pricing behavior and temporary sales

A standard assumption in macroeconomic models is that selling prices, both in product and labour markets, are sticky – that is, both firms and workers are unwilling or unable to adjust their prices immediately in response to other changes in the economy. However, the degree of price stickiness has been a bone of some contention in recent research. Using a pricing model that relates current inflation to expected future inflation and either deviations of current marginal cost or output from steady-state, estimates suggested that on average prices change only once every fifteen to eighteen months (Gali and Gertler, 1999), or even only once every two years (Smets and Wouters, 2003).

In practice, however, direct studies of observed prices have revealed that prices change much more frequently than that. The precise duration of prices varies,

depending on what type of prices are being observed, and with what frequency. Bunn and Ellis (2009) report results for the United Kingdom, finding that consumer services prices change least frequently, with consumer goods and producer prices exhibiting more variation. Supermarket prices, which are available on a weekly basis, appear to change most frequently.

While interesting in a different context, this disparity between the microeconomic evidence and the implications from the aforementioned macro models is not the key focus of this paper. Rather, it is what can be learnt from these very high-frequency datasets, where prices and sales are observed on a weekly basis.

One of the key characteristics of these datasets, such as the one used by Kehoe and Midrigan (2007), is the high number of surprisingly short-lived price changes. These temporary price changes in these supermarket micro datasets are often referred to as 'sales', and can be defined either in terms of whether the price returns to its original value within a given time frame, or reverses at a subsequent point in time, or any deviation from a so-called 'reference price', as proposed by Eichenbaum *et al* (2008), which is the modal price within a given period. The underlying notion is that producers or supermarkets cut prices temporarily either to boost cashflow or to run down a stock overhang (or both), and then reinstate the original prices.

These frequently observed sales have led many economists to suggest that these temporary price changes, which are subsequently reversed within two or three weeks, are not economically meaningful, and should be ignored. However, quite apart from revealing that the actual degree of nominal rigidity in the economy may not be very pronounced at all, these frequent price changes offer a wealth of information to marketing professionals who study and forecast demand and optimal prices. In this sphere, previous research by Gupta (1988) found that sales could induce brand switching, with consumers temporarily switching between substitute products for the duration of the sale. However, those temporary promotions rarely have persistent effects on sales volumes, which swiftly return to pre-promotional levels once the offer has expired (Pauwels *et al*, 2004). Chevalier *et al* (2000) also used these types of data to uncover evidence of counter-cyclical markups during periods of strong seasonal demand. What these temporary sales can also uncover, however, is a reliable estimate of the price elasticity of demand.

## 3. Characteristics of high-frequency data

When producers try to gauge the impact of temporary promotions on sales volumes in practise, they often use relatively simple techniques, such as linear regression tools or, far less frequently, ARIMA models

or the like. The analysis is generally conducted on aggregated data, however – adding up all the sale volumes of a particular product or products across a wide number of stores and locations. Because the marketing department knows when the promotion started and ended, this resulting analytics essentially serve as a simple form of event study.

However, as previous research has shown – not least in the context of pricing and demand, as demonstrated by Mumtaz *et al* (2009) – simply focusing on these sorts of aggregated data at best ignores the full wealth of data that are available, and at worst can yield very misleading results. In fact, the cross-

sectional variation that is present in the underlying micro data can be used as a natural control for all the unobserved factors, other than price, that may also affect consumer demand.

Consider a single product, such as a branded chocolate bar. Even for an identical product such as this, the price trajectory of this item across different retail stores may look something like Figure 1. While widespread promotions are held, their implementation will vary. Furthermore, individual stores may also change prices themselves to manage stocks or cashflow, or some locations may be slower to put the promotion in place than others.

