Does Merger Simulation Work? Evidence from the Swedish Analgesics Market

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Abstract

We analyze a large merger in the Swedish market for analgesics (painkillers). We confront the predictions from a merger simulation study, initiated during the investigation, with the actual merger effects over a two-year comparison window. The merger simulation model predicted a large price increase by the merging firms of up to 34%, because there is strong market segmentation and the merging firms are the only competitors in the largest segment. The actual price increase after the merger is of a similar order of magnitude, but even larger: +42% in absolute terms and +35% relative to the non-merging rivals. These findings are supportive of merger simulation, but a closer look at a wider range of merger predictions leads to more nuanced conclusions. First, both merging firms raised their prices by a similar percentage, while the simulation model predicted a larger price increase for the smaller firm. Second, one of the outsider firms also raised price by a fairly large amount after the merger, while the model predicted only a very small price increase of the outsiders. This in turn implied a lower than predicted market share drop for the merging firms.

Keywords: merger simulation, ex post merger evaluation, constant expenditures nested logit, analgesics or painkillers

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1 Introduction

There is an ongoing debate on the usefulness of structural econometric models to predict counterfactual outcomes. Angrist and Pischke (2010) document the recent successes of "design-based" or "treatment effects" approaches in various fields, such as labor and development economics. They suggest that industrial organization would also greatly benefit from these approaches, taking empirical merger analysis as a test case example. At a minimum, they write, empirical evidence should be provided that structural econometric models can deliver reasonably accurate predictions. In a response, Nevo and Whinston (2010) acknowledge that the treatment effects approach may be useful to estimate the effects from mergers. But they also point out limitations, and discuss several circumstances where a structural model and merger simulation can be more useful. The most obvious instance arises when a competition authority has to evaluate the likely price effects of a proposed merger, and does not have information from closely comparable past mergers in the same or related markets. Both Angrist–Pischke and Nevo–Whinston agree that more retrospective merger analysis is clearly needed.

In this paper we provide such an analysis based on a large recent merger between AstraZeneca Tica (AZT) and GlaxoSmithKline (GSK) in the Swedish market for over-the-counter analgesics (painkillers). The merger raised competition concerns, since AZT and GSK were the only companies in the largest market segment, which is based on the active substance paracetamol (called acetaminophen in the U.S.). During the investigation, we conducted a merger simulation study for the Swedish competition authority. We estimated two variants of the nested logit model: the typical unit demand specification and an alternative constant expenditures specification, where price enters logarithmically instead of linearly and market shares are in values instead of volumes. The model predicted a substantial price increase in the paracetamol segment in the absence of efficiencies and new entry: +34% under Bertrand competition and + 28% under partial coordination (before and after the merger). The competition authority nevertheless decided to clear the merger in April 2009. First, it still expected sufficient competition from the other two main segments (and it referred to our predictions, which did not rule out negligible price effects under sufficiently large cost savings). Second, it was optimistic that the coming deregulation of the pharmacy monopoly would encourage new entry and competition.

A few years after the merger we are able to perform an ex post merger analysis. We confront the predicted price effects, using the simulation methodology as developed during the investigation, with the actual price effects under a two-year comparison window. We obtain striking findings. The merging firms' actual price increase is of a similar order of magnitude, but in fact even somewhat larger than the price increase predicted by the model: +42% in absolute terms, or +35% relative to the competing firms who raised prices by a much smaller amount. This price increase materialized almost immediately, just one month after the merger, and remained for the entire two-year window after the merger.

These results are supportive of the merger simulation approach in competition policy, and for the usefulness of structural models more generally. However, more nuanced conclusions are warranted after examining a wider range of merger predictions than simply the average price effect of the merging firms. First, our model predicts that the smaller firm in the merger, GSK, would raise its prices by much more than the larger firm, AZT, while in reality the two companies raised their prices by approximately the same percentage. Second, our model predicts that the outsiders raise price by only a small amount after the merger (under Bertrand behavior), while in reality one of the outsiders responded with a fairly large price increase. This in turn implies a market share drop instead of a predicted market share increase for this outsider, and a smaller than predicted market share drop for the merging firms. We discuss possible reasons for the divergence between the predicted and actual effects, i.e. the possibility that other things did not remain constant after the merger or that the model specification can be improved. It was possible to test these rich merger predictions, thanks to the unusually large size of the considered merger (where the two merging firms are the only competitors in a segment with limited substitution from other segments).

Our paper contributes to three related strands in the literature: merger simulation, ex post merger evaluation and especially to ex post evaluation of merger simulation.

Merger simulation Merger simulation as a tool for competition policy was introduced by Hausman, Leonard and Zona (1994) and Werden and Froeb (1994). Subsequent research has looked at a variety of issues, such as alternative demand models, e.g. Nevo (2000), Epstein and Rubinfeld (2001) or Ivaldi and Verboven (2005). Some of this work has explicitly compared different demand models and showed how different functional forms may result in rather different price predictions, see Crooke, Froeb, Tschantz and Werden (2003), Huang, Rojas and Bass (2008) and Slade (2009). While these comparisons are informative, it is difficult to disentangle the sources of the differences since the compared models differ in many respects. In contrast, we compare different specifications in a unified demand framework, the nested logit model. As an alternative to the typical unit demand model, we propose the constant expenditures demand model. This enables us to concentrate on the role of the functional form of the price variable, while abstracting from other sources of specification differences (such as more flexible substitution patterns for the cross-price elasticities).

Quite surprisingly, the constant expenditures nested logit model has not been used before in empirical work, although it is equally tractable as the unit demand model. It can also be easily integrated in Berry, Levinsohn and Pakes' (1995) random coefficients logit model. Only three simple modifications of the typical unit demand set-up are required: (i) price enters logarithmically instead of linearly, (ii) market shares are expressed in values instead of volumes, and (iii) the potential market size refers to the potential aggregate expenditures (in values) instead of the potential number of consumers or households. Apart from the additional flexibility from a new functional form for the price variable, the constant expenditures specification has a particular feature that may also be relevant in other applications: the pattern of price elasticities across models is quasi-independent of price, instead of quasi-linearly increasing in price as in logit, nested logit and random coefficients logit models with unit demand.

Our simulation model also provides greater flexibility on the supply side. We do not only allow for a standard multi-product Bertrand Nash model. We also allow for the possibility that firms partially coordinate, already before the merger. We introduce a partial coordination parameter, the weight that firms give on their competitors' profits when setting prices. This enables one to better calibrate the premerger marginal costs if reliable outside information on cost is available.

Ex post merger evaluation Ex post merger analysis has moved in parallel with merger simulation, and mainly aimed to evaluate the relevance or effectiveness of competition policy towards mergers. Early work focused on mergers in major industries, such as airline markets (Borenstein, 1990; Kim and Singal, 1993), banking (Facacelli and Panetta, 2003), petroleum (Hastings, 2004; Gilbert and Hastings, 2005; Hosken, Silvia and Taylor, 2011) and appliances (Ashenfelter, Hosken and Weinberg, 2013). Ashenfelter and Hosken (2008) take advantage of scanner data to assess mergers in five different branded goods industries. They find moderate but significant price effects in the range of 3–7%. Among other things, they argue that their estimates may be viewed as a lower bound on price increases that would have occurred for other mergers that were blocked.

Ex post evaluation of merger simulation There is only a small recent literature that combines both traditions to compare the predictions from mergers simulations with the actual merger effects. Peters (2006) looks at the simulated and actual price increases by the merging firms' in several airline mergers. Weinberg (2011) and Weinberg and Hosken (2012) look at the price increases of both the merging firms and their competing rivals. Friberg and Romahn (2012) look at price effects after a merger with divestiture. These papers find that the qualitative predictions of merger simulations are broadly in line with the data, but the quantitative predictions show some divergence. Relative to this interesting earlier work, we make three related important contributions. First, we evaluate the performance of merger simulations based on a merger simulation framework that had already been specified during the investigation, i.e. before the merger had been consummated. Second, we consider a large merger in a concentrated market. This results in large price predictions, which enables us to make quite sharp comparisons, even if other things have changed after the merger. Third, we consider more demanding tests for the merger simulation methodology, since we assess a broader set of merger predictions: we distinguish between the price predictions for each of the merging firms and their competitors, and we also consider the implied market share predictions. More broadly speaking, testing a broader set of predictions is of interest beyond evaluating the performance of merger simulations. It sheds light on the relevance of policy counterfactuals in a variety of other oligopoly settings with differentiated products (such as environmental policies, trade policies, taxation, etc).

The paper is organized as follows. Section 2 discusses the industry background, including the merger decision and the dataset. Section 3 develops the framework for merger simulation, as developed during the investigation. Section 4 discusses the empirical results for the demand model and merger simulations. Section 5 provides the ex post analysis. We first present additional predictions from the merger simulations, not presented during the case but based on the same methodology. Next we confront these predictions with what actually happened in terms of prices and market shares of the merging firms and their competitors.

2 The market, the merger and its effects

In April 2009, the Swedish competition authority cleared the acquisition of AstraZeneca Tika (AZT) by GlaxoSmithKline (GSK). In this section we provide the relevant industry background, the data, the merger and its effects. These facts will motivate our analysis in the next sections, where we will evaluate the performance of merger simulation and the empirical relevance of various assumptions.

2.1 The market for OTC painkillers

Substances and forms Over-the-counter analgesics or painkillers are non-prescription drugs to treat pain and fever. Painkillers come in three main active substances: paracetamol (called acetaminophen in the U.S.), ibuprofen and acetylsalicylic acid (ASA or aspirin). There are also two less important active substances: diclofenak and naproxen. The active substances may differ in the types of pains they relieve and in their side effects. Paracetamol treats most pains and fevers, and is known for having little side effects (except that it may damage the liver). Ibuprofen also treats most pains and fevers and is often used to reduce inflammations, but it may have side effects on the stomach. The ASA substance also has a blood-diluting effect, which has both advantages and disadvantages. Each active substance may therefore relieve pain and reduce fever in different ways and with different side effects.

Painkillers also come in various administrative forms. Tablets are the most important form, followed by fizzy tablets. There are also some other forms (such as liquid, suppository and powder), but these are much less important. Table 1 shows the market shares of the three main substances and the two main administrative forms, according to the total value of sales in 2008.[1] With a market share of 42%, paracetamol is by far the most important substance. Ibuprofen and ASA each have a comparable market share of 29%. Paracetamol and Ibuprofen are mainly sold as tablets, whereas ASA is dominantly sold as fizzy tablets.

Table 1: Market shares in 2008, by form and active substance

Form	Paracetamol	Ibuprofen	ASA	Total
Tablet	36.1	29.0	2.6	67.7
Fizzy tablet	6.0		26.3	32.3
Total	42.1	29.0	28.9	100

Note: This table shows the market shares of the main administrative forms and active substances, according to the total value of sales in 2008. Paracetamol is known as acetaminophen in the U.S.

