Price Rigidity in Multi-product Firms:

The Role of Technological Economies of Scale

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Abstract:

This study examines the evidence for multi product firms using technological economies of scale to overcome the limitations of changing prices due to menu costs. Using a data set from a Spanish supermarket of scanner price data, I have assed whether the size and frequency of price changes are consistent with the effects of a constant menu cost. I have also employed a within store synchronisation test as a way of finding out whether the store is showing the use of technological economies of scale when setting prices. My results show that over 70% of the price changes are small in absolute value and that the frequency of price changes is high over short periods of time. Further more I find that prices are not synchronised within the store, casting doubt as too whether these small price changes are due to technological economies of scale.

Contents

Introduction

It is well known in the field of economics that prices are "sticky". Bils and Klenow (2004) are one of the most recent to study this and have found that prices do adjust sluggishly using a data set of prices from BLS. Their findings show that in the US economy half of the prices observed adjusted less than once every 4.3 months. The important question to then ask is whether these firm level rigidities have any macro economic consequences and is there any evidence of a process at the firm level that should be incorporated into macro economic models? These rigidities at the firm level are explained by the existence of "menu costs". These are the costs to the firm of changing price and as the firm is profit maximising, menu cost theory suggests that only large price changes will be made as small price changes will be unprofitable.

Contrary to this theory some of the literature into the movement of prices at firm level have found that as well as large price changes, there are also price changes that are small in absolute value. Midrigan (2006) notes that around 30% of price changes within the data set are small in absolute value. Lach and Tsiddon (2005) put forward the concept that the firm may face interactions in its costs, instead of an exogenous fixed cost and so can take advantage of these interactions to make optimal price changes, whether they be small or large. Lach and Tsiddon (2005) suggest that these interactions are from firms taking advantage of "technological economies of scale"[1]. By looking at micro price data, can we find evidence of these technological economies of scale and account them to any changes in price? And if we can find this evidence, how does this link into the bigger picture of the macro economic models?

This study investigates a data set from a supermarket to see if there is evidence of the firm overcoming menu costs by being able to make small and large price changes. Secondly it will investigate whether these price changes can be attributed to the firm interacting with costs using technological economies of scale. Most of the literature into this area has been studied using data sets primarily from the US and so to contrast with this; my data set is from Europe. The data is taken from a Spanish supermarket and so the results can be compared with those taken from the US in previous studies[2].

[1] Technological economics of scale is defined here as the improvement in technology allowing a lower cost in changing price and is not to be confused with improvement in technology allowing the product to be made cheaper, and hence cause a price change.
[2] Kashyup (1995), Klenow & Kryvtsov (2004), Midrigan (2006)

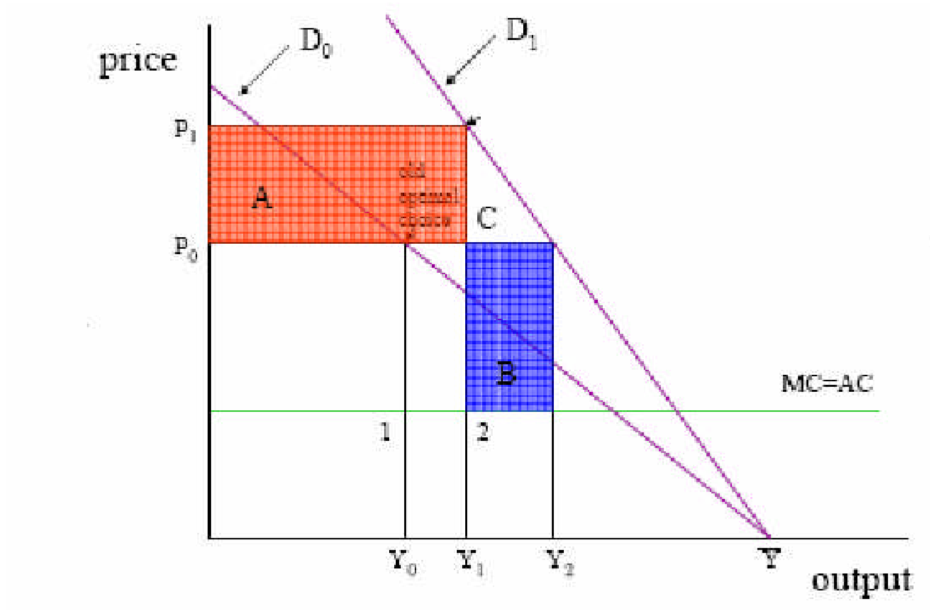
With this data set I have looked at the size of price changes and their frequency. I have compared positive and negative price changes and have searched for evidence of technological economies of scale. To do this I tested for “within store synchronisation”. My results show that there is evidence for both small and large prices changes. However I found very little evidence of within store synchronisation of price changes and so these smaller price changes cannot be completely attributed to the store enjoying economies of scale.

Literature Review

Menu costs

Firstly it is important to define what a menu cost is and why it affects price changes. Mankiw (1985) looked at monopolistic competition to show how menu costs could affect the distribution of nominal prices. He considered a monopolistic firm with linear demand that produced a differentiated good and had constant marginal costs and no fixed costs. There is also the assumption that there are menu costs for changing of prices and that nominal wages are fixed.

Figure 1



A = Profit gain from moving to P1
B = Profit gain from keep price at P0

Figure 1 shows an increase in aggregate demand; this could be because of a monetary shock. The monopolies demand moves Do to D_1. The firm then has a choice. It can both increase its price from its old profit maximising level Po to P_1, the new profit maximising level and incur the menu cost z, or it can choose not to change its price at all. If it does choose to change to price P_1, then output is at Y_1. If it chooses not to keep the current price P_0, output will increase to Y_2. A + C is the gain in consumer surplus if the firm choose not to change its price. By taking all of this information into account the firm will decide not to change price if and only if the menu cost for changing price is greater than the profit gain from adjusting the price.

I.e. there will be no price change if $z > A - B$.

There are two things that can be induced from this. Firstly is that if the profits gain from a small rise in the aggregate demand for a firm, it doesn't automatically mean that the firm will move to the new profit maximising price. Even though menu costs are small they can stop firms constantly changing prices as the firms demand shifts. This means that prices will not be distributed evenly for similar firms. Prices will only change when the gain in profit is more than the menu cost. This would mean we would expect to see only larger price changes and not lots of small ones, especially over short periods of time. Also menu costs are only likely to effect firm's decision making when the change in aggregate demand is small. With larger changes in demand it is more likely that the gains from changing prices will be a lot bigger than the menu cost.