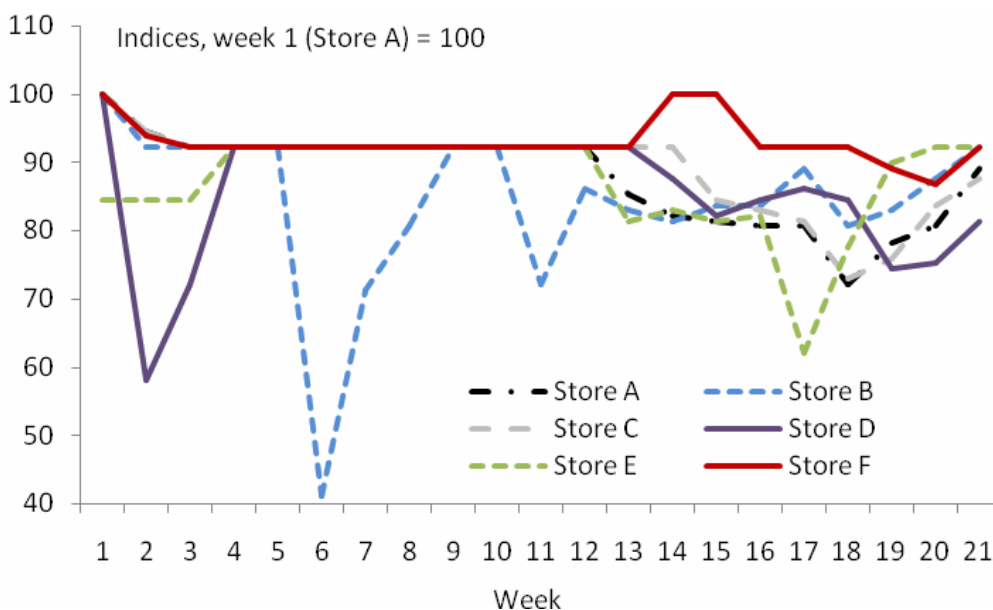


Fig. 1. Typical store-level prices for an identical product

The price trajectories shown in Figure 1 are typical of those in the data set compiled by Ellis (2009). That paper examines the frequency and magnitude of price changes from a monetary policy perspective. But it is also possible to use the same information to explore a useful technique for studying and forecasting the demand for individual products, from a marketing perspective.

**4. Results and discussion**

The dataset was compiled from sales at major UK supermarkets between February 2005 and February 2008. The dataset covered around 240 different stores located throughout Great Britain, including Tesco, Asda, Sainsbury’s, Morrison’s, Somerfield (now taken over by The Co-operative) and Waitrose. At each store data was compiled for over 280 unique, distinct products, which were typically identified at the bar code level. While not all stores stocked all products in all weeks, overall there were around 5½ million individual observations – or, on average,

around 35,000 records of prices and sales for each week in the data set. In all, by value the dataset accounted for a little under 5% of annual household expenditure between 2005 and 2008.

The different products in the dataset were broken down into ten different categories: alcohol, bakery, confectionary, dairy, fresh (eg fruit and vegetables), frozen, grocery, household, personal (eg health care), and soft drinks. By value, the ‘fresh’ category clearly dominated the dataset (Table 1), although by volume ‘grocery’ was slightly larger.

Based on these data, on average 40% of supermarket prices changed each week, on an unweighted basis. Weighting individual products by shares of total spending, that increased to 60% of prices, reflecting the high weight of ‘fresh’ products and the high frequency with which they change prices (Table 2). Excluding ‘fresh’ items, and weighting by sales shares, the average proportion of prices changing each week again fell to 40%.

Table 1. Share of sales by product category

Category	Frequency		Sales	
	Number	Percentage of total	JMillion	Percentage of total
Alcohol	319,195	5.6	6449	5.9
Bakery	161,087	2.8	1624	1.5
Confectionary	544,268	9.6	2138	2.0
Dairy	614,746	10.8	12778	11.7
Fresh	1,030,831	18.1	61890	56.7
Frozen	255,294	4.5	1986	1.8
Grocery	1,234,536	21.7	10323	9.5
Household	408,352	7.2	3430	3.1
Personal	492,449	8.7	2460	2.3
Soft drinks	621,778	10.9	6033	5.5
Total	5,682,536	100	109,110	100

Table 2. Frequency of price changes by product category

Category	Fraction of prices changing each week		
	Per cent changing	Per cent rising	Per cent falling
Alcohol	58.0	29.0	29.0
Bakery	48.5	24.8	23.7
Confectionary	32.2	16.5	15.7
Dairy	28.6	15.7	12.9
Fresh	75.0	37.4	37.6
Frozen	32.4	16.2	16.1
Grocery	38.8	20.0	18.8
Household	35.7	17.8	17.9
Personal	40.9	20.5	20.4
Soft drinks	55.1	27.9	27.2

As in other studies, a significant number of the prices changes at UK supermarkets appeared to be temporary changes – depending on how these were identified, between a third and two-fifths of all price changes. This still means that, excluding these, roughly a quarter of all supermarket prices, excluding fresh products, change each week, and resulting hazard functions were also very steeply sloped.