Firms and brands All companies specialize in one or at most two active substances. They typically sell one main brand per active substance, and sometimes an additional smaller brand. Table 2 shows the 2008 market shares of the companies and their brands, broken down by active substance. This shows that the two mering companies AZT and GSK are the only companies in the paracetamol segment: AZT sells Alvedon as its main brand and Reliv as a smaller brand, whereas GSK sells the popular brand Panodil. McNeil (selling Ipren) and Nycomed (selling Ibumetin) are the main companies in the Ibuprofen segment. McNeil (selling Treo) is by far the largest company in the ASA segment. There are two other companies with much smaller market shares: Meda and Bayer.

While consumers may base their purchasing decision on the active substance and its associated medical effects, their perceptions regarding the companies' brands may also be

[1]Taken together, these three substances and two forms account for 90% of the market.

important. This is evident from the large amount of advertising in the sector. So it is ultimately an empirical question to which extent brands with different active substances are substitutes.

Distribution Until the deregulation of 2009, the companies distributed all their drugs through the state-owned pharmacy monopoly, Apoteket AB. In 2008 Apoteket operated 850 community pharmacies, 76 hospital pharmacies and 30 shops for over-the-counter and health care services. The pharmaceutical companies determined the wholesale prices, but indirectly also the retail prices, since Apoteket applied a fixed percentage markup on the wholesale prices. After a market investigation, the Swedish government decided to deregulate the distribution of pharmaceutical products in 2009. Several state pharmacies were sold to private companies, and non-pharmacy retail outlets became entitled to sell non-prescription drugs. The reforms also gave more freedom to the pharmacies in various respects. For example, there were no longer obligations to sell all available products in a non-discriminatory fashion, and it became possible to set different retail prices across the country. The government expected that the deregulation of the distribution system would increase competition and encourage entry of new products.

2.2 The merger

GSK notified its planned acquisition of AZT on December 22, 2008. Although the merging firms were the only competitors in the paracetamol segment, the Swedish competition authority formally cleared the merger on April 3, 2009.[2] The competition authority justified its Decision on the grounds that consumers base their decisions more on the brand than on the active substance. Furthermore, and probably more importantly, the competition authority stated that it expected increased competition because of the coming deregulation of the state-owned pharmacy monopoly. This view is well summarized in the competition authority's 2009 Annual Report:[3]

> "GSK and AZT were the only companies providing over-the-counter (OTC) pharmaceuticals on the Swedish market that included the active substance "paracetamol", i.e. Alvedon, Reliv and Panodil. Much of the work associated with the investigation involved assessing the potential effects of the pending deregulation of the pharmacy

[2] The justification of the Decision was very short, see p. 5-6 on http://www.kkv.se/upload/Filer/Konkurrens/2009/Beslut/beslut_08_0706_2008.pdf (in Swedish).

[3] See http://www.kkv.se/t/Page____5925.aspx.

Table 2: Market shares in 2008, by brand and active substance

Firm	Brand	Paracet.	Ibupr.	ASA	Total
AZT	Alvedon	29.3			31.5
	Reliv	2.2			
GSK	Panodil	10.6			10.6
McNeil	Ipren		19.1		44.7
	Treo			22.5	
	Magnecyl			3.1	
Nycomed	Ibumetin		9.2		9.2
Meda	Alindrin		0.7		3.6
	Albyl			0.2	
	Bamyl			2.7	
Bayer	Aspirin			0.4	0.4
	Alka-seltzer			0.0	
Total		42.1	29.0	28.9	100

Note: This table shows the market shares of the main firms and brands and active substances, according to the total value of sales in 2008. Paracetamol is known as acetaminophen in the U.S.

market. Deregulation would mean that players other than Apoteket would be able to provide OTC pharmaceuticals and at the same time pharmaceutical companies would no longer be able to determine prices for customers. Deregulation would also enable new pharmaceutical stakeholders to enter the Swedish self-care market with their brands; for example including the paracetamol substance. In this way, the buying power of pharmacies and retailers would improve, which could possibly result in improved price competition between the different products available in the self-care market. After conducting a special investigation, the Swedish Competition Authority found that GSK's acquisition of AZT would not manifestly impede effective competition and no action was taken regarding this concentration."

Check whether/how we want to talk about our merger simulation study at this stage. In its Decision, the competition authority described that it based its analysis on a large number of contacts in the industry. It also made a brief reference to the merger simulation study we had conducted for the competition authority during the investigation.[4] It wrote that the simulation study showed that mergers would not lead to significant price increases. As we discuss in detail below, our simulation study covered a wide range of scenario's, with and without efficiencies, and with and without partial coordination between companies. Our simulations only predicted insignificant price increases in one scenario with large efficiencies. Hence, the competition authority's reference to our simulation results may suggest it implicitly had in mind large efficiencies. An alternative possibility is that the competition authority put a large weight on the coming deregulation of the pharmacy monopoly and considered this sufficiently promising to create new competition and compensate for the increase in market power without deregulation.

2.3 Dataset

Our main dataset comes from the national distributor Apoteket AB and contains product-level sales information for Sweden, at a monthly frequency during the period 01/1995–05/2011. A product is defined as a brand, form, package size and dose. For example, one of AZT's products is Alvedon tablet, 30 pieces, 500 mg/piece. An observation for product j in month t contains information on the total sales value or revenue across all pharmacies in Sweden, r_{jt}, and the total sales volume, q_{jt}, from which we compute the price per unit $p_{jt} = r_{jt}/q_{jt}$. The sales dataset was combined with two other datasets: one on marketing expenditures by brand and month (collected by Sifo RM), and one on macro-economic variables (from Statistics Sweden), such as nominal and real GDP, the number of sick men and sick women (all monthly) and total population of men and women (yearly).[5]

Note that there is no unambiguous measure for the unit of consumption in the market for painkillers, and hence no obvious measure for the sales volume q_{jt} and the price per unit p_{jt} of each price. In particular, it is not appropriate to measure q_{jt} as the number of sold

[4] Since the merger was cleared very quickly after our report, the merging parties did not comment on the merger simulation study.

[5] The data set was collected in two stages. During the investigation, the Swedish competition authority collected the three datasets (sales, marketing and macro-economic variables) for the period 1995-2008. The competition authority collected the dataset for a general descriptive analysis, but in particular also to enable the simulation study we conducted during the investigation. Two years after the investigation, we updated the sales dataset for 01/2008–05/2011. Since this was delivered by a different entity after the deregulation (Apotekens Servicebolag AB instead of Apoteket AB), we again requested the information for the year 2008: this enabled us to verify whether the updated data was consistent with the initially obtained data, and this was indeed the case. We also updated some of the macro-economic variables, i.e. nominal and real GDP. We no longer collected information on the other variables, since they were only used for estimating the demand model, and we did not use this in our ex post analysis.

packages and p_{jt} as the price per sold package, since the products are sold in different package sizes (number of tablets) and in different doses (mg per tablet). We consider three different measures for the unit of consumption. The first measure is the "tablet" (or fizzy tablet). The second measure is the defined daily dose, or "ddd", as defined by the World Health organization. The third measure is the "normal dose", i.e. the number of doses used on a normal single consumption occasion. We thus have three measures of the sales volume q_{jt} and three corresponding measures of the price p_{jt}: price per tablet, price per ddd, and price per normal dose. These price measures correspond with the actual transaction price paid by every consumer, since Apoteket is required to set uniform prices across all its pharmacies in Sweden.

Table 3 presents summary statistics of the main variables over the pre-merger period 1995-2008. We focus on products from the three main active substances (paracetamol, ibuprofen and ASA) and the two main administrative forms (tablets and fizzy tablets). This covers about 90% of the total value of sales of analgesics. The total number of observations is 7,240, which amounts to an average of 43 products per month. Total sales value r_{jt} per product/month is on average 1.24 million SEK. The number of tablets is on average 1.11 million across products and months, so the average price per tablet is 1.1SEK. The average price per normal dose is slightly higher, 1.6 SEK, and the average price per defined daily dose (ddd) is 6.0 SEK. More importantly, these measures do not just differ through a scale factor: for example, the ratio of the means to the standard deviations suggest there is more variation in the price per ddd or normal dose than in the price per tablet. We will focus our discussion on the results from the first measure (price per tablet and number of sold tablets), but we also considered the other three measures and we report below where this gives different results.

2.4 The price and market share effects of the merger

We can now consider the price and market share effects following the merger. We use a two-year comparison window around the merger event of April 3, 2009, so we compare the periods April 2007–April 2009 and May 2009–May2011. It will be useful to summarize the results by segment, since the merging firms are the only firms in one of the segments (paracetamol) and these firms are not active at all in the other two segments (ibuprofen and ASA). We will also consider more detailed results by firm.

Price effects Figure 1 shows the price evolution during both periods for the three main segments: paracetamol, ibuprofen and ASA. The results are striking. In the paracetamol

Table 3: Summary statistics for the Swedish market for analgesics, 1995-2008

Variable	Mean	St. Dev.	Min.	Max.
revenue ($r_{jt} = p_{jt}q_{jt}$)	1.24	2.56	.00	22.95
number of tablets(q_{jt})	1.11	2.19	.00	16.61
number of defined daily doses (q_{jt})	.21	.43	.00	3.07
number of normal doses (q_{jt})	.77	1.57	.00	11.08
price per tablet (p_{jt})	1.06	.46	.27	2.55
price per defined daily dose (p_{jt})	6.02	2.21	1.74	15.50
price per normal dose(p_{jt})	1.61	.60	.43	3.88
marketing	564.1	1445.7	0	13536
sickwomen	822.9	197.0	391	1204
sickmen	524.5	108.0	254	763
GDPnom (in billions)	621.6	107.4	443.2	859.7
popwomen (in thousands)	4524.2	54.8	4471.4	4652.6
popmen (in thousands)	4437.4	72.5	4366.1	4603.7

Note: 7240 observations (products, years, months). Sales value or revenue (r_{jt}) is in 1 million SEK (including VAT), price per unit (p_{jt}) is in SEK, sales volume (q_{jt}) is in 1 million. 1€ = 10.8 SEK, 1$ = 8.0 SEK in December 2008.

segment, where the merging firms AST and GSK are the only competitors, average prices increase from about 1.5 SEK to 2 SEK, already one month after the merger. The price increase is especially striking since prices only show a small gradual increase two years prior to the merger (from SEK1.4 to SEK 1.5) and remained more or less constant after the sharp increase just after the merger. Only near the end of the period, there is a slight tendency of a price drop, perhaps associated with new entry threats following the deregulation.[6] In sharp contrast, in the ibuprofen segment prices remained stable after the merger, whereas in the ibuprofen segment they appear to increase by a modest amount (from 1.4 SEK to 1.55 SEK). This suggests that the sharp price increase by the merging firms was indeed due to the merger, and not due to a general cost or demand shock unrelated to the merger.

[6] In fact, despite the large increase in paracetamol prices, new entry only came late and remained surprisingly limited after the deregulation. One recent new entrant was Apofri, the private label of the former state monopoly Apoteket AB. One of the reasons for the slow entry of private labels relates to a legislation, which prohibits pharmacies to also be producers. For private labels, the question is then if packaging under the distributor's own brand constitutes producing drugs.