Kashyap (1995) collected data from retail catalogues form the years 1953-1987, allowing him to see updated prices every 6 months. The study finds that prices sometimes stay fixed for large amounts of time while others can adjust quite frequently. This would go against the theoretical concept put forward by Mankiw (1985). This combination of many periods of no change and many small changes would suggest that when small price changes do occur, the cost of changing price must be small or the benefits large. At other times, the cost must be large or benefits smaller. Models that generate price rigidity by assuming a constant cost of changing prices in an otherwise stationary environment cannot explain these results.

Macro economic models

Time dependant pricing models

One of the explanations as to why prices are not continuously reset presumes that either the information to induce a price change is not available to the price setter, or that the costs to the price setter of making high frequency changes are prohibitive. These models suggest that price setters will only intervene when the relevant information is available. Assuming that firms stick to these ad-hoc policy rules, the source of the price rigidity is not modelled.

Time dependant models are based around this idea and assume that the timing of a price change is exogenous and unresponsive to the state of the world. Caplin and Spulber (1987) derived a time dependant model of firms following pricing policies, with the log of real prices uniformly dispersed and found that money shocks were found to be neutral. They describe that nominal changes such as monetary growth do not have aggregate real effects, despite the presence of menu costs of price adjustment. The theory behind it being that a positive monetary shock induces more firms to change their prices and when more firms change their prices, the average size of adjustment is larger. Endogenous bunching of price changes speeds up price adjustment and dampens the short run effects on real output. They conclude that the real effects of money shocks may depend more on fixed length contracts than simply on asynchronous price adjustment, highlighting the importance of cross sectional timing assumptions in macro economic models.

A more recent study by Golosov and Lucas (2004) also supports the use of a time dependant model. They created a model of a monetary economy, which included idiosyncratic shocks as well as inflation, building on the model put forward by Caplin and Spulber, using a data set compiled by Klenow and Kryvtsov of individual US prices to calibrate the menu costs and the variance and autocorrelation of the idiosyncratic shocks. This model allows for firm level disturbances capable to match the fact that the magnitude of price changes is large in the US economy, 10% on average, much larger than what can be explained by aggregate shocks alone. Golosov and Lucas summarise that their model accounts for microeconomic evidence of US price behaviour as well as accounting for changes due to different inflation rates. However, it does not appear to be consistent with large real effects of monetary instability. Their model produces very little output volatility from monetary shocks and shows that when most prices stay the same from day to day, then nominal shocks can be almost neutral.

State dependant pricing models

Kashyup (1995) notes that the leading alternative explanation as to why firms do not continuously adjust prices is that it makes a trade off between the level of inflation and the cost of changing price. With a fixed cost of changing price and a predictable amount of inflation the firm will not adjust its prices until the accumulated inflation drives the real price down to a lower limit. Only then will the price be reset to a new upper limit. Allowing for cost and demand shocks implies that price should be set to a band that varies over time.

Klenow and Kryvtsov (2004) used their own data as used by Golosov and Lucas to create their own state dependant model. Their state dependant model uses newly available non-linear solution methods to investigate the implications of persistent menu cost shocks, sticky plans and idiosyncratic marginal cost shocks. From their model they document that there is very little synchronisation of price changes across firms in the US going against the time dependant model. They find that the state dependant model is able to reproduce the same magnitude of price changes that the time dependant model can but also produces larger output variability from monetary shocks. I am more inclined towards this type of model as it takes account of the cost shocks at the time of price change instead of making the effect exogenous as in time dependant models.

However this type of state dependant model doesn’t look at the price adjustment practices that are right at the firm level, looking at the microeconomic foundations and that these consistencies are needed to be able to apply the aggregate conclusions of the model.

Technological economies of scale

Midrigan (2006) looks at US price scanner data and tries to model the decisions at the firm level into a state dependant model. From observing the data she finds that there are a large frequency of price changes that are large in magnitude, as found by Klenow and Kryvtsov. However also noted are a high number of small price changes greater than absolute zero. This is at odds with menu cost theory that suggests that price changes will only be large as the menu cost stops a significant amount of profit being made from smaller price change.

Midrigan cites Lach and Tsiddon (2005) in arguing that small price changes could come from multi-product firms who face interactions in the costs of price adjustment.
Here the example of a restaurant is considered. If a restaurant wants to re price an item on its menu it must reprint the menu incurring a "menu cost". However by incurring this menu cost, changing the price of any other items is free. This technological economics of scale allowing the firm to make small and large price changes and we should be able to observe this in the data. Midrigan (2006) finds that prices of narrow product categories adjust in tandem in multi product firms (supermarkets) arguing that this needs to be developed into state dependant models to be able to evaluate the aggregate shocks the models produce. Midrigan, like most of the studies above, uses the US price data.

Lach and Tsiddon (1996) back up this theory by finding within store synchronisation of price adjustments in their data set. However in this case the findings were from small grocery stores, not big supermarkets. The amount of cost to change prices would vary in size of the store/ firm, as would the ability to take advantage of technological economies of scale. This paper looks at a data set for a large supermarket to see if the data is consistent in Europe as well as the US.

Methodology

As stated in the introduction the two objectives for this paper are to observe price changes in the data to see if there is evidence against the standard theory of menu costs and to test for technological economies of scale. The first objective will be accomplished by providing and analysing graphs and tables of summary data, allowing the analysis of the distribution of price changes, the size and the length at which they occur. This will give a clear indication of whether the data is for or against the standard theory.[3]

Within the literature described in this paper, there are two models that provide evidence into whether the store is showing signs of using technological economies of scale to make optimal price changes. The first is from Lach & Tsiddon (1996) and details how to check for technological economies of scale by looking for "within store synchronisation". This is done by comparing the proportions of price change for each time scale in the data with expected values from the model. The second model is from Midrigan (2006) and is a discrete choice model of the stores price adjustment practices. As this second model requires data on not only price changes but also labour costs and idiosyncratic cost disturbances, I shall be using the first model, as I cannot obtain that data.