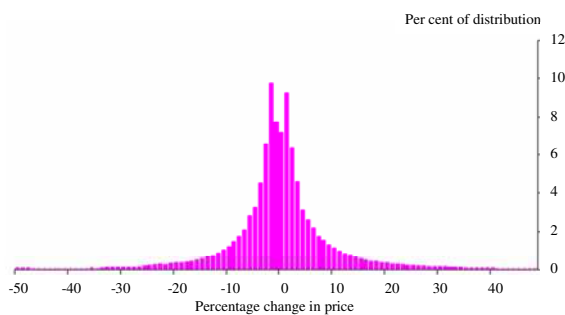


Fig. 2. Distribution of price changes

Interestingly, there appears to be considerable variation in the magnitude of price changes, as shown in Figure 2. But the dataset also tracks sales volumes, and the dispersion here was even more pronounced (Figure 3).

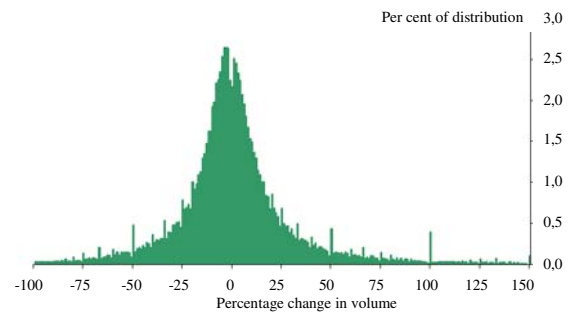


Fig. 3. Distribution of volume changes

The fact that both prices and sales volumes are captured in the data set allows us to attempt to uncover the price elasticity of demand (PED). Using aggregated data, we would need to include conditioning variables such as income, confidence, expectations etc – anything that could cause a shift in the demand curve, rather than a shift along it, which we are trying to capture. To be complete, we should also take account of factors that may shift the producer or retailers’ supply curves. Such an exercise would be costly, complex and likely to yield highly uncertain results.

However, the high frequency of the dataset, and the staggered nature of the prices changes across stores for individual goods (Figure 1), allows us to con-

sider a different approach. For any one consumer, the likelihood of a change in non-price demand factors (confidence, employment, wages etc) is relatively small. While some individuals will move or lose jobs in any given week, we know from employment data that most will not – even during the recent recession, the transition rates from employment into unemployment were lower than many economists had forecast. On this basis, many individuals’ circumstances (and non-price demand factors) will be unchanged from week to week. If we could focus on these individuals, we could calculate the price elasticity of demand (PED) simply by dividing the percentage change in sales volumes of individual products by the percentage change in price:

$$PED_i = \frac{\% \Delta volume_i}{\% \Delta price_i} \tag{6}$$

There are two key challenges to this approach. The first is that sales volumes may not respond immediately to changes in price, so the PED estimates in equation (6) may be inaccurate. In practice, however, this proved not to be the case – cross-correlations revealed that the strongest (negative) correlation between prices and sales volumes in the data was indeed contemporaneous (Figure 4).

The second key challenge is how we can identify those consumers whose circumstances have typically not changed from week to week. This is where using aggregated data, in particular, proves problematic. However, because we have sales records for identical products from different stores, we can calculate store-level PEDs for individual products. Based on these individual weekly observations, we can then examine the whole distribution of these quasi-PEDs.