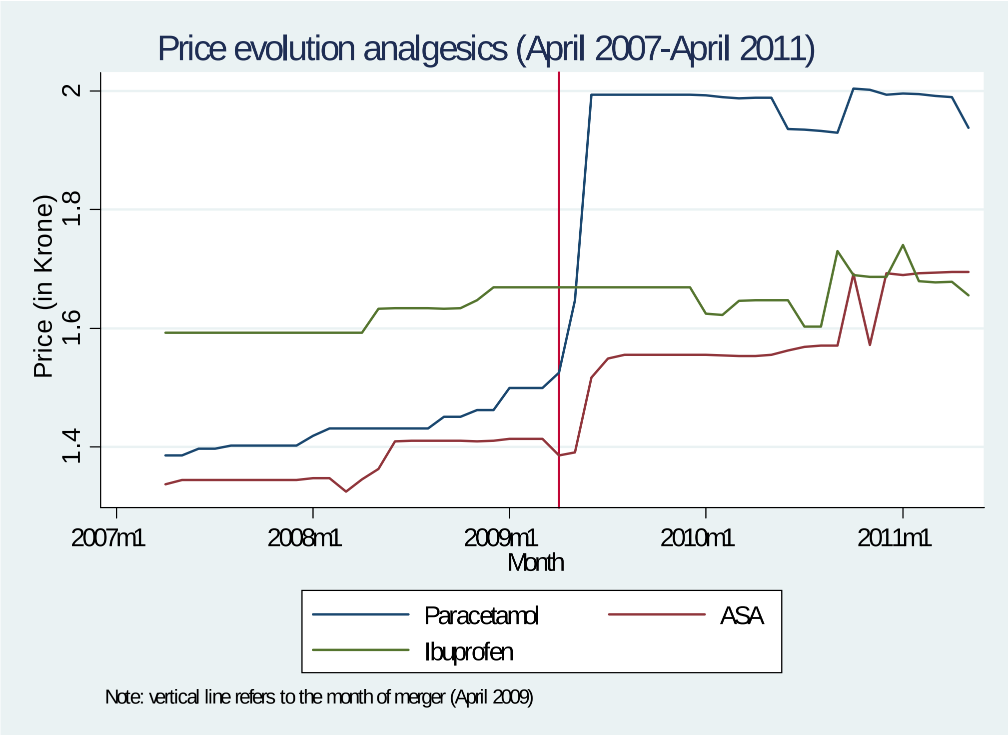

Figure 1: Price evolution analgesics (April 2007 - April 2011)

To gain further insights on this, we estimate the following regression, in line with Ashenfelter and Hosken (2008) and other recent work on ex post merger evaluation discussed in the introduction

$$\ln p_{it} = \alpha_i + \beta_i PostMerger_t + \varepsilon_{it}, \tag{1}$$

where p_{it} is the average price of "product group" i, and $PostMerger_t$ is a dummy variable equal to 1 after the merger event.[7] The literature sometimes assumes that the merger does not have an impact on the competitors' prices. If this assumption is satisfied, one can interpret this regression as a difference-in-difference estimator, where the difference between the merging firms' β_i and the competitors' β_i measures the merger price effect. In practice, it is possible that the merger raises the competitors' prices (under Bertrand competition, but especially if there is some coordination, as the merger simulations also predict). If this is the case, the difference between the merging firms' and the competitors' β_i's can be viewed as a lower bound for the merger price effect.

[7] Our specification is slightly more general than Ashenfelter and Hosken (2008) and other work. They typically constrain the same effect for the control group after the merger, whereas we allow different product groups i to have different price changes.

We define the product group i in the above regression at two levels: the substance and the substance×firm. Table 4 shows the results. According to the top left panel, the merger led to a log price increase of 0.351 in the paracetamol segment, implying an average price increase of the merged firms' products by 42%. At the same time, the merger left prices in the ibuprofen segment essentially unchanged (+0.1%). But the prices in the ASA segment increased by 0.10 (in logs) or 11%.

The bottom left shows the estimated price effects at the level of the substance×firm. The merging firms, who are the only ones in the paracetamol segment, raised their prices substantially and more or less proportionately: AZT by 0.356 (in logs) or 42.8% and GSK by a slightly larger amount of 0.379 or 46.1%. The competitors raised their prices by much lower amounts. In the Ibuprofen segment, price increases were very low: McNeil raised its pices by only 2.4% and Nycomed by only 1.2%, while Meda did not change its prices. In the ASA segment, firms raised prices by higher amounts: McNeil by 0.143 or 15.4%, Bayer by 0.103 or 10.8% and Meda by 0.068 or 7.0%.

Why did the large and sudden price increase by the merging firms not raise a significant amount of controversy in Sweden? In fact, the merged firm AZT-GSK implemented the price increase by reducing their package sizes from 30 to 20 tablets, while reducing prices per package by only a small amount, for example from 41.5 crowns to 38.5 crowns for one of their most selling products. The reduction in package size had been required by the Swedish medical products agency (Läkemedelsverket), because of concerns with a too wide availability of painkillers. The firms argued that the resulting increase in the price per tablet was warranted because of the increased costs with the reduced package size. However, it is rather implausible that this explains the entire price increase of 42%, because the companies in the ASA segment had also been required to lower their package sizes and they only raised prices by on average 11%. In our merger simulation analysis below, we will consider more systematically how reduced package size may have raised costs and to which extent this may have been responsible for the price rises. Before doing this, we first consider how the changes in market shares following the merger.

Market share effects Did the large price increase of the merging firms also affect market shares? Figure 2 shows the market share evolution (expressed in volumes), using the same comparison window as Figure 1. This shows that the market share of the merging firms' paracetamol segment suddenly dropped by a sizeable 5%, down from about 47% to about 42%. The market share of ibuprofen (where prices did not change) increased sharply, from about 27% to 32%. The market share of ASA (where prices moderately increased) remained more or less unchanged. It is less clear from Figure 2 whether these market share changes

Table 4: Actual price and market share effects, two year window

	Price effects		Market share effects	
	Estimate	Stand. err.	Estimate	Stand. err.
	Regressions at the level of the substance			
Constant	.303	.007	.467	.003
Ibuprofen	.171	.008	-.198	.003
ASA	.208	.008	-.202	.004
Paracetamol×merger	.351	.007	-.033	.003
Ibuprofen×merger	.001	.005	.050	.001
ASA×merger	.100	.004	-.017	.003
R^2	.969		.986	
	Regressions at the level of the firm × substance			
Constant	.304	.006	.344	.002
firm × substance fixed effects	yes		yes	
Paracetamol				
AZT×merger	.356	.006	-.036	.003
GSK×merger	.379	.009	.005	.002
Ibuprofen				
McNeil×merger	.024	.004	.026	.001
Meda×merger	-.000	.000	-.002	.001
Nycomed×merger	.012	.003	.006	.005
ASA				
McNeil×merger	.143	.006	-.026	.004
Meda×merger	.068	.048	.020	.002
Bayer×merger	.103	.008	.007	.001
R^2	.982		.993	

Note: This table shows actual price and market share effects, based on the regression model (1) for price and analogous model for market share. Robust standard errors are reported.

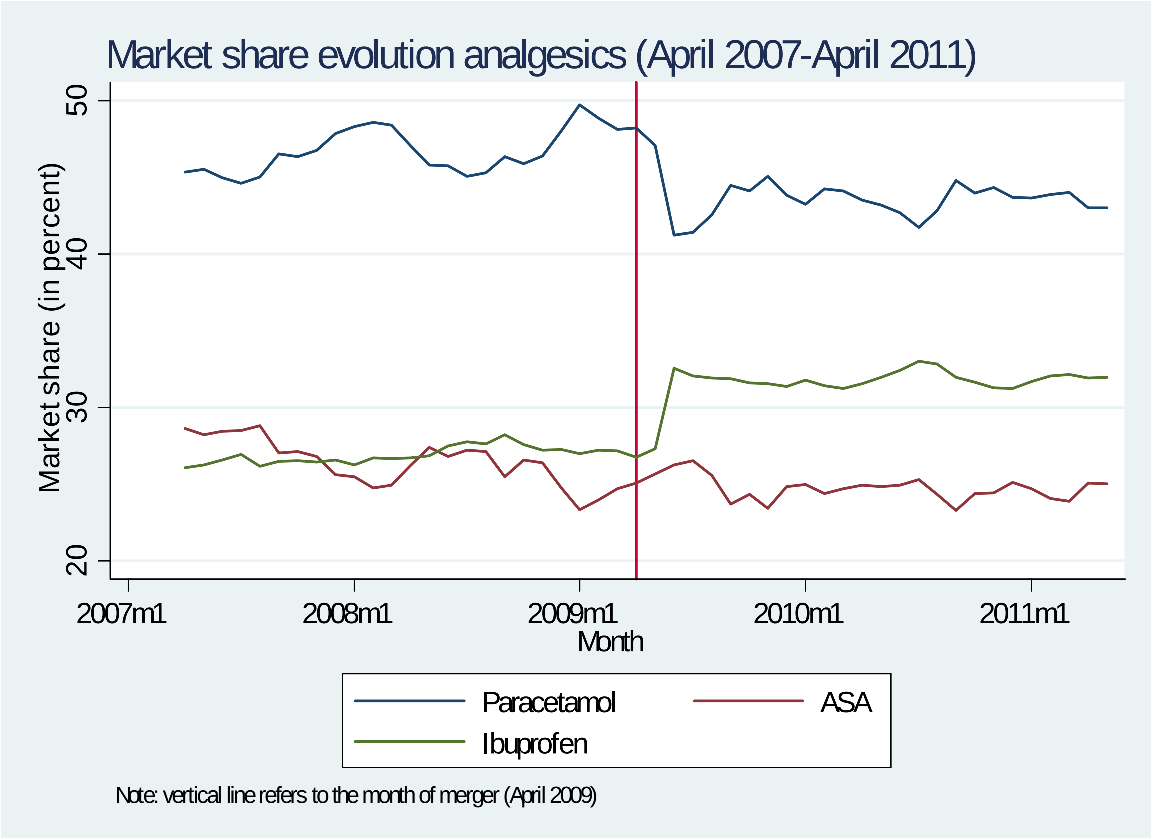

Figure 2: Market share evolution analgesics (April 2007 - April 2011)

were permanent, since they show some volatility over the sample. We therefore estimated a regression similar to (1), but with the log of price replaced by the market share as the dependent variable (again, in line with Ashenfelter and Hosken's (2008) ex post study).

The right panel of Table 4 shows the results. The market share of the merging firms' paracetamol segment dropped by a significant 3.3% over the considered period (95% confidence interval of 2.7%–3.9%). This loss was entirely in favor of the ibuprofen market share, which increased by a substantial 5.0%. The market share of ASA decreased by 1.7%, consistent with our earlier finding that ASA prices increased rather substantially after the merger (in contrast with ibuprofen prices).

Interesting additional findings obtain for the market shares at the level of the substance $\times$ firms (bottom right panel in Table 4). Despite the fact that prices increased slightly more for GSK than for AZT products, only AZT experienced a largest market share drop (by –5.6%); the market share of GSK remained more or less unchanged. In the ibuprofen segment, only McNeil experienced a market share increased (while Meda's market share remained unchanged). Finally, in the ASA segment, McNeil (-2.6%) lost market share to Meda (+2.0%), consistent with the earlier finding that McNeil raised its prices by a larger amount than Meda.