Within store synchronisation model (Lach and Tsiddon (1996))

Within store synchronisation is the issue of whether stores tend to change the prices of different products simultaneously. That is to ask whether or not the change in price in a particular store is usually accompanied by changes in prices in the same store. Note: this is a synchronisation of the timing of the price change between different products not cross correlation of their prices.

Proportion of price changes

A natural measure of the degree of within store synchronisation is the proportion of products whose prices have changed during a month. In our notation this proportion is:

$$\varphi_{it} = \frac{1}{|G_{it}|} \sum_{j \in G_{it}} X_{it} \tag{1}$$

[3] searching for the consequences of incurring a menu cost as detailed in Mankiw (1985)

Where G is the set of products whose prices were recorded between the month's t-1 and t and where X is defined as 1 for a price change and 0 for no price change. We start by asking what values of φ we should expect for within store synchronisation. Clearly we cannot define a correct answer without the model but we can be fairly sure that with high inflation, there is a very low probability of 0 price changes occurring at all. Hence seeing many φ's equal to zero would be indicative of within store synchronisation.[4]

The null hypothesis in this test is the case of no within store synchronisation. This is interpreted as saying that the sequence {Xit} is pair wise independent over products j. Under this hypothesis the expected value of φ is:

$$E(\varphi_{it}) = \frac{1}{|G_{it}|} \sum_{j \in G_{it}} P_{it} \tag{2}$$

Where Pit = Prob {Xit = 1] is the unconditional probability of observing a prince change in product j at store i during month t.

The variance of φ is

$$V(\varphi_{it}) = \frac{1}{|G_{it}|^2} \sum_{j \in G_{it}} P_{it}(1 - P_{it}) \tag{3}$$

And so for large G[5], is approximated distributed as a standard normal variable (footnote)

$$z = \frac{\varphi_{it} - E(\varphi_{it})}{\frac{\sqrt{V(Q_{it})}}{\sqrt{G}}} \tag{4}$$

[4] The same conclusion can be reached if all prices are changed during the month, φ = 1. a problem with this conclusion is that with a positive rate of inflation and with a long enough interval of time, a store will eventually change all its prices and we will observe φ=1.
[5] Lach & Tsiddon state large G as G > 6

Since neither E(φ) or V(φ) are specified in the null hypothesis, they need to be estimated. Under the null hypothesis we do not need to estimate the joint probability of X…..,Xt, and then integrate out the marginal probabilities. The estimation of Pit is greatly simplified since it allows us to ignore the information embodied in the behaviour of the other products.

We assume that {Xit} is independent, not identically distributed, over t.

Since we are taking explicit account of the dynamics in the Xit process we also assume P(Xit / Iit) = P(Xit/ Xit-1). This assumption states that the probability of observing Xit conditional on all the relevant information available to store i at time t, Iit, is the same as the probability conditional only on information on what happened to product j during the previous period.

Under these assumptions we can dispense with the store and time subscripts and denote the probability of a price change in product j conditional on Xit-1 as Pj(0) and Pj(1) according to whether Xit-1 is 0 or 1. In order to get unconditional probabilities featured in equation (2), we need to know the probability distribution of the initial stage of Xit. However the model concludes that irrespective of the values of the initial probabilities, it takes at most 2 or 3 periods to get within 3 decimal places of the limiting probabilities. That is, Pj is very close to πj for t > 3. We therefore use estimates of πj to estimate Pjt in equation (2).

These are given by

$$\hat{\pi}_j = \frac{\hat{P}_j(0)}{1 + \hat{P}_j(0) - \hat{P}_j(1)} \tag{5}$$

Data

This study uses scanner price data taken from a balanced panel of 534 brands from a supermarket called Sebastian De la Fuente S.A. The data contains monthly observations of the scanner price of each product over a period of 29 months, from January 1990 up until May 1992. I chose this data set as it represents a supermarket store in Europe and it allows me to compare and contrast with the other literature. It also contains many products that can be grouped into homogeneous categories. It is important to be able to do this because we want the decision to change price to be directly down to the store. If the products were to be very competitive then we might find that concepts such as advertising and market branding may influence when certain products change in price, rather than down to technological economies of scale. By trying to pick out only homogeneous we assume the products are free of any major competition.

The three product groups in which I have organised data from the data set are Wine, Coffee and Chocolate[6]. Wine consists of 33 products, Coffee consists of 22 products and Chocolate consists of 18 products. Overall the data set I have analysed consists of 73 different products and gives a total of 2117 prices.

Table 1:

	Summary Statistics		
	Wine	**Coffee**	**Chocolate**
mean	**0.11**	**-2.26**	**1.07**
sd	**13.9**	**13.6**	**12.1**
min	**-52**	**-52**	**-35**
max	**39**	**41**	**66**

Wine

The wine group consists of 33 products and therefore over the 29 months leaves a possible 924 time periods. Out of 924, there were 254 price changes and therefore 670 non-price changes. Therefore in wine there were 27% price changes. The summary statistics of the price changes in table 1 show that the mean for wine was close to zero and that the standard deviation is quite high at 13.9. With min and max values at 39 and -52 it would suggest there were many positive and negative price changes and it is likely that they were both small and large due to the high standard deviation.

[6] a list of the products in each group can be found in appendix 1

Figure 2:

Figure 2 shows the distribution of the actual price changes in the product group wine. It shows that many of the price changes were small but that many of these small price changes were positive. It also shows that of the positive and negative prices changes it would seem there were more, large negative price changes.

Coffee

The coffee product group consisted of 22 products and therefore over a 29 month period leaves a possible 616 time periods for price changes to occur. Out of those time periods, there were 186 price changes, and so 430 non-price changes. This means that out of the total time periods, price changes 30% of the time. The summary statistics show that the coffee product group had a mean of -2.26 and a standard deviation of 13.6. The minimum and maximum actual price changes were -52 and 41. This would again suggest that in coffee there were lots of negative and positive price changes, with more negative than positive. The standard deviation would suggest the data is quite spread out.