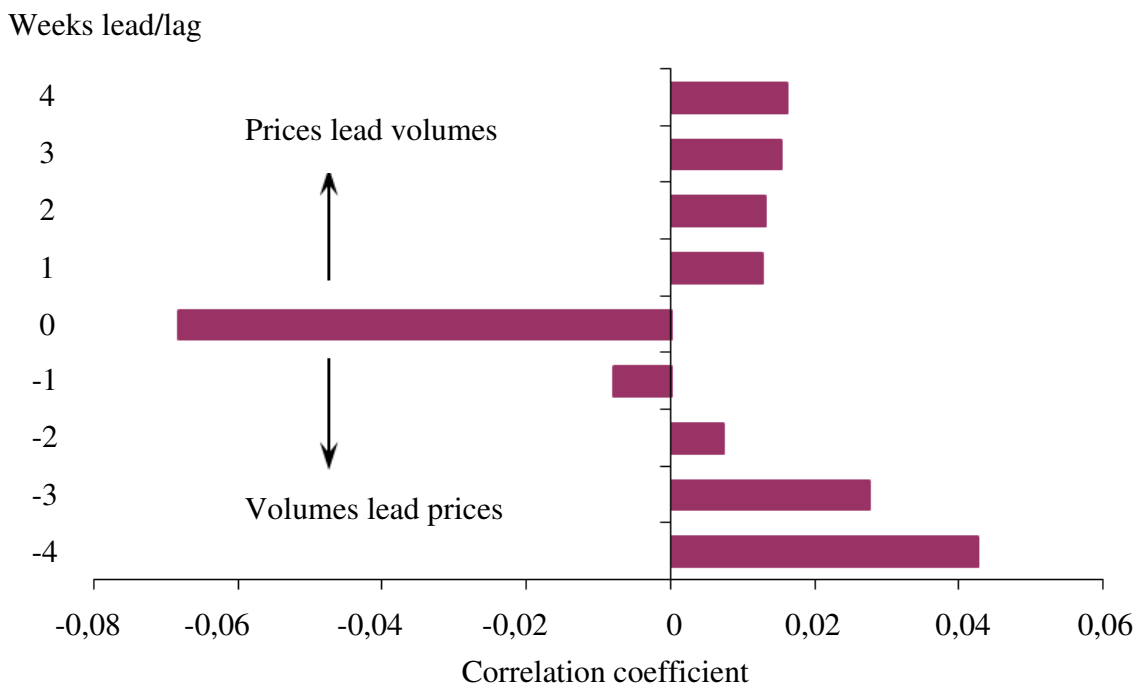


Fig. 4. Cross-correlations between price and volume changes

Table 3. Distributions of quasi-PEDs by product category

Category	Percentiles				
	5 <sup>th</sup>	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>
Alcohol	-190.67	-22.81	<b>-5.13</b>	5.83	135.24
Bakery	-24.86	-5.96	<b>-1.57</b>	2.20	17.36
Confectionary	-54.18	-10.56	<b>-2.71</b>	2.92	36.25
Dairy	-32.93	-6.41	<b>-1.22</b>	2.49	24.11
Fresh	-16.17	-2.93	<b>-0.48</b>	2.03	14.01
Frozen	-70.83	-11.74	<b>-2.55</b>	1.82	37.50
Grocery	-44.83	-8.19	<b>-2.15</b>	2.63	34.46
Household	-268.50	-22.95	<b>-3.36</b>	7.62	119.51
Personal	-101.25	-12.96	<b>-3.04</b>	4.71	72.87
Soft drinks	-43.00	-9.33	<b>-2.72</b>	1.18	32.37

The results from this approach are shown in Table 3. It is clear that, for all categories of products, there is considerable variation in the degree to which price and volume changes move together. The lack of control for the impact of non-price factors on demand clearly generates a wide range of estimates. But, at the same time, those estimates in the tails of the distribution are likely to represent those types of large, infrequent changes in individuals' circumstances that we have not controlled for. On the basis of the 75<sup>th</sup> percentile, all product categories exhibit positive price elasticities of demand, suggesting that sales volumes rise as prices rise. But this is almost certainly driven by changes in other factors, such as rising incomes. At the same time, the extreme negative estimates at the 25<sup>th</sup> percentile do not necessarily reflect the true price elasticity of demand, but are likely to encompass occurrences where individuals have lost their jobs or revised down their expectations of future income.

As such, the best guide to the true price elasticity of demand is likely to be the median of the distribution. Due to the large ranges and skews of the elasticity distributions, this will be a better estimate than the mean elasticity – consistent with aggregated data not providing as good a steer as this micro-based approach. And the median estimates reported in Table 3 are consistent with what simple theory would suggest – in particular, those products that are more storable over time, such as alcohol and household goods, exhibit higher elasticities, consistent with consumers 'stocking up' when prices fall. Fresh products, which quickly spoil, are relatively price inelastic. Furthermore, the general finding that most product types are price elastic – ie volumes change by more than prices – is consistent

with the previous research on the impact of sales reported earlier.

Overall, then, the high frequency of price and sales volume observations, across a range of locations, offers a natural control for the non-price factors that drive consumer demand. Provided producers and retailers use this wealth of information correctly, and do not just rely on aggregate data or models, it is possible to uncover a good estimate of the price elasticity of demand, and hence the optimal markup that producers base prices on in order to maximise profits.

## Conclusions

This paper has explored a key topic for producers and marketing professionals – how to accurately gauge prices and sales volumes in order to maximise profits. While the theoretical approach to this problem is relatively simple, in practice many firms rely on aggregated data and models in order to do so. This paper has set out a new approach, based on microdata on sales volumes and prices for individual products across a wide range of retailers and locations, and demonstrated that it is possible to obtain good estimates of consumers' price elasticity of demand. By focusing on the distribution of possible responses, rather than just the average, we can also glean far more detail on the range of potential outcomes. Importantly, while this paper has presented results for broad categories of products, it would also be simple to replicate this approach for individual brands and items. This technique therefore offers marketing professionals the genuine ability to study and forecast demand, and set prices correctly to maximise profits.

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