Summary The merger led to a large price increase by the merging firms in the paracetamol segment, and a corresponding market share drop (although this came entirely at the expense of the largest company, AZT, since GSK's market share remained unchanged). Prices of the competitors in the ASA segment also partly increased after the merger, but only McNeil experienced a corresponding market share drop. Finally, prices in the ibuprofen segment remained more or less unchanged, and market shares increased (mainly for McNeil).

In the next section we evaluate how well a merger simulation predicts these facts. We take into account that the merger coincided with another change: the package size reduction by the merging firms, as well as by the firms in the ASA segment, which may have altered the marginal costs and perceived qualities of these products.

3 Framework for merger simulation

We now present the framework for the merger simulation. We first motivate and discuss our adopted demand model, used to estimate the substitution patterns across products. We then present the model of oligopolistic price-setting behavior, used to uncover premerger marginal costs and to predict post-merger prices.

3.1 Demand model

To conduct the merger simulation, we develop an discrete choice model for the demand for painkillers. This approach starts from an individual utility specification and allows one to incorporate heterogeneous valuations for various product characteristics to obtain rich substitution patterns. While discrete choice models were initially developed for estimation with micro-level choice data, Berry (1994) and Berry, Levinsohn and Pakes (1995), henceforth BLP, show how such models can be estimated with aggregate sales data. Popular models include the logit, nested logit and the random coefficients logit model.

We focus our analysis on a two-level nested logit model, which allows for unobserved consumer heterogeneity in the valuation of two discrete product dimensions: the products' active substance (paracetamol, ibuprofen and ASA) and their administrative form (tablet of fizzy tablet). The nested logit model accounts for the possibility of market segmentation, by allowing cross-price elasticities to be greater between products that have the same active substance and/or form. Accounting for segmentation according to active substance is particularly relevant for the proposed merger, since the merging companies are the only ones active in the paracetamol segment. As a robustness check, we also consider BLP's random coefficients logit model, which in addition allows for unobserved heterogeneity in the valuation of continuous variables, such as the products' price or package size.

Although discrete choice models allow for potentially rich substitution patterns, they are in practice restrictive in the adopted functional form for the price variable. The aggregate discrete choice literature since Berry (1994) and Berry, Levinsohn and Pakes (1995) has adopted a utility specification where price enters linearly (or, more generally, enters additively with income). This specification has the property that consumers buy one unit of their preferred product. While this may be an appealing property for some commodities such as automobiles, it may be less realistic for many frequently purchased consumer items. More importantly, the linear price specification implies that the price elasticities of different products are quasi-linearly increasing in prices: if product A is twice as expensive as product B, it also tends to have a price elasticity that is twice as high. This property does not only hold in the logit and nested logit model; it is also present to some extent in the random coefficients logit model.

For example, in an interesting paper on the same industry, Chintagunta (2002) estimates a random coefficients logit model for five main (U.S.) painkiller brands.[8] Although he finds significant consumer heterogeneity in the valuation of price, the estimated own-price elasticities show an increasing relationship with prices across products.[9] This pattern is not unrealistic per se, but it does follow from the linear price specification. In our application, we were particularly concerned with the linear price specification because, unlike Chintagunta (2002), we have many brands and, as shown in Table 3, prices vary by a factor of more than nine (compared with a factor of only two in Chintagunta, 2002).

We therefore consider an alternative possible utility specification, where price (as well as income) enters logartithmically instead of linearly. We build on the work of Hanemann (1984), who proposed a framework to model discrete-continuous choices, and showed how to estimate such models with micro-level choice data.[10] In our specification, consumers do

[8]To our knowledge, there are no other papers estimating discrete choice models for painkillers at the brand level. Chevalier, Kashyap and Rossi (2001) estimate a log-log demand model at the category level, and obtain an estimated price elasticity for the painkiller category equal to -1.87.

[9]Tables 2 and 5 in Chintagunta (2002) show the following relationship between own-price elasticities and average prices: Advil -2.996 vs. 7.41; Tylenol, -2.69 vs. 6.16; Motrin -2.66 vs. 5.95; Bayer -2.25 vs. 4.95; Store -1.81 vs. 3.55. This pattern is also present in other logit or random coefficients logit applications.

[10]Hendel (1999) and Dubé (2004) estimate multiple-discrete choice models with micro-level data, where consumers can buy multiple units as well as multiple products.

not buy one unit of their preferred product (perfectly inelastic conditional demand), but rather a constant expenditure (unit elastic conditional demand). We show how this leads to a natural extension of the aggregate discrete choice demand models of Berry (1994) and BLP, with three differences: price enters logarithmically instead of linearly, market shares are measured in values instead of volumes, and the potential market refers to the potential aggregate budget instead of the potential number of consumers. The implied own- and cross-price elasticities are quasi-constant in price, instead of quasi-linearly increasing in price as in the unit demand model. To our knowledge, no other work has departed from the unit demand model in discrete choice models with aggregate sales data.

In the discussion below, we compare the unit demand and the constant expenditure specification in an aggregate nested logit model. In the Appendix, we show how this extends to a random coefficients logit model.

Utility There are L consumers, $i = 1, \ldots, L$. Each consumer chooses one out of $J + 1$ differentiated products, $j = 0, \ldots, J$; good 0 is the outside good or no-purchase alternative. Suppose consumer i has the following conditional indirect utility for good $j = 0, \ldots, J$:

$$u_{ij} = x_j\beta + \xi_j + \alpha f(y_i, p_j) + \varepsilon_{ij}, \tag{2}$$

where x_j is a vector of observed product characteristics of product j, p_j is price, ξ_j captures unobserved product characteristics, y_i is income of individual i, β and α are utility parameters, and ε_{ij} is a random utility term or an individual-specific taste parameter for good j.

Conditional on buying product j, a consumer i's demand for product j follows from Roy's identity, $d_j(y_i) = -(\partial f/\partial p_j)/(\partial f/\partial y_i)$. We consider the following two specifications for $f(y_i, p_j)$:

$$\begin{array}{lrcll} \text{Unit demand} & f(y_i, p_j) & = & y_i - p_j & \Rightarrow \quad d_j(y_i) = 1 \\ \text{Constant expenditures} & f(y_i, p_j) & = & \gamma^{-1} \ln y_i - \ln p_j & \Rightarrow \quad d_j(y_i) = \gamma \frac{y_i}{p_j} \end{array} \tag{3}$$

Conditional on choosing j, an individual buys one unit in the first specification, and spends a constant fraction of her budget, γ, in the second specification. The first specification is typically adopted in aggregate discrete choice models (sometimes under a variant such as BLP's Cobb Douglas $f(y_i, p_j) = \ln(y_i - p_j)$, which also implies unit demand). The second specification is a special case of Hanemann's framework for micro-level discrete choice models, and we will show here how it can be incorporated in an aggregate discrete choice framework.

For the two specifications (3), we can write utility (2) more compactly as follows

$$u_{ij} = K_i + \delta_j + \varepsilon_{ij}, \tag{4}$$

where in the unit demand specification $K_i = \alpha_i y_i$ and $\delta_j \equiv x_j\beta - \alpha p_j + \xi_j$; and in the constant expenditures specification, $K_i = \alpha_i \gamma^{-1} \ln y_i$, and $\delta_j \equiv x_j\beta - \alpha \ln p_j + \xi_j$. Intuitively, one can interpret δ_j as the mean utility component of product j. In both specifications, we normalize the mean utility of the outside good to zero, $\delta_0 = 0$.

Choice probabilities Each consumer i chooses the product j that maximizes her random utility u_{ij}. Assume that the random utility terms follow the extreme value distributional assumptions of a two-level nested logit model. Partition the set of products into G groups, $g = 0, \ldots, G$ (where group 0 consists of the outside good 0) and further partition each group g into H_g subgroups, $h = 1, \ldots, H_g$. Each subgroup h of group g contains J_{hg} products, so that $\sum_{g=1}^{G} \sum_{h=1}^{H_g} J_{hg} = J$.

Given random utility maximization, the probability that a consumer i chooses product $j = 1, \ldots, J$ takes the following well-known form:

$$s_j = s_j(\boldsymbol{\delta}, \sigma) \equiv \frac{\exp(\delta_j/(1-\sigma_1))}{\exp(I_{hg}/(1-\sigma_1))} \frac{\exp(I_{hg}/(1-\sigma_2))}{\exp(I_g/(1-\sigma_2))} \frac{\exp(I_g)}{\exp(I)}, \tag{5}$$

where I_{hg}, I_g, and I, are the inclusive values or "log sum" formulas (see Appendix), $\boldsymbol{\delta}$ is a $J \times 1$ vector containing the mean utilities δ_j, and $\sigma = (\sigma_1, \sigma_2)$ are the nesting parameters associated with the nested logit distribution. Note that the separable terms K_i cancel out from the choice probabilities (5).

The nesting parameters capture the preference correlation across products of the same subgroup (σ_1) or group (σ_2), and should satisfy $1 \geq \sigma_1 \geq \sigma_2 \geq 0$ (McFadden, 1978). When σ_1 is high, preferences are strongly correlated across products of the same subgroup, and when σ_2 is high, preferences show additional correlation across products of the same group. If $\sigma_1 = \sigma_2 = 0$, the model reduces to a simple logit model, so that preferences are not correlated across products from the same subgroups or groups.

Aggregate and inverted aggregated demand Aggregate demand for a product j is the probability that a consumer buys that product, multiplied by the quantity purchased, $d_j(y_i)$, aggregated over all L consumers according to income distribution P_y:

$$\begin{aligned} q_j &= \int s_j(\boldsymbol{\delta}, \sigma)\, d_j(y)\, \mathrm{d}P_y(y)\, L \\ &= s_j(\boldsymbol{\delta}, \sigma) \int d_j(y)\, \mathrm{d}P_y(y)\, L. \end{aligned}$$

The second equality follows from the fact that the choice probability $s_j(\delta, \sigma)$, given by (5), does not depend on income. Using (3), we can solve the remaining integral. For the unit demand specification, we simply have $\int d_j(y) \mathrm{d}P_y(y) L = L$, whereas for the constant expenditures specification we have $\int d_j(y) \mathrm{d}P_y(y) L = \gamma Y/p_j$, where $Y = \int y \mathrm{d}P_y(y) L$ is total income of all consumers. Substituting and rearranging then gives expressions for the choice probabilities in terms of observables:

$$\begin{array}{ll} \text{Unit demand} & \frac{q_j}{L} = s_j(\boldsymbol{\delta}, \sigma) \\ \text{Constant expenditures} & \frac{p_j q_j}{B} = s_j(\boldsymbol{\delta}, \sigma) \end{array} \tag{6}$$

where we define $B = \gamma Y$ as the total potential budget allocated to the differentiated products in the economy, a constant fraction γ of total income of all consumers Y. Hence, the choice probabilities are equal to the market shares in volume terms for the familiar unit demand specification, whereas they are equal to market shares in value terms for the constant expenditures specification.