Figure 3

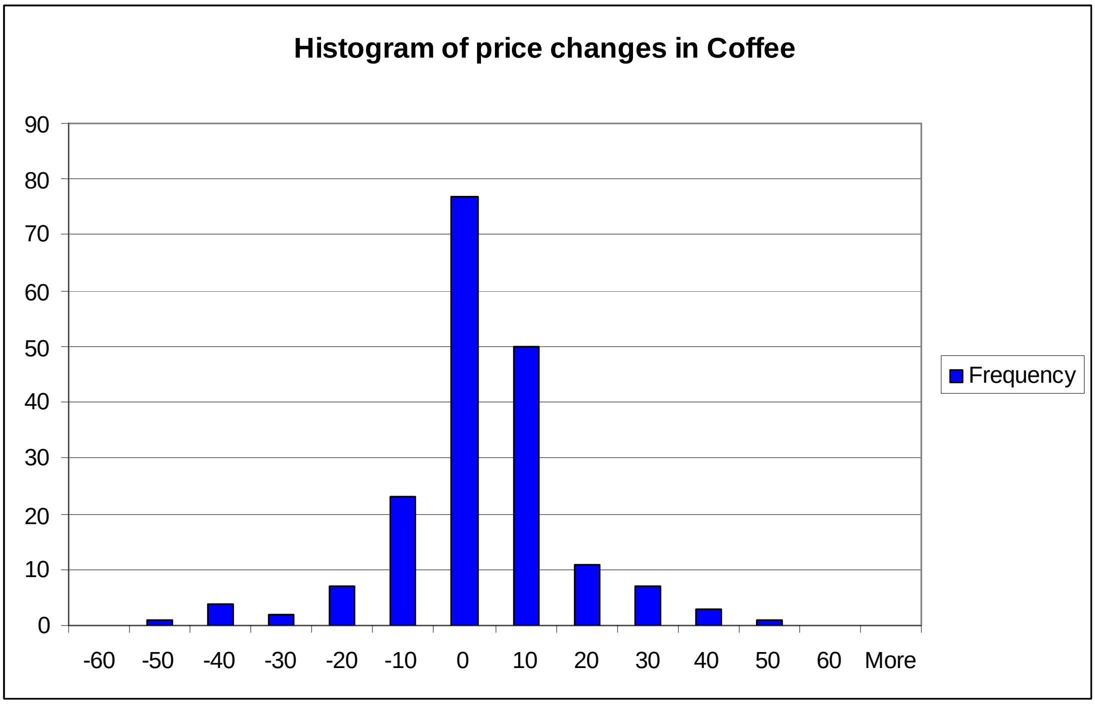


Figure 3 shows the distribution of the actual price changes in the product group of coffee. It shows that many of the price changes were small and that they were both positive and negative. The distribution of the negative price changes is quite uneven and so it would seem that there were a large number of large negative price changes, compared to the positive changes, whose distribution decreases more evenly.

Chocolate

The chocolate product group is the smallest consisting of 18 products and therefore over a 29 month period provides a possible 504 times periods for price changes to occur. Out of those time periods there were 186 price changes and so 318 non-price changes. Out of the total time periods, there were 36% price changes. The summary statistics show that the mean actual price change was 1.07 and the standard deviation was 12.01. The minimum and maximum of product group was -35 and 66. The positive mean would suggest that there were more positive than negative price changes but with a large distribution across each. The minimum and maximum show that the large positive price changes are higher than the large negative price changes.

Figure 4

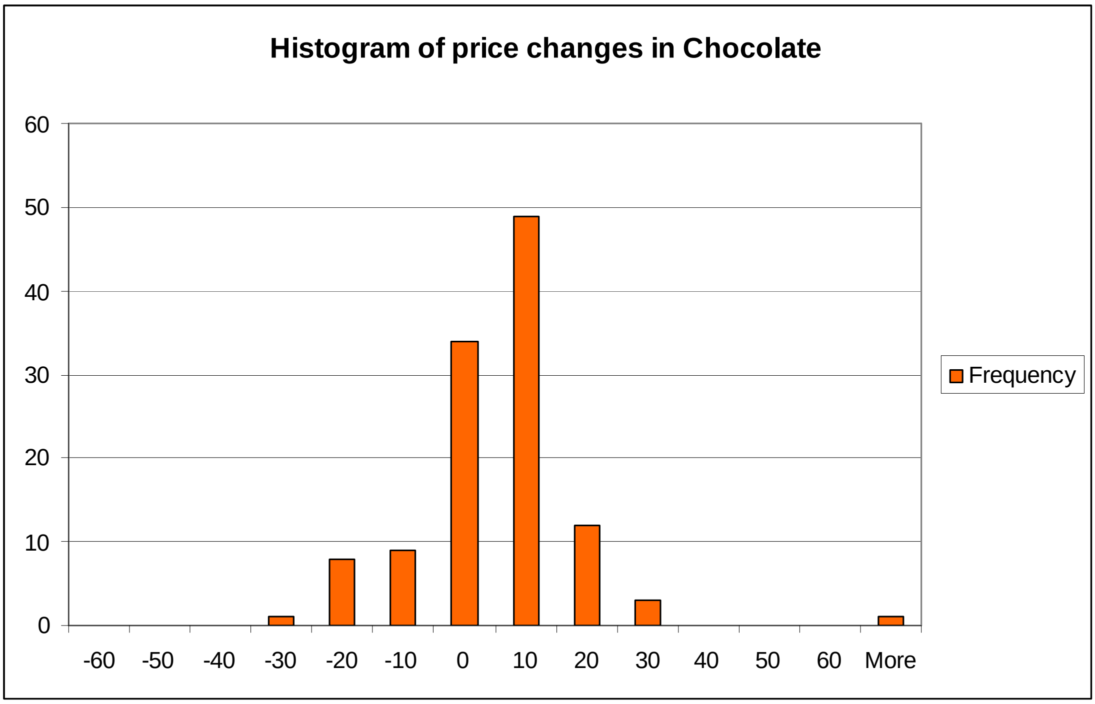


Figure 4 shows the distribution of actual prices within the Chocolate product group. It shows that more of the price changes were positive than negative and that a lot of these price changes were small in value. The graph also shows that there were quite a few large outliers indicating that in the chocolate product group there were a few very large positive price changes.

Cross group

When looking at table 1 of the summary statistics and of figures 2, 3 and 4 it is interesting to note the differences between the groups. The Wine product group with the most products has the smallest percentage of price changes at 27% which chocolate has the largest percentage with 33%. It would appear that the Coffee product group has more negative price changes than positive, unlike the other two groups. All three groups show a high distribution of low actual price changes.