The goal is to estimate the parameters (α, β, σ) entering the demand system (6). The econometric error term ξ_j enters non-linearly through the mean utility terms δ_j. To obtain a tractable model, we can follow the same approach as proposed by Berry (1994) for both specifications, i.e. invert the system of choice probabilities $s_j = s_j(\boldsymbol{\delta}, \sigma)$, $j = 1, \ldots, J$, to solve for the mean utilities $\delta_j = \delta_j(\mathbf{s}, \sigma)$. Following Berry (1994) for the one-level nested logit and Verboven (1996) for the two-level nested logit), we obtain an analytical solution for the inverted choice probability system:

$$\ln(s_j/s_0) = \sigma_1 \ln(s_{j|hg}) + \sigma_2 \ln(s_{h|g}) + \delta_j, \tag{7}$$

where $s_{j|hg}$ is the market share of j within subgroup hg, and $s_{h|g}$ is the market share of subgroup hg in group g.

In the familiar unit demand specification, one can substitute $\delta_j \equiv x_j \beta - \alpha p_j + \xi_j$, and the market shares are in volume terms and relative to the total number of consumers L. In the constant expenditures specification, there are three differences. First, one should substitute $\delta_j \equiv x_j \beta - \alpha \ln p_j + \xi_j$, so price enters logarithmically instead of linearly. Second, one should substitute the market shares in value terms, as evident from (6). Third, the potential market is now the total potential budget as a fixed fraction γ of GDP, $B = \gamma Y$, instead of the total number of buyers, L.[11] We will not estimate γ, but impose a specific value (or range), similar to the practice of imposing values for L in unit demand specifications.

[11] Some other papers have used a logarithmic price term, for example Peters (2006) or Gowrisankaran and Rysman (2009). Verboven (1996) uses a Box-Cox transformation of the price term, $\left(p_j^{\mu} - 1\right)/\mu$ to nest both the linear and logarithmic specifications. While these approaches are useful to obtain a more flexible

Both variants of (7) are linear in the error term ξ_j. They can be estimated using an instrumental variable regression of volume or value market shares (relative to outside good market shares) on product characteristics, price (or log price) and subgroup and group market shares, where the endogenous variables are price and the (sub)group market shares.

In the Appendix, we provide further details and also show how to extend the constant expenditure specification to BLP's random coefficients model. We also derive the price elasticities of demand, and show that they are quasi-constant in price for the constant expenditure specification (instead of quasi-linear in price for the unit demand specification).

3.2 Oligopoly model

The oligopoly model serves two purposes. First, in combination with the demand parameters it enables one to uncover the premerger marginal costs. Second, based on the demand parameters and uncovered marginal costs, it can be used to predict the price effects of the merger.

Each firm f owns a portfolio of products F_f. Its total variable profits are given by the sum of the profits for each product $k \in F_f$:

$$\Pi_f(\mathbf{p}) = \sum_{k \in F_f} (p_k - c_k)\, q_k(\mathbf{p}) \tag{8}$$

where c_k is the constant marginal cost for product k and $q_k(\mathbf{p})$ is demand, as given by (6), now written as a function of the $J \times 1$ price vector $\mathbf{p}$. The profit-maximizing price of each product $j = 1, \ldots, J$ should satisfy the following first-order condition:

$$q_j(\mathbf{p}) + \sum_{k \in F_f} (p_k - c_k) \frac{\partial q_k(\mathbf{p})}{\partial p_j} = 0. \tag{9}$$

A price increase affects profits through three channels. First, it directly raises profits, proportional to current demand $q_j(\mathbf{p})$. Second, it lowers the product's own demand, which lowers profits proportional to the current markup. Third, it raises the demand of the other products in the firm's portfolio, which partially compensates for the reduced demand of the own product. If the first-order conditions (9) hold for all products $j = 1 \cdots J$, a multiproduct Bertrand-Nash equilibrium obtains.

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functional form for price, they are not consistent with utility maximization. As we show here, the logarithmic specification can be made consistent after some simple adjustments regarding the computation of market shares and the potential market (and it is straightforward to generalize this to the Box-Cox transformation, but the model is then no longer linear in the parameters).

To write this system of J first-order conditions in vector notation, define the $J \times J$ matrix $\boldsymbol{\theta}^F$ as the firms' product ownership matrix, a block-diagonal matrix with a typical element $\theta^F(j,k)$ equal to 1 if products j and k are produced by the same firm and 0 otherwise. Let $\mathbf{q}(\mathbf{p})$ be the $J \times 1$ demand vector, and $\boldsymbol{\Delta}(\mathbf{p}) \equiv \partial \mathbf{q}(\mathbf{p})/\partial \mathbf{p}'$ be the corresponding $J \times J$ Jacobian matrix of first derivatives. Let $\mathbf{c}$ be the $J \times 1$ marginal cost vector. Using the operator $\odot$ to denote element-by-element multiplication of two matrices of the same dimension, we have

$$\mathbf{q}(\mathbf{p}) + \left(\boldsymbol{\theta}^F \odot \boldsymbol{\Delta}(\mathbf{p})\right)(\mathbf{p} - \mathbf{c}) = 0.$$

This can be inverted to give the following expression:

$$\mathbf{p} = \mathbf{c} - \left(\boldsymbol{\theta}^F \odot \boldsymbol{\Delta}(\mathbf{p})\right)^{-1} \mathbf{q}(\mathbf{p}). \tag{10}$$

It is straightforward to generalize this expression to allow for (partial) coordinated behavior. Suppose that firms put a weight $\phi \in (0,1)$ on the profits of their competitors and modify the objective function (8) accordingly. The same expression (10) then obtains, where the zeros in the matrix $\boldsymbol{\theta}^F$ are replaced by the parameter ϕ.[12] We will focus on the non-cooperative case where $\phi = 0$. However, in an extension we also consider a case where $\phi > 0$, to see whether this brings the merger predictions closer to reality.

Intuitively, (10) decomposes the price into two terms: marginal cost and a markup, which depends on the own- and cross-price elasticities of demand. The lower the own-price elasticities and the greater the cross-price elasticities, the greater will be the markup over marginal cost.

Equation (10) serves two purposes. First, it can be rewritten to uncover the pre-merger marginal cost vector $\mathbf{c}$ based on the pre-merger prices and estimated price elasticities of demand, i.e.

$$\mathbf{c}^{pre} = \mathbf{p}^{pre} + \left(\boldsymbol{\theta}^{F,pre} \odot \boldsymbol{\Delta}(\mathbf{p}^{pre})\right)^{-1} \mathbf{q}(\mathbf{p}^{pre}). \tag{11}$$

Second, (10) can be used to predict the post-merger equilibrium. The merger involves two possible changes: a change in the product ownership matrix from $\boldsymbol{\theta}^{F,pre}$ to $\boldsymbol{\theta}^{F,post}$ and, if there are cost changes, a change in the marginal cost vector from $\mathbf{c}^{pre}$ to $\mathbf{c}^{post}$. To simulate the new price equilibrium, we used fixed point iteration on (10), where we apply a dampening factor less than 1 to the last term in case of no convergence. We also considered the Newton method and this gave the same results.

[12] It would be possible to allow for more general patterns of coordinated behavior, allowing ϕ to vary across products, but since there is little information about the possibility and the extent of coordination we keep a simple specification.

4 Empirical analysis

In this section we present the empirical results from various demand models, and we compare their predicted price effects under the most standard merger simulation (where there are no other changes except firm ownership). In the next section we then focus on the demand model with price predictions closest to the actual price effects, and we discuss how various supply side assumptions may explain the differences between predicted and actual effects.

4.1 Specification and estimation

We estimate both the unit demand and the constant expenditures specification of the demand model. We focus on the two-level nested logit with form (tablet or fizzy tablet) as the upper nest and active substance (paracetamol, ASA, ibuprofen) as the lower nest. Under this nesting structure, consumers are most likely to substitute to another product of the same form and substance, and would substitute more to another substance than to another form. We also estimated a model with the reverse nesting order (where consumers would substitute more to another form than to another substance), but this led to estimates of the nesting parameters $\sigma_1 < \sigma_2$, inconsistent with random utility theory. Following common practice (e.g. Goldberg, 1995), we therefore limit attention to the model that gave parameters consistent with random utility theory ($1 \geq \sigma_1 \geq \sigma_2 \geq 0$). As a robustness check, we also consider a random coefficients logit model, again under both a unit demand and constant expenditures specification. In this model, we incorporate unobserved consumer heterogeneity through random coefficients for price and brands without relying on a nesting structure.

For the various demand models, we define a product j as a brand, form, package size and dose. We obtained comparable findings under a more aggregate product definition at the brand and form level (where we control for the number of aggregated products, i.e. package sizes and doses). We also estimated the demand models using the three different measures for the consumption unit: tablet, defined daily dose, and normal dose at a single occasion. Since all three measures gave similar conclusions, we only present the results based on the tablet measure.

We include the following variables as determinants of mean utility (relative to the outside good): price (unit demand) or log of price (constant expenditures), marketing expenditures, the fraction of sick women and sick men in the total population, a time trend and monthly dummy variables capturing seasonal effects. In addition, since we observe a panel of multiple periods (all months during 1995-2008), we also include a set of fixed effects per product j. These fixed effects account for time-invariant unobserved product characteristics affecting mean utility, such as package size and dose. We can estimate the effects of these characteristics in a second stage regression of the fixed effects on these product characteristics (as in e.g. Nevo, 2000).

Aggregate discrete choice models require one to determine the size of the potential market, i.e. the total number of potential consumers L in the unit demand and the total potential budget B in the constant expenditures specification. For both variants, we assume that the potential market is twice the average amount spent over the entire period, in units for the first specification and in values for the second specification. We performed a sensitivity analysis with alternative factors: 1.5, 2 (base), 4 and 6 and obtained similar results.

Finally, to estimate the model it is necessary to specify a reasonable set of instruments. We start from the commonly used identification assumption that the product characteristics, other than price, are uncorrelated with the error terms. The products' own characteristics are then natural instruments, but additional instruments are required to identify the price coefficient and the distributional parameters (the nesting parameters in the nested logit and the standard deviations of the random coefficients in the random coefficients logit). BLP suggest to use functions of the other product characteristics as additional instruments.[13] For the nested logit model, our instrument set includes the products' own characteristics and counts of the number of other products: overall, by group, by subgroup, by firm, by firm and group and by firm and subgroup. The Appendix shows summary statistics on the variation of these instruments, and also presents the first stage regressions of the endogenous variables (price and the shares $\ln s_{j|hg}$ and $\ln s_{h|g}$) on the instrument set.[14] For the random coefficients logit model, we use the same instruments as in BLP in a first stage (sums of other product characteristics of the same firm and of other firms for each variable with a random coefficient), and optimal instruments in a second stage following Chamberlain (1987) and Berry, Levinsohn and Pakes (1999); Reynaert and Verboven (2014) provide detailed Monte Carlo evidence to demonstrate that optimal instruments improve the efficiency of the estimator). Note that, as in Chintagunta (2002), we treat price as an exogenous variable in both models. This assumption may be justified to the extent that the set of product fixed effects takes away the main source of correlation with the error term. We also considered a specification where marketing expenditures are treated as endogenous (using the same instrument set), and this gave closely comparable results.

[13]More specifically, they suggest to use counts and sums of the characteristics of the other products of the same firm and of the other products of the other firms. For the nested logit model, Verboven (1996) suggested to take counts and sums by subgroups and groups as additional instruments. Bresnahan, Stern and Trajtenberg (1997) followed a similar approach for their "principles of differentiation" GEV model.

[14]As a sensitivity check, we also included the sums of two product characteristics, package size and dose, across all other products of the same firm, and across other products of other firms. This gave comparable results.

4.2 Parameter estimates, elasticities and predicted price effects

Parameter estimates Table 5 presents the estimated demand parameters for the four demand models: two-level nested logit and random coefficients logit, both under the unit demand and constant expenditures specification.

Consider first the results from the nested logit model (first two columns of Table 5). As in Chintagunta (2002), marketing expenditures have a positive effect on the products' demands. There is a positive and significant time trend, and monthly dummy variables (not shown) indicate that the demand for painkillers is especially strong during some of the winter months December and March. Demand grows with the number of sick men but, surprisingly, in the unit demand specification it decreases with the number of sick women. This may be because this variable picks up some other effects, or because women use other drugs (perhaps prescription drugs) when they report sickness.

The time-invariant product characteristics (estimated in a second stage regression of the fixed effects) show the following. Consumers do not have significantly different mean valuations for tablets and fizzy tablets. Relative to paracetamol, they have a higher mean valuation for ASA and a lower mean valuation for ibuprofen. Consumers have a significantly higher valuation for products with a higher dosage. Finally, consumers do not value package size per se: they do not have a significantly different mean valuation for products that come in a higher or lower package size.

In both specifications the price coefficient α has the expected sign. The subgroup and group nesting parameters are fairly comparable ($\sigma_1 = 0.93$ and $\sigma_2 = 0.79$ in the linear specification, and $\sigma_1 = 0.84$ and $\sigma_2 = 0.67$ in the constant expenditures specification). These estimates satisfy the requirements for the model to be consistent with random utility theory, $1 \geq \sigma_1 \geq \sigma_2 \geq 0$. In both specifications, the inequalities are strict, which implies that consumers perceive products of the same form and substance as the closest substitutes, products of a different substance but the same form as weaker substitutes, and products with both different substance and different form as the weakest substitutes.

The parameter estimates of the random coefficients model (shown in the last two columns of Table 5) usually have similar signs. Instead of nesting parameters, this model includes the standard deviations for XXX random coefficients: these are XXX ....

Price elasticities Table 6 summarizes what these parameter estimates imply for the price elasticities and the predicted price effects of the merger. We provide a comparison here for the four different demand models. In the next section, we then focus on one of the demand models to discuss how supply side factors may explain the differences between the predicted and actual merger effects.

Table 5: Empirical results from nested logit model

	Const. expend. demand		Unit demand	
	Parameter	St. Error	Parameter	St. Error
price ($-\alpha$)	-.304	.101	-2.042	.157
subgroup (σ_1)	.835	.021	.928	.013
group (σ_2)	.667	.025	.792	.012
marketing expenditures	15.50	2.90	8.85	1.82
sickwomen	.357	.129	-.699	.079
sickmen	1.145	.244	.809	.157
time trend	.0013	.0005	.0007	.0002
R^2	0.983		0.972	
	Implied price elasticities (December 2008)			
	Average	St. Error	Average	St. Error
Own-price elasticity	-2.68	.63	-12.4	2.6
Cross: same subgroup	.164	.068	1.45	.38
Cross: different subgroup	.039	.012	.245	.022
Cross: different group	.006	.002	.016	.001
	Min	Max	Min	Max
Own-price elasticity	-2.84	-1.91	-24.1	-3.9
Cross: same subgroup	.00	.93	.00	8.3
Cross: different subgroup	.00	.29	.00	1.76
Cross: different group	.00	.06	.00	.16

Note: 7,240 observations for 1995–2008. Monthly fixed effects and 56 product fixed effects are included. Robust standard errors are reported. For the elasticities, these are computed with the delta method (for an average product in December 2008).

The top part of Table 6 provides summary information on the own-price elasticities implied by the estimates. The numbers refer to the average and range across products during December 2008, the last month of the dataset used to estimate the demand model. For the nested logit models, we find the following. In the constant expenditures specification, the own-price elasticity is on average -2.7 (standard error of 0.6), and it ranges between -2.84 and -1.91. Furthermore, **the cross-price elasticities are much larger for products of the same substance and form (on average 0.16) than for products of a different substance but the same form (0.04), which are in turn larger than for products of different substance and form (0.01).** There is a similar pattern in the unit demand specification, but the level of elasticities is considerably higher. More interestingly, the range of price elasticities is much higher, and is here essentially proportional to the wide range in prices across products.[15]

For the random coefficients logit models, we find that ....

MAY STILL CONSIDER TO PRESENT CROSS PRICE ELASTICITY HERE IN THE TABLE AS WELL (NEED TO GET MEASURE THEN FOR THE BLP MODEL, PERHAPS AGGREGATE ELASTICITY!)

MAY ALSO BRIEFLY MENTION THE MARKUPS, SUMMARIZING THE ELASTICITIES AND MARKET POWER.

Predicted price effects Finally, the bottom part of Table 6 shows the predicted price effects of a basic merger simulation. This is based on the non-cooperative multi-product pricing oligopoly model of section 3.2, where only the ownership changes because of the merger between AZT and GSK and where there are no cost or other supply side changes. Since in such a simple setting the predicted merger effects only depend on the own-price and cross-price elasticities, this is also a simple way to summarize the combined role of these elasticities. We present the average predicted price increases for each of the three active substances. Recall that the merging firms are only active in the paracetamol segment, and no other firms are active in that segment. Hence, the merging firms' average price increase coincides with the price increase in the paracetamol segment, while the outsiders' price increases correspond with the price increases in the other segments.

The nested logit model predicts the following. For the constant expenditures specification, there is a quite substantial price increase in the merging firms' paracetamol segment by

[15] It is of interest to compare these estimates with the ones from a unit demand (random coefficients) logit, obtained by Chintagunta (2002). As discussed above, his estimated price elasticities for the five analgesics brands range between -1.8 and -3.0. These elasticities are also proportional to prices (but the range is smaller than in our case, since the price range is smaller).

37.4%. This follows from the strong market segmentation by substance ($\sigma_1 > \sigma_2$), which implies low cross-price elasticities between products of the merging firms and the rivals who sell different substances. For the unit demand specification, the predicted price increase is 15.9%, which is lower but still quite important. This reason for the lower effect is the higher estimated own-price elasticity, as seen earlier in Table 5. Hence, for the constant expenditure specification the predicted price increase of 37.4% is quite close to the merging firms' actual price increase of 43.6% (obtained earlier in Table 4, using a two-year comparison window). For the unit demand specification the model considerably underestimates the price effects of the merging firms.

The random coefficients logit model generallly results in lower predicted price effects, by XXX% for the constant expenditures specification and by XXX% for the unit demand specification. This is due to two factors. First, the random coefficient for the paracetamol dummy, while significant, is apparently quantitatively less important than the nesting parameter in the nested logit model. Second, there other sources of consumer heterogeneity which raises the extent of substitution to other products with different active substances. ELABORATE/REWRITE ONCE FINAL SPECIFICATION. ALSO HERE STILL COMPARE WITH ACTUAL EFFECTS, AND CONCLUDE UNDERESTIMATION.

Note that, in all models, the predicted price increases by the competing firms in the other segments are very small, compared with the price increase in the paracetamol segment. Competitors thus respond only weakly to the price increase initiated by the merging firms. This is because of our finding of limited substitution between segments, combined with the fact that there are many competing firms. The largest competitor effects are in the BLP model and are mainly initiated by the largest firm McNeil according to the basis merger simulation. ELABORATE....,

SHOULD WE ALSO DO 10% COST DROP, AS AN EXAMPLE TO EXPLAIN THE EXTENT OF COST-PASS-THROUGH (WITH FOOTNOTE TO THE ACTUAL MERGER INVESTIGATION)

CONCLUDE THAT CES NESTED LOGIT APPEARS CLOSEST TO THE ACTUAL PRICE EFFECTS. THEN MOVE FORWARD WITH THAT MODEL IN THE NEXT SECTION.

5 Evaluating merger simulation

The previous section focused on comparing different demand models. We ended this comparison with basic merger simulations, which only considered a change in the merging firms' product ownership. So we only considered a pure "loss of competition" effect from the mergers, and abstracted from the role of cost changes or conduct.

We now focus on the demand model that gave price predictions closest to the actual price effects, the constant expenditures nested logit model. We ask how well the loss of competition effect explains the price effects, and how observed and unobserved supply side factors may bring predictions closer to reality. This approach is broadly similar to Peters' (2006) decomposition of the observed price effects, with the following differences. First, Peters looked at several mergers, and limited attention to the explaining the price changes of the merging firms. We instead consider a single merger, but consider a more detailed set of predictions: price changes by firm, and in addition also market share changes. Second, we do not only consider the role of cost changes but also assess the role of conduct.

Basic merger simulation: only accounting for loss of competition Table 7 summarizes the results. The first column shows the predicted price effects of the basic merger simulation, where only the merging firms' product ownership changes. This is essentially the same information as already shown in Table 6 (for the constant expenditures nested logit model), except that the effects are now broken down by both substance and firm, instead of only by substance. The last column shows the actual price effects (found earlier in Table 4, using a two-year comparison window). As we saw before, the standard merger simulation predicts the merging firms' average price increase in the paracetamol quite well. However, the individual predicted price increases by firm deviate quite substantially from the actual effects in several respects.

First, the predicted price increase of the larger firm AZT (27.2%) is much lower than that of the smaller firm GSK (+68.4%), whereas in practice both firms raised prices by comparable magnitudes (+42.8% versus 46.1%).[16] Intuitively, the lower predicted price increase for AZT than GSK follows from the fact that the markups of small firms tend to be lower than those of large firms, and these markups become equalized after a merger (see already Anderson and de Palma, 1992).

Second, the outsider firms are predicted to raise prices by relatively low amounts, with the largest price increase by the largest firm, McNeil (+1.7% in the ibuprofen segement and +1.8% in the ASA segment). In practice, the price increases were much higher for all firms in the ASA segment: McNeil (+15.3%), Meda (+7.0%) and Bayer (+10.8%).

Accounting for cost increases stemming from package size reductions A important change that coincided with the merger event in 2009 was the reduction in package size

[16]We obtained similar findings for the other demand models: in all cases, the predicted price increase for the larger firm (AZT) was much lower than that of the smaller firm (GSK).

by several brands. As discussed in section 2, in the paracetomol segment the merged firm AZT-GSK reduced the package size of its brands Panodil and Alvedon from 30 to 20 tablets. Moreover, in the ASA segment, McNeil and Meda removed all their large package size (containing 100 tablets). A possible explanation for the larger than predicted price increases in the paracetamol segment could therefore be the increase in marginal cost associated with a reduced package size. To assess this possibility, we used the premerger data to perform a logarithmic regression of products' marginal costs, as backed out from the oligopoly model using (11), on the product fixed effects and a time trend; in a second stage we then regressed the product fixed effects on the same time-invariant product characteristics as those included in the demand model. The results, presented in the Appendix, show that the elasticity of marginal cost with respect to package size is negative and highly significant at –0.429, with a standard error of 0.054. This implies that the reduction in package can lead to a considerable increase in marginal costs for the concerned firms.