Analysis

Evidence of the store pricing against menu cost theory

Figure 5

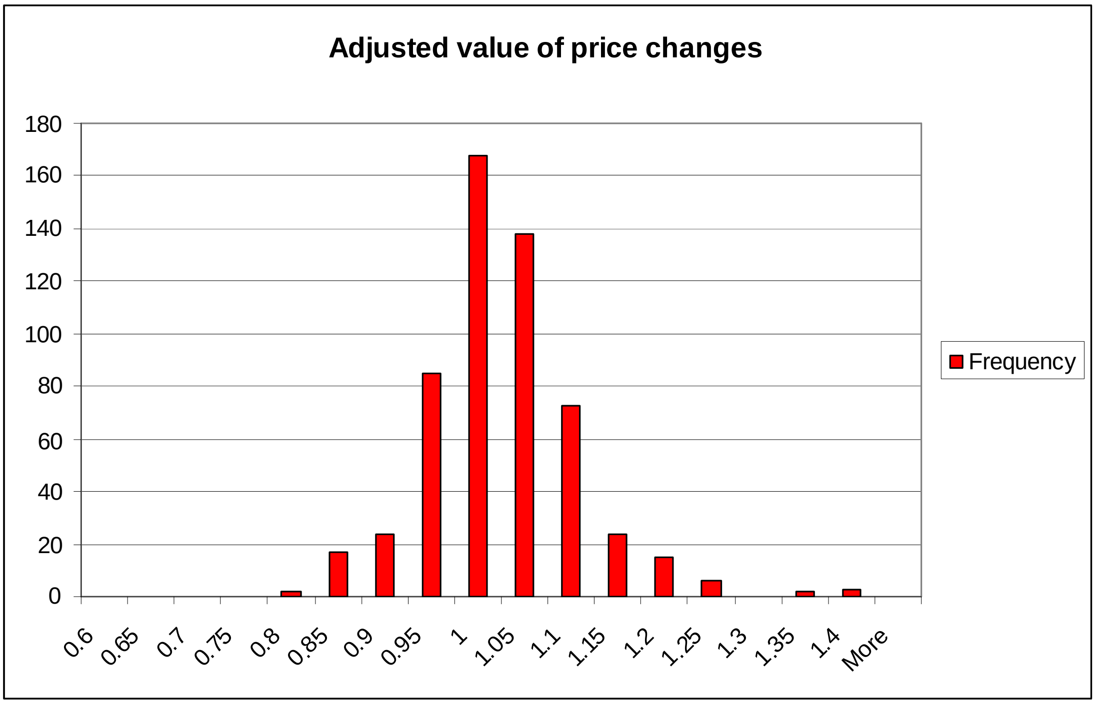


Figure 5 is a histogram of adjusted values of price change. The changes in price were adjusted by (P_t / P_{t-1}) so as to make the distribution easier to interpret. In my data there are a large number of positive and negative price changes and this has affected the shape of the distribution. Around the adjusted value of one we can see a high frequency. This indicates a large number of small positive price changes as well as a significant number of small negative price changes. This would suggest that the firm is overcoming menu costs to make small price changes. It is important to measure if these price changes are small in absolute value. As the level of inflation in Spain at the time this data set was taken was 6%, we can set this as the level below which a price is "small" in absolute value[7]. In this data set, 70% of price changes are small in absolute value

The size of a price change is not the only way of testing for a firm pricing against menu cost theory. It is important to check the frequency of price changes as well.

[7] Method used in Lach and Tsiddon (1996)

Table 2

Months between price change	frequency
0	150
1	125
2	60
3	45
4	11
5	12
6	9
7	4
8	6
9	7
10+	12

Table 2 shows the frequency of the different time lengths between price changes. It shows that a high number of price changes are close to each other in terms of the time interval between them. The average gap between price changes is 1.86 months. This again points to the store overcoming menu costs to be able to price when it pleases whether that be a short or long interval since the last price change.

The results shown here are consistent with other evidence taken from the literature. Klenow and Kryvtsov (2004) report that in their data set, 40% of price changes are less that 5% in absolute value. Kashyup (1995) documents that 44% of prices in his data set are less than 5% in absolute value. It is also well documented in the literature that supermarkets adjust their prices frequently such as Dutta, Bergen and Levy (2002). However it is apparent that my estimates are larger than those given in the literature. This may well be due to the size of my data set as much of the literature uses much bigger data sets than my own and so I may well have seen data closer to theirs if I had been able to collect data on more than one store.

It is clear that the store is not affected by a standard constant cost to change its prices as it is able to make large and small price changes as frequently as it wants. But is this due to the store taking advantage of technological economies of scale? To find out we must test for within store synchronisation.

Within store synchronisation

To test for within store synchronisation I used the model by Lach & Tsiddon (1996) which is outlined in the methodology. Firstly the actual proportions of price changes within each month were calculated using equation (1).[8]

Table 3

		Proportions of price changes for each product group							
		0	0.0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1	1	total
Wine	obs	0	9	16	2	1	0	0	28
	%	0	33	57	7	3	0	0	100
coffee	obs	1	4	17	5	0	1	0	28
	%	3	14	62	18	0	3	0	100
chocolate	obs	1	11	15	1	0	0	0	28
	%	3	40	54	3	0	0	0	100

Table 3 shows the proportions of price changes for all three of the product groups. The first thing that's striking about the proportions is that only two of the groups have a zero proportion in it. According the Lach and Tsiddon, the natural evidence for within store synchronisation is the presence of zero proportions in the groups of products. In the Wine product group there were no months when there were no price changes at all. Even in the Chocolate group and the Coffee there was only one month when there were no price changes. Table 3 does show some similarities between the 3 groups. All three have their highest percentage of proportions between the values of 0.2-0.4 suggesting that in most of the monthly time intervals there were only a small amount of price changes. Both the wine and chocolate groups also have a high percentage of proportions within the range of 0.0-0.2 at 33% and 40%. This could be evidence of within store synchronisation as although not all prices are kept constant there were only a few price changes during these intervals. To be able to analyse further we should check the actual values of proportion against the expected values from the model.