To assess how this can have affected prices, we redid the merger simulation, but now combining both the ownership change (as before) and the marginal cost increase because of the package size reduction for the relevant products. The second and third column in Table 7 show the results. Marginal costs are estimated to increase on average by 14.1% for AZT and by 13.6% for GSK. This in turn implies a predicted price increase for AZT that is even closer to the observed price increase for AZT. However, for GSK we now find a stronger overprediction than without accounting for the cost increase.

For the outsiders' products in the ASA segment, we find an average marginal cost increase for McNeil's ASA brands by 2.8% and for Meda's ASA brands by 7.8%. These cost increases in turn imply larger predicted price increases for these brands. For Meda's ASA brands, the predicted price increase is +7.8% which is close to the actually observed price increase of 7.0%. For McNeil's ASA brands, the predicted price increase is now 6.6%, but this is still much below the actually observed price increase of 15.3%. Furthermore, for the remaining ASA brand of Bayer, we still estimate only a negligible price increase of 0.1%, while the actual price increase was 10.8%.

Finally, for the outsiders' products in the ibuprofen segment there are no package size changes and hence no marginal cost changes. But the model now predicts a slightly higher price increase for McNeil's ibuprofen brand, close to the actual price increase. The higher predicted price increase follows from the fact that McNeil also raised the prices of its ASA brands.

In sum, the package size reduction can better explain the price increase of one of the merging firms (AZT), but leads to stronger overprediction of the price increase of the other merging firm (GSK). Furthermore, the package size reduction partly or completely explains the price increases of the ASA brands of McNeil and Meda but not of Bayer, which raised its prices in line with the other ASA brands although it did not reduce its package sizes.

Accounting for (partial) coordinated behavior (Partial) coordinated behavior may explain some of the differences between the predicted and the observed price effects. First, it may help to explain why large and small merging firms raise their price by more similar amounts than predicted by a non-cooperative pricing model. Second, it may explain why some of the outsiders raise their prices so much, even if they did not experience a marginal cost increase.

To assess the role of partial coordinated behavior, we set the weight that firms put on the profits of the competitors $\phi = 0.75$ (assumed the same before and after the merger). This number is somewhat arbitary, except that it raises the pre-merger markups to a level that is more in line with the firms' estimates provided during the investigation. If we would have reliable information on marginal opportunity costs, we could calibrate a weighting parameter such that we retrieve marginal costs. Since such information is not available to us, we use the weighting parameter $\phi = 0.75$ for illustrative purposes to see the direction of changes in the merger predictions.

The fourth and fifth column in Table 7 show the results of the predicted price effects when firms partially coordinate (accounting in addition for the cost increases following the package size reduction).[17] The gap between the predicted price increases of the merging firms is now small, closer to the actual price changes. On the one hand, the predicted price increase of AZT only slightly drops, and remains close to the actual price change. On the other hand, the predicted price increase of GSK drops considerably, from 87.4% to 67.4%, and gets a lot closer to the actual price change of 46.1%.

The predicted price increases of the outsiders' products give a more mixed picture. Generally speaking, because of partial coordination the outsiders respond with higher price increases than in the previous cases. This helps to better predict price increases that were previously underpredicted, mainly McNeil's and Bayer's price changes in the ASA segment. But it also implies worse predictions in cases where we previously already (slightly) overpredicted, mainly Meda's price increase in the ASA segment.

In sum, enriching the model to allow for partial coordinated behavior better explains the price increases of the merging firm (since they now have more proportional price increases).

[17] The estimated marginal cost increases due to the package size reduction (fourth column) differ only slightly from the earlier estimated cost increases (second column). The small differences are due to the fact that marginal costs are now uncovered under the assumption of partial coordination instead of non-cooperative Bertrand pricing.

But it does not unambiguously improve the predictions for outsider firms.

Accounting for unobserved cost changes to fit the actual price changes We can calibrate marginal costs after the merger in such a way that the predicted price changes of every firm are equal to the actual price changes, similar to Peters (2006). To the extent that these calibrated unobserved marginal cost changes are small, we can conclude that the merger simulation performs well in predicting prices. The sixth column shows these calibrated marginal cost changes by firm and substance (adding to the marginal cost changes because of the package size reduction, already accounted for in the earlier cases). These cost changes then by construction translate into the actual price changes of the last column.

For one of the merging firms, AZT, only a small unobserved marginal cost change (+2.9%) is required to "rationalize" its actual price change. For GSK, an unobserved cost reduction of 12.5% is needed to explain the lower than predicted price increase. One interpretation is that GSK, as the acquiring firm, was able to restructure its operations to favour GSK brands, translating in a lower economic cost of selling this brands.

For the outsiders' products in the ASA segment, only a minor unobserved cost change is required to explain Meda's price increase. But for McNeil and Bayer, a relatively large unobserved increase in marginal costs by about 8–10% is required to explain their price increases. A possible interpretation is that these firms responded more cooperatively after the merger, though there is no clear indication of this. Finally, for the outsiders' products in the ibuprofen segment, only minor unobserved cost changes are required to explain the actual price changes.

Explaining market shares We now ask to which extent the model accurately market share changes. We focus on the last case, where we calibrated the cost changes to obtain predicted price increases that match the actual price increases. We then essentially ask the question whether the demand model predicts the data well, or whether there are unobserved demand changes required to explain the market share changes.

We find that the predicted market share changes of the merging firms...

STILL DECIDE WHETHER TO INCLUDE HERE OR IN PREVIOUS SECTION WHERE WE COMPARE THE FOUR DEMAND MODELS

OLD TEXT

Now consider the predicted market shares effects from the merger, measured in volume terms. Under Bertrand competition the paracetamol market share is predicted to decrease by 7.1% (from 47.9% to 40.8%). This comes to the benefit of both ibuprofen and ASA (+3.8% and +3.3%). The larger firm AZT is predicted to suffer a market share drop of –3.4%

(from 36.1% to 32.7%), while the smaller partner GSK will suffer a proportionately more substantial market share drop of -3.7% (from 11.8% to 8.1%). These market share effects are qualitatively similar under partial coordination, though quantitatively less pronounced.

Table 6: Predicted price and market share effects in the preferred model

	Price effects		Market share effects	
	Bertrand	Partial coord.	Bertrand	Partial coord.
	Predictions at the level of the active substance			
Paracetamol	+34.1%	+28.0%	–7.1%	–5.4%
Ibuprofen	+0.7%	+4.1%	+3.7%	+2.7%
ASA	+0.8%	+3.0%	+3.3%	+2.7%
	Predictions at the level of the firm			
AZT	+21.3%	+19.5%	–3.4%	-2.7%
GSK	+59.8%	+45.1%	–3.7%	-2.7%
Nycomed	+0.6%	+4.0%	+1.3%	+0.9%
Meda (Ellem)	+0.1%	+2.7%	+0.6%	+0.5%
McNeil	+1.7%	+4.1%	+5.1%	+3.9%
Bayer	+0.1%	+2.5%	+0.1%	+0.1%

Note: This table shows predicted price and market share effects, based on the preferred model.

5.1 Predictions in actual merger case

STILL DECIDE WHETHER TO KEEP PART OF THIS AT THE END AS AN ANECDOTE ABOUT THE CASE.

During the merger investigation we reported the predicted price effects under both the unit demand and the constant expenditures specifications. For each specification, we considered four scenario's: no cost savings versus 25% cost savings, and multiproduct Bertrand competition versus partial coordination. The partial coordination parameter was calibrated to $\phi = 0.75$, i.e. both before and after the merger all firms take into account their competitors' profits by 75% when setting their own prices. Calibrating $\phi = 0.75$ leads to premerger marginal costs in line with outside information available to the competition authority, so it has some intuitive appeal as an alternative to Bertrand competition.

Table 5 shows the pre-merger markups and predicted price increases, under the four scenario's and the two demand specifications. The predicted price increases are average percentage price increases in the paracetamol segment, where the merging firms (and no other firms) are active. Table 5 is essentially what we reported during the competition investigation.[18] We defer a richer and more systematic set of predictions from the merger simulations to our ex post analysis below.

Table 7: Predicted price effects of the merger during the investigation

	percentage price increase		pre-merger markup
	no cost saving	25% cost saving	
	Constant expenditures specifications		
Bertrand	+34.0%	+4.7%	.49
partial coordination	+28.4%	–0.1%	.76
	Unit demand specification		
Bertrand	+12.9%	+1.6%	.16
partial coordination	+16.1%	+9.0%	.54

Note: This table shows the pre-merger markups and the predicted price effects of the merging firms under alternative scenario's, exactly as reported in the merger investigation.

According to the constant expenditures specification, the merger between AZT and GSK would lead to rather substantial price increases in the absence of efficiencies: +34.1% under Bertrand competition, and +28.4% under partial coordination. The predicted price effects only become small or negligible if the merger involves at least 25% marginal cost savings (price increase of +4.7% under Bertrand competition and –0.1% under partial coordination). These results therefore imply large efficiency requirements for the merger to benefit consumers. Nevertheless, as we stressed during the investigation, such large price increases may not materialize if they trigger entry, a possibility that became more likely in light of the then coming deregulation of the distribution system.

According to the unit demand model, the predicted price effects from the merger are considerably smaller, but they remain quite substantial. In the absence of efficiencies, the model predicts that the merging firms would raise prices by +12.9% under Bertrand competition and by +16.1% under partial coordination. The lower predicted price effects are due to the larger estimated price elasticities in the unit demand model. If we account for 25% cost

[18] In the report to the Swedish competition authority we also presented the results from a constant expenditure specification based on the full dataset instead of the reduced dataset. This gave very similar results.

savings, the predicted price effects become negligible under Bertrand competition, but they remain significant under partial coordination. In the unit demand model, the cost savings are passed on to a lesser extent than in the constant expenditures specification. This clearly follows from the functional form: in the unit demand model consumers tend to become more price elastic as price increases, whereas they remain more or less equally price elastic in the constant expenditures specification.

Despite the rather large predicted price increase, the constant expenditures specification may be more appealing for two reasons. First, as discussed above, the price elasticities do not increase in a quasi-linear way with prices, and they do not depend on the chosen unit of consumption (tablet, defined daily dose, or normal dose on a single occasion). Second, the computed premerger markups appear more plausible. As shown in the last column of Table 5, in the constant expenditures model the average premerger markups are 49% under Bertrand competition, and 76% under partial coordination. These numbers were broadly in line with the variable cost information provided by the parties during the investigation (cost of purchasing the active substance, production cost and packaging cost). In contrast, in the unit demand specification, the average premerger markups are much smaller (16% under Bertrand competition and 54% under partial coordination) and in fact well below the markups from the parties' information.

In sum, the merger requires substantial cost savings, in the order of at least 25%, for the price effects to become small. In the absence of cost savings, the constant expenditures specification predicts a very large price increase: +34% under Bertrand competition and +28.4% under partial coordination before the merger. The unit demand specification predicts lower price increases, but still well above 10%. If one were to apply a SSNIP test for market definition, the conclusion would clearly be that the merging firms constitute a monopoly by themselves.

6 Conclusions

We have made use of a unique merger case to evaluate the usefulness of merger simulation as a structural approach to predict the effects from mergers. The merger case is unique for several reasons. First, it involves large players who have no other competition in their own segment. This leads to large merger predictions, enabling us to test a broad range of predictions. Second, the merger simulation methodology was initiated during the case, when the actual merger effects were not yet known.

The merger simulation model started from a two-level nested logit demand system, where we proposed a constant expenditures specification as a possible alternative to the typical unit demand specification. Our empirical results show the following two key points. First, market segmentation according to active substance is a very important differentiation dimension. This implies that the two merging firms form a strong competitive constraint on prices before the merger. Second, the constant expenditures specification entails a more plausible pattern of price elasticities across products. Based on these two findings, the model predicts a large price increase of 34% by the merging firms.

Our ex post analysis shows that the actual price increase by the merging firms is of a similar order of magnitude, but in fact even larger than the price increase predicted by the model: +42% in absolute terms, or +35% in a difference-in-difference interpretation where the other firms are the control group. The average price predictions are thus quite accurate, but a closer look leads to more nuanced conclusions. First, both merging firms raised their prices by a similar percentage, while the simulation model predicted a larger price increase for the smaller firm. Second, one of the outsiders responded with a fairly large price increase, while the simulation model predicted only small price responses by the outsiders. This in turn implies a market share drop instead of a predicted market share increase for this outsider (and a smaller than predicted market share drop for the merging firms). We discussed possible reasons for the divergence between the predicted and actual effects, i.e. the possibility that other things did not remain constant after the merger or that the model specification can be improved. It was possible to test these richer predictions, thanks to the unusually large size of the considered merger (where the two merging firms are the only competitors in a segment with limited substitution from other segments).

It is interesting to observe that our predictions were obtained from a fairly simple differentiated products oligopoly model without the "elaborate superstructure" to which Angrist and Pischke refer in their discussion. In future research it may nevertheless be interesting to consider various extensions of the model (alternative equilibrium, further sensitivity of functional form of demand) to see whether these can improve the accuracy of the predictions. But in our view more importantly, it would be interesting to see a lot more work that confronts the merger simulations during a case with the actual merger effects.

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7 Appendix

7.1 Further empirical results

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7.2 Demand model

Further details on the nested logit model In the text, we showed that

$$\begin{array}{ll} \text{Unit demand} & \frac{q_j}{L} = s_j\left(\boldsymbol{\delta}, \sigma\right) \\ \text{Constant expenditures} & \frac{p_j q_j}{B} = s_j\left(\boldsymbol{\delta}, \sigma\right) \end{array} \tag{12}$$

where $s_j\left(\boldsymbol{\delta}, \sigma\right)$ is given by (5). We now provide several details not provided in the text.

1. The inclusive values or "log sum" formulas I_{hg}, I_g, and I are defined by:

$$\begin{aligned} I_{hg} &\equiv (1-\sigma_1)\ln\sum_{k=1}^{J_{hg}}\exp((\delta_k)/(1-\sigma_1)) \qquad (13) \\ I_g &\equiv (1-\sigma_2)\ln\sum_{h=1}^{H_g}\exp(I_{hg}/(1-\sigma_2)) \\ I &\equiv \ln\left(1+\sum_{g=1}^{G}\exp(I_g)\right). \end{aligned}$$

2. The estimating equation (7) can be written out as follows for the unit demand specification:

$$\ln \frac{q_j}{L - \sum_{j=1}^{J} q_j} = x_j \beta - \alpha p_j + \sigma_1 \ln \frac{q_j}{\sum_{j \in H_{hg}} q_j} + \sigma_2 \ln \frac{\sum_{j \in H_{hg}} q_j}{\sum_{h=1}^{H_{hg}} \sum_{j \in H_{hg}} q_j} + \xi_j \tag{14}$$

and for the constant expenditures model

$$\ln \frac{p_j q_j}{B - \sum_{j=1}^{J} q_j p_j} = x_j \beta - \alpha \ln p_j + \sigma_1 \ln \frac{p_j q_j}{\sum_{j \in H_{hg}} p_j q_j} + \sigma_2 \ln \frac{\sum_{j \in H_{hg}} p_j q_j}{\sum_{h=1}^{H_{hg}} \sum_{j \in H_{hg}} p_j q_j} + \xi_j. \tag{15}$$

Note that the unit demand specification can immediately be interpreted as an inverse demand system (by writing price on the left hand side). This is not the case for the constant expenditures specification.

3. The price elasticities can be computed as follows. First, the derivatives of the choice probability $s_j(\boldsymbol{\delta}, \sigma)$, as given by (5), with respect to the mean utility δ_k can be shown to be

$$\frac{\partial s_j}{\partial \delta_k} = s_j \left(\frac{1}{1-\sigma_1} D^1_{jk} - \left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2} \right) s_{j|hg} D^2_{jk} - \frac{\sigma_2}{1-\sigma_2} s_{j|g} D^3_{jk} - s_j \right) \tag{16}$$

where we define three dummy variables: $D^1_{jk} = 1$ if $j = k$, $D^2_{jk} = 1$ if j and k are in same subgroup, $D^3_{jk} = 1$ if j and k are in same group (and zero otherwise). Second, using (12), the aggregate demand derivatives are

$$\begin{array}{lcl} \text{Unit demand} \quad \frac{\partial q_j}{\partial p_k} & = & -\alpha \frac{\partial s_j}{\partial \delta_k} L \\ \text{Constant expenditures} \quad \frac{\partial q_j}{\partial p_k} & = & -\alpha \frac{\partial s_j}{\partial \delta_k} \frac{B}{p_j p_k} - s_j \frac{B}{p_j^2} D^1_{jk}, \end{array} \tag{17}$$

Substituting (16) into (17), one can obtain the following expressions for the aggregate price elasticities. In the unit demand specification, we have

$$\frac{\partial q_j}{\partial p_k} \frac{p_k}{q_j} = -\alpha \left(\frac{1}{1-\sigma_1} D^1_{jk} - \left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2} \right) s_{j|hg} D^2_{jk} - \frac{\sigma_2}{1-\sigma_2} s_{j|g} D^3_{jk} - s_j \right) p_j,$$

while in the constant expenditures specification we have

$$\frac{\partial q_j}{\partial p_k} \frac{p_k}{q_j} = -\alpha \left(\frac{1}{1-\sigma_1} D^1_{jk} - \left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2} \right) s_{j|hg} D^2_{jk} - \frac{\sigma_2}{1-\sigma_2} s_{j|g} D^3_{jk} - s_j \right) - D^1_{jk}.$$

This shows that the price elasticities are increasing quasi-linearly in prices across products in the typical unit demand specification, whereas they are quasi-independent of prices in the constant expenditures demand specification. In both cases, we write "quasi", since there is indirect dependence on the prices through the market shares.

Extension to random coefficients logit We start from a generalization of consumer i's conditional indirect utility (2) of good j to:

$$u_{ij} = x_j \beta_i + \xi_j + \alpha_i f(y_i, p_j) + \varepsilon_{ij}, \tag{18}$$

where β_i and α_i are now individual-specific valuations of the product characteristics, modelled as random coefficients. Following BLP, Nevo (2000) and others, specify the random coefficients β_i and α_i as

$$\begin{pmatrix} \beta_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \beta \\ \alpha \end{pmatrix} + \Sigma \nu_i$$

where β and α are means and Σ is a diagonal matrix with standard deviations of the random coefficients, and ν_i is a vector of standard normal random variables.

For the two conditional demand specifications (3), we can again write utility (2) more compactly:

$$u_{ij} = K_i + \delta_j + \mu_j(\nu_i) + \varepsilon_{ij}, \tag{19}$$

where δ_j is the mean valuation for product j as before, and $\mu_j(\nu_i)$ is an individual-specific valuation for product j, with $\mu_j(\nu_i) = \begin{pmatrix} x_j & p_j \end{pmatrix} \Sigma \nu_i$ in the unit demand specification and $\mu_j(\nu_i) = \begin{pmatrix} x_j & \ln p_j \end{pmatrix} \Sigma \nu_i$ in the constant expenditures specification. The unit demand and constant expenditures specification essentially differ in the fact that price enters linearly or logarithmically in both δ_j and $\mu_j(\nu_i)$.

Given random utility maximization and an extreme value (logit) distribution for ε_{ij}, the conditional probability that consumer i chooses product j is:

$$\pi_j(\boldsymbol{\delta}, \sigma, \nu_i) \equiv \frac{\exp\left(\delta_j + \mu_j(\nu_i)\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_k + \mu_k(\nu_i)\right)}, \tag{20}$$

where σ is the vector of standard deviations in the diagonal matrix Σ.

Aggregate demand for product j is the probability that a consumer buys product j multiplied by the quantity purchased, $d_j(y_i)$, aggregated over all L consumers according to income distribution P_y and the distribution of taste parameters P_ν, assumed to be independent of income

$$\begin{aligned} q_j &= \int \pi_j(\boldsymbol{\delta}, \sigma, \nu)\, d_j(y)\, \mathrm{d}P_\nu(\nu)\, \mathrm{d}P_y(y)\, L \\ &= \int \pi_j(\boldsymbol{\delta}, \sigma, \nu)\, \mathrm{d}P_\nu(\nu) \int d_j(y)\, \mathrm{d}P_y(y)\, L \\ &= s_j(\boldsymbol{\delta}, \sigma) \int d_j(y)\, \mathrm{d}P_y(y)\, L. \end{aligned} \tag{21}$$

The second equality follows from the fact that the choice probability $\pi_j(\boldsymbol{\delta}, \sigma, \nu_i)$ is independent of income. The third equality substitutes the usual unconditional choice probability of BLP's aggregate random coefficients model:

$$s_j(\boldsymbol{\delta}, \sigma) \equiv \int \frac{\exp\left(\delta_j + \mu_j(\nu)\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_k + \mu_k(\nu)\right)} \mathrm{d}P_\nu(\nu). \tag{22}$$

Similar to the nested logit model, the integral in (21) is simply $\int d_j(y) \mathrm{d}P_y(y) L = L$ in the unit demand specification, and $\int d_j(y) \mathrm{d}P_y(y) L = \gamma Y / p_j$ in the constant expenditures specification. This results in the same expressions for the choice probabilities in terms of observables derived in the text (6), where $s_j(\boldsymbol{\delta}, \sigma)$ is now given by the market share integral (22).

This shows that the constant expenditures specification is a straightforward variant of BLP's unit demand specification, where the unconditional choice probability should be set equal to the market share in value terms instead of volume terms, and price enters logarithmically instead of linearly. Estimation is otherwise similar as in BLP, i.e. the market share system can be solved numerically for the mean utility δ_j using BLP's contraction mapping and simulated GMM can be applied.