[8] Proportion data for every month and product found in appendix 2

Table 4

		Proportions of price changes for each product group							
		0	0.0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1	1	total
Wine	obs	0	9	16	2	1	0	0	28
	exp	0	19	9	0	0	0	0	28
coffee	obs	1	4	17	5	0	1	0	28
	exp	1	24	3	0	0	0	0	28
chocolate	obs	1	11	15	1	0	0	0	28
	exp	3	27	0	0	0	0	0	28

Table 4 shows the observed proportion of price changes for each product group compared with the expected values worked out from the model. By using equations (3) and (4) the statistical significance between the observed values and the expected values was also determined. From this test 94% of the observed values were found to be significantly different from the expected values. [9]

Therefore using Table 4 to make comparisons we can find evidence that within store synchronisation does not take place in this particular store. The expected values show that for within store synchronisation to take place we would expect to see a greater frequency of lower proportions of price changes in all three of the product groups. We would also expect to see a lower frequency of higher proportions of price changes. This coupled with the earlier observation of a very small amount of zero proportion price changes concludes that no within store synchronisation of prices has taken place. This is at odds with the literature. Lach and Tsiddon (1996) find plenty of evidence for within store synchronisation. In their data sets they observe that their two product groups have zero proportion price changes at 57.8% and 15.3% of the total frequency of proportions observed. Midrigan (2006) also finds within store synchronisation is observed in her data set. However that is using a different model. The differences in data could be reconciled by the size of data sets. My data set is much smaller and is only from one store. Both Lach and Tsiddon (1996) and Midrigan (2006) use data sets that obtain data from many different stores, it is possible that within store synchronisation is not evident in all the stores in their data sets and hence my results.

[9] probabilities of price change, unconditional probabilities, expected values, variance and statistical significance test results found in appendix 3

Positive and negative price changes

Table 5

	No. of Positive price changes	No of Negative price changes
Wine	128	126
Coffee	75	111
Chocolate	66	50

One final observation of my results is the number of small and large price changes in my data. I find that the number of positive to negative price changes is almost 50:50. This I did not expect to find as during the period the data set was collected, the Spanish inflation was falling from 7% to 6%. Although this is a drop it's still quite high. Lach and Tsiddon (1996) conclude that the existence of positive and negative price changes is due to relative two sided idiosyncratic shocks invoked to generate a stable distribution of the relative prices.[10]

[10] Tsiddon (1993) and Callebero and Engel (1991) present models based on two sided shocks

Conclusion

In this paper I have taken a data set of scanner price data for a Spanish supermarket and analysed it. In this analysis I have looked at the various evidence for the store being subject to menu costs and analysed whether the store is taking advantage of technological economies of scale by modelling the level of within store synchronisation.

I conclude that the store is able to overcome a standard constant menu cost, if it exists, by the magnitude of small price changes and the frequency of short time intervals between prices. However I have not found satisfactory evidence that the store uses technological economies of scale when setting its prices. Unlike in the literature, my analysis shows that there is no evidence of within store synchronisation in the three groups of products my data is ordered into. This is not to say that the store can't be using technological economies of scale when setting prices, it is obviously finding some way to overcome the cost of setting prices as it frequently changes them. Another explanation for this is that there is a time varying cost to changing price. This data set would appear to lend itself more to the state-dependant models of pricing than time-dependant models. The cost shock to induce a price change appears to change over time and is more likely to be endogenous than exogenous.

It would appear that the main shortcoming of this paper is the data itself. From the analysis it is clear that even thought it matches most of the literature, it has produced wide ranging results. The data set itself is too small as it only covers scanner price data for one store. To get a more complete picture, it would be much better to have data covering a wide range of stores. One store is not enough of a sample to be able to apply the results and analysis convincingly. Another problem with the data set is the lack of information, either on sales or whether there is more than one price change in a month etc. Time was also a factor. With more time it might have been possible to collect data to apply the model in Midrigan (2006). This would have meant collecting data on the labour market and investigating the decision making of the firm.

Looking further a field, possible extensions of the paper could be to investigate whether there is synchronisation between the product categories, see if there is any correlation in price changes. Even though this paper didn't prove within store synchronisation, other literature has. It might be possible to find synchronisation across product categories or, applying it the store itself, checking to see whether products in the aisle synchronise their price changes.

The above are further ways I would like to investigate price rigidity in multi product firms in the future.

Bibliography

Bils, M. and Klenow, P. (2004), “Some evidence on the importance of sticky prices”, NBER working paper 9069.

Caballero, R. and Engle, E. (1991), “Explaining Investment Dynamics in US Manufacturing: A generalised (S,s) approach”, Econometrica, 67(4): 783-826.

Caplin, A. and Spulber, D. (1987), “Menu Costs and the Neutrality of Money”, Quartely Journal of Economics, 102(4): 703-25

Dutta, S. Bergen, M. and Levy, D. (2002), “Price flexibility in channels of distribution: Evidence from Scanner Data,” Journal of Economic Dynamics and Control.

Golosov, M. and Lucas, R. (2004), “Menu Costs and the Phillips Curves”, NBER working paper 10187.

Kashyap, A. (1995), “Sticky Prices: New Evidence From Retail Catalogs”, Quartely Journal of Economics, Feburary, 245-274.

Klenow, P. and Kryvtsov, O. (2004), “State Dependant or Time Dependant Pricing: Does it Matter for Recent US inflation?”, mimeo.

Lach, S. and Tsiddon, D. (1996), “Staggering and Synchronisation in Price-Setting: Evidence from Multiproduct Firms”, American Economic Review, 86(5): 1175-1196.

Lach, S. and Tsiddon, D. (2005), “Small Price Changes and Menu Costs”, mimeo

Mankiw (1985), "Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly", Quarterly Journal of Economics 100 (2), pp. 529-37.

Midrigan, V. (2006), “Menu Costs. Multi-Product Firms, and Aggregate Fluctuations”, Job market paper, Ohio State Uiversity, Jan.

Tsiddon, D. (1993), “The (Mis) Behaviour of the Aggregate Price Level”, Review of Economic Studies, Dec.

Appendix 1

Products in Group Coffee

CAFE S. F. INSTANTANEO 200 G
CAFE S. F. SUP.MOLIDO 250 GR
NESCAFE DESCAFEINADO 200 GRS
CAFE S. F. INSTANTANEO 100 G
CAFE BONKA SUPER.GRANO 250 G
NESCAFE DESCAF.SOBRES 10X2 G
CAFE BONKA SUPER.MOLIDO 250
CAFE FORTALEZA SUP.GRANO 250
CAFE S. F. DESCAFEINADO 200G
CAFE BAQUE MEZCLA MOLIDO 250
CAFE FORTALEZA DES.GRANO 250
CAFE FORTALEZA SOBRE DESCAF.
CAFE BAQUE DESCAF MLDO 250
NESCAFE DESCAFEINADO 100 GRS
CAFE S. F. DESCAFEINADO 100G
CAFE BAQUE SUPER.GRANO 250 G
CAFE BAQUE G.SABOR MLDO. 250
CAFE S. F. SUP. GRANO 250 GR
NESCAFE INSTANTANEO 100 GRS
CAFE FORTALEZA SUP.MLDO. 250
NESCAFE INSTANTANEO 200 GRS
CAFE FORTALEZA TORREFACT.250

Products in Group Chocolate

CHOC.ZAHOR FAMILIAR 200 GRS.
CHOC.LINDT CHOCOLE-AVELL.100
CHOC.S.F. LECHE Y ALMENDRA
CHOC.VALOR TAZA 300 GRS.
CHOC. NESTLE DOLKA LECHE 150
CHOC.VALOR LECHE 300 GRS.
CHOC.NESTLE LECHE 150 R3406
CHOC.LINDT LECHE EXTRAF. 125
CHOC.ZAHOR BLANCO 75 GRS.
CHOC.LINDT CHOCLET.PRALI.100
CHOC.VALOR PURO 300 GRS.
CHOC.NESTLE ALMEND.150 R3431
CHOC.VALOR ALMENDRA 250 GRS.
CHOC.LINDT ALMENDRA 125 GRS.
CHOC.VALOR INTERNACIONAL 200
CHOC.S.F. BLANCO 75 GRAMOS
CACAO NESTLE 500 GRAMOS
CHOC.LINDT PISTACHO 100 GRS.

Appendix 1

Products in Group Wine

VINO SE¥. SARRIA ROSADO 3/4
VINO DON SIMON TINTO BRICK L
VINO DON SIMON ROSADO BRIK L
VINO S.F. ROSADO 2§ A¥O 3/4
VINO AGE SIGLO SACO TINTO 85
VINO CAMPO VIEJO TINTO 1982
VINO ELEGIDO TINTO LITRO
VINO OLARRA OTO¥AL 87 ROSADO
VINO MORILES MORENO 3/4
VINO LOS MOLINOS TINTO 3/4
VINO PINORD BLANCO SUAVE 3/4
VINO PINORD ROSADO 3/4
VINO C.V.N.E 3 A¥O
VINO CVNE MONOPOL 3/4
VINO CAMPO VIEJO ROSADO 3/4
VINO AGE SIGLO TINTO 3/4
VINO FAUSTINO VII TINTO
VINO LOS MOLINOS ROSADO 3/4
VINO PATERN TINTO AZUL 3/4
VINO COSECHERO CLARETE 3/4
VINO ELEGIDO ROSADO LITRO
VINO CARTA PLATA ROSADO 3/4
VINO VI¥A POMAL TINTO 3/4 85
VINO CASTILLO OLITE ROSADO
VINO S.F. TINTO 2§ A¥O 3/4
VINO CASTILLO OLITE TINTO
VINO S.F. COSECHERO ROSADO
VINO COSECHERO TINTO 3/4
VINO S.F. COSECHERO TINTO
VINO PE¥ASCAL ROSADO 3/4
VINO CAMPO VIEJO TINTO 3/4
VINO CAMPO VIEJO BLANCO 3/4
VINO FAUSTINO VII ROSADO

Appendix 2

Proportion of price changes for each month

	Proportion of price changes for each month		
Month	Wine	Coffee	Chocolate
2	0.060606061	0.093663912	0.333333333
3	0.090909091	0.140495868	0.444444444
4	0.121212121	0.187327824	0.277777778
5	0.151515152	0.23415978	0.388888889
6	0.181818182	0.280991736	0.166666667
7	0.212121212	0.327823691	0.166666667
8	0.242424242	0.374655647	0.111111111
9	0.272727273	0.421487603	0.388888889
10	0.303030303	0.468319559	0.388888889
11	0.333333333	0.515151515	0.166666667
12	0.363636364	0.561983471	0.333333333
13	0.393939394	0.608815427	0.333333333
14	0.424242424	0.655647383	0.055555556
15	0.454545455	0.702479339	0.222222222
16	0.484848485	0.749311295	0.277777778
17	0.515151515	0.796143251	0.277777778
18	0.545454545	0.842975207	0.222222222
19	0.575757576	0.889807163	0.055555556
20	0.606060606	0.936639118	0.277777778
21	0.636363636	0.983471074	0.222222222
22	0.666666667	0	0.277777778
23	0.696969697	1.077134986	0.111111111
24	0.727272727	1.123966942	0.166666667
25	0.757575758	1.170798898	0
26	0.787878788	1.217630854	0.277777778
27	0.818181818	1.26446281	0.166666667
28	0.848484848	1.311294766	0.166666667
29	0.878787879	1.358126722	0.166666667

Appendix 3

Probabilities of price changes

wines			Coffee			Chocolate		
month	Pj(0)	Pj(1)	month	Pj(0)	Pj(1)	month	Pj(0)	Pj(1)
2	0.36	0	2	0.21	0	2	0.18	0
3	0.15	0.12	3	0.09	0	3	0.12	0.12
4	0.24	0	4	0.12	0	4	0.09	0.06
5	0.18	0.09	5	0.18	0	5	0.09	0.12
6	0.03	0	6	0.18	0	6	0.09	0
7	0.36	0	7	0.24	0.09	7	0.09	0
8	0.03	0	8	0.12	0.24	8	0.03	0.03
9	0.12	0	9	0.09	0.12	9	0.18	0.03
10	0.12	0	10	0.15	0.12	10	0.18	0.03
11	0.12	0.03	11	0.06	0.09	11	0.06	0.03
12	0.27	0.09	12	0.21	0	12	0.06	0.03
13	0.09	0.18	13	0.27	0.27	13	0.15	0.03
14	0.09	0.12	14	0.06	0.18	14	0.03	0
15	0.24	0	15	0.03	0.09	15	0.12	0
16	0.24	0.12	16	0.15	0.06	16	0.15	0
17	0.39	0.3	17	0.18	0.12	17	0.12	0.03
18	0.12	0	18	0.09	0.06	18	0.06	0.06
19	0.21	0.12	19	0.09	0.09	19	0.03	0
20	0.27	0.15	20	0.12	0.06	20	0.15	0
21	0.09	0.21	21	0.09	0.03	21	0.09	0.03
22	0.12	0.09	22	0.09	0.09	22	0.15	0
23	0.36	0.03	23	0.24	0.03	23	0.06	0
24	0.21	0.18	24	0.06	0.09	24	0.06	0.03
25	0.12	0.06	25	0.06	0.09	25	0	0
26	0.18	0	26	0.15	0	26	0.15	0
27	0.18	0.09	27	0.18	0	27	0.09	0
28	0.33	0.15	28	0.15	0	28	0.09	0
29	0.06	0.15	29	0	0	29	0.06	0.03

Appendix 3

Unconditional probabilities

Wine		Coffee		Chocolate	
month	π_j	month	π_j	month	π_j
2	0.26	2	0.17	2	0.15
3	0.15	3	0.08	3	0.12
4	0.19	4	0.11	4	0.09
5	0.17	5	0.15	5	0.09
6	0.03	6	0.15	6	0.08
7	0.26	7	0.21	7	0.08
8	0.03	8	0.14	8	0.03
9	0.11	9	0.09	9	0.16
10	0.11	10	0.15	10	0.16
11	0.11	11	0.06	11	0.06
12	0.23	12	0.17	12	0.06
13	0.1	13	0.27	13	0.13
14	0.09	14	0.07	14	0.03
15	0.19	15	0.03	15	0.11
16	0.21	16	0.14	16	0.13
17	0.36	17	0.17	17	0.11
18	0.11	18	0.09	18	0.06
19	0.19	19	0.09	19	0.03
20	0.24	20	0.11	20	0.13
21	0.11	21	0.08	21	0.08
22	0.12	22	0.09	22	0.13
23	0.27	23	0.2	23	0.06
24	0.2	24	0.06	24	0.06
25	0.11	25	0.06	25	0
26	0.15	26	0.13	26	0.13
27	0.17	27	0.15	27	0.08
28	0.28	28	0.13	28	0.08
29	0.07	29	0	29	0.06

Appendix 3

Expected values and statistical analysis

Wine				
month	Expected	variance	Z-value	sig 0.05%
2	0.26	0.0058	7.77	yes
3	0.15	0.0039	11.03	yes
4	0.19	0.0047	4.18	yes
5	0.17	0.0047	5.86	yes
6	0.03	0.0009	0.05	yes
7	0.26	0.0058	7.54	yes
8	0.03	0.0009	0.05	no
9	0.11	0.003	1.17	no
10	0.11	0.003	7.53	yes
11	0.11	0.003	4.19	yes
12	0.23	0.0054	10.16	yes
13	0.1	0.0027	18.8	yes
14	0.09	0.0025	13.8	yes
15	0.19	0.0047	4.19	yes
16	0.21	0.005	3.85	yes
17	0.36	0.007	22.65	yes
18	0.11	0.003	1.04	no
19	0.19	0.0047	11.73	yes
20	0.24	0.0055	13.9	yes
21	0.11	0.003	19.9	yes
22	0.12	0.0032	9.13	yes
23	0.27	0.006	8.89	yes
24	0.2	0.0048	15.8	yes
25	0.11	0.003	7.34	yes
26	0.15	0.0039	2.76	yes
27	0.17	0.0043	8.76	yes
28	0.28	0.0061	14.7	yes
29	0.07	0.0197	3.27	yes

Appendix 3

Expected values and statistical analysis

Coffee				
month	Expected	variance	Z-value	sig 0.05%
2	0.17	0.0064	8.2	yes
3	0.08	0.0033	4.08	yes
4	0.11	0.0044	4.95	yes
5	0.15	0.0058	7.39	yes
6	0.15	0.0058	7.39	yes
7	0.21	0.0075	15.7	yes
8	0.14	0.0055	25.3	yes
9	0.09	0.0037	16.9	yes
10	0.15	0.0058	15.4	yes
11	0.06	0.0026	14.7	yes
12	0.17	0.0064	8.2	yes
13	0.27	0.0077	28.9	yes
14	0.07	0.003	24.8	yes
15	0.03	0.0013	19.5	yes
16	0.14	0.0055	10.8	yes
17	0.17	0.0064	16.4	yes
18	0.09	0.0037	10	yes
19	0.09	0.0037	13.9	yes
20	0.11	0.0044	11.3	yes
21	0.08	0.0033	8.16	yes
22	0.09	0.0037	13.9	yes
23	0.2	0.0073	11	yes
24	0.06	0.0026	14.7	yes
25	0.06	0.0026	14.7	yes
26	0.13	0.0051	5.9	yes
27	0.15	0.0058	7.4	yes
28	0.13	0.0051	5.9	yes
29	0	0	0	n/a

Appendix 3

Expected values and statistical analysis

Chocolate				
month	Expected	variance	Z-value	sig 0.05%
2	0.15	0.0071	9.1	yes
3	0.12	0.0059	17.7	yes
4	0.09	0.0041	11.9	yes
5	0.09	0.0041	19.2	yes
6	0.08	0.0041	5.3	yes
7	0.08	0.0041	5.3	yes
8	0.03	0.0016	8.5	yes
9	0.16	0.0075	10.8	yes
10	0.16	0.0075	10.8	yes
11	0.06	0.0031	7.6	yes
12	0.06	0.0031	20.6	yes
13	0.13	0.0063	10.7	yes
14	0.03	0.0016	2.12	yes
15	0.11	0.0054	6.4	yes
16	0.13	0.0063	7.5	yes
17	0.11	0.0054	9.2	yes
18	0.06	0.0031	12.1	yes
19	0.03	0.0016	2.12	yes
20	0.13	0.0063	7.5	yes
21	0.08	0.0041	9.27	yes
22	0.13	0.0063	7.5	yes
23	0.06	0.0031	3.8	yes
24	0.06	0.0031	7.6	yes
25	0	0	0	n/a
26	0.13	0.0063	7.5	yes
27	0.08	0.0041	5.3	yes
28	0.08	0.0041	5.3	yes
29	0.06	0.0031	9.5	yes