UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Tougher rules on mandatory substitution brought forth price drop in the Swedish pharmaceutical market

- Estimating the impact of the new rules of 2009 using Difference-in-Difference regression.

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Abstract

In 2009 the governmental monopoly on the Swedish pharmaceutical market was abolished. Coinciding with this reform, a new set of rules and proceedings concerning mandatory substitution was adopted. In this paper a difference in difference analysis is applied in order to estimate the immediate impact of theses new rules on the prices of the pharmaceuticals.

The result was an estimated average prices drop of 4.9% among products facing generic competition. Further inquiries into the factors behind the effect, points to a pattern of price drops increasing with the number of competitors a product faces. A pattern such as this could be indicative of low levels of competition within a market.

Content

1. Introduction

There is no obvious reason to consider any factor but price when choosing among generic drugs. They all contain the same active ingredient. The drug companies thus possess but one means of competition: to reduce price. The market for generics should thus shove the companies into a price-cutting race where they continuously underbid one another in order to dominate the market. Alas, the overall market share of the cheapest products only amounted to around 41%, in 2008. Such a low market share undoes the will to cut prices, making for less competition and higher prices.
The government subsidizes pharmaceutical products and has a vested interest in the lowest possible prices. Therefore new practices were introduced October 2009 to make the patients more susceptible to price differences, and thereby enhancing price competition. The new rules forces pharmacies to always offer their costumers the cheapest product on the market. This paper aims to evaluate if the reform was successful or not.

Methodology and data

The main problems in estimating the causal effect of the reform on generic drug prices is the many other factors affecting prices in a market, including for example increasing costs, business cycles and demand shocks. To isolate the causal effect of the reform on the prices of generics I have therefore used a control group of other drugs, namely all drugs not facing generic competition. More precisely, I have studied how the prices of generic drugs changed around the time of the reform, compared to how the prices of other drugs changed during the same time period. The idea is that the external factors such as cost inflation affect the prices of generic drugs and the control drugs in roughly the same way. Thus, if the prices of drugs facing generic competition fell more than the prices in the control group, it is plausible that the reform has had an effect. This methodology is usually referred to as a difference in difference (DiD) analysis.
I have limited the comparison to eight month before and eight month after the reform. This limitation is due to the assumption of parallel trend that is necessary in order for DiD analysis to yield unbiased results. I have collected a sample of prices observed

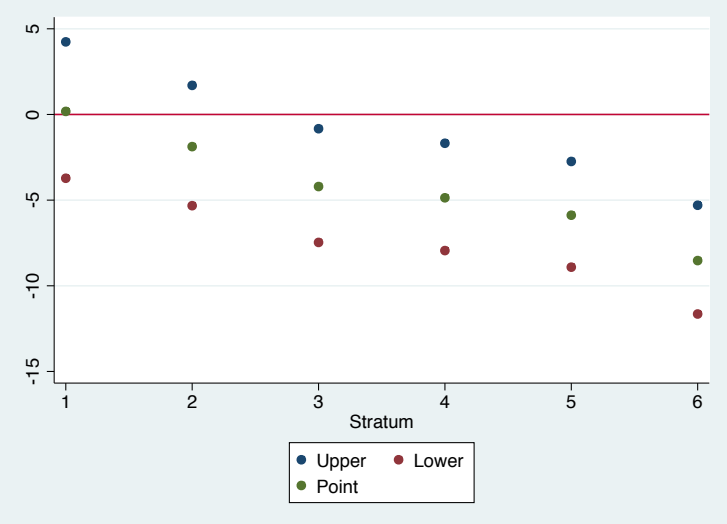
through rulings conducted by TLV. The price[1] will be observed as price per defined daily dosage.

Results

The estimation acquired through this method indicated an average price drop among affected products of -4.90% within the eight months following the reform. Taking the standard error of the estimate into account, the effect, the true average effect of reform, with 95% probability is found within the closed interval [-7.74, -1.97]. This could in this case be considered a quite wide interval but still it is obvious that the average price drop is statistically significant among products facing generic competition. This implies that the reform has on average had an effect on the price of pharmaceuticals in the time periods following the reform.

What does the change in prices say about the level of competition?

A more detailed analysis reveals that prices fell more in markets with more competitors. In markets with only two competitors the effect was virtually zero while in markets with sixteen or more competitors the prices fell by almost 9 %. These results are presented below in Table 1 and illustrated in Graph 1.



Graph 1. Upper and lower boundary level along with point estimation of the parameters β_1 to β_6

Group	Point Estimate
$Comp_1$	0,18
$Comp_2$	-1,88
$Comp_3$	-4,21*
$Comp_4$	-4,86**
$Comp_5$	-5,88**
$Comp_6$	-8,53**

Table 1. Estimated price drop in %
Notes: the asterisks **, * indicate significance at level 0.05 and 0.01 based on robust standard errors.

[1] The sample will not include products meant for inhalation. This is because of technical issues with observing these prices in terms of price per defined daily dosage.

These results may be interpreted as an indication that competition is relatively lax in the generic market.

Standard oligopoly theory (Bertrand competition with differentiated goods) suggests that the intensity of market competition is determined both by the number of competing products and how willing consumers are to substitute between the products. When competition is lax these two factors are complementary. For example, a willingness to substitute does not have any effects if only one product is supplied. And having several products doesn't create price competition if consumers are not willing to substitute. But when competition is hard the two factors are substitutes. For example, if there are very many firms in the market and consumers are at least modestly willing to substitute, then prices will be close to cost. Then, increasing the consumers' willingness to substitute will have little effect on prices.

Background and previous studies

Sweden's system of statutory health insurance has covered pharmaceutical cost for Swedish citizens wholly or in part since 1955. The Swedish market for pharmaceuticals consists of brand name products and generics. The cost of this coverage amounted in 2008 to around 1.2% of Sweden's GDP according to OECD (OECD, 2008). In order to lessen the cost of coverage, the principals governing the way and the extent in which a product is subsidized, on several occasions have been reformed.

In 1993 the reference price system was implemented. This system dictated that the government was to cover a sum equal to 110% of the price of the cheapest available pharmaceutical product at the pharmacy. If the patient out of free will were to choose a product with a price above the covered level he would have to cover the difference in price out of pocket. According to a study conducted by Rudholm, Aronsson and Bergman(2001) the market share of brand products that kept a relatively high price significantly decreased as an effect of this reform. This implies that price sensitivity would have increased among consumers and the cost of coverage for the government, decreased.

Reference pricing was further reformed in 2002 to include mandatory substitution. Mandatory substitution brought new rules for Swedish pharmacists, who now were obligated to inform and offer the costumer the cheapest product available in stock. This is unless the prescribing doctor explicitly prohibits substitution. The primary goal of this

is increasing information among consumers. In addition the reform also changed the level of reimbursement from 110% of the cheapest product to 100%. This further increases the incentive among consumers to choose the cheapest product available. Making pharmacist obligated to inform the consumer about the costs of choosing a more expensive product were supposed to make the consumers more prices sensitive. This would in turn increase the degree of substitution among the competing products. If this were to be the case the manufacturers would be more inclined to lower its prices resulting in lower subsidizing costs for the government. Generally the role consumer information plays when determining the price of a product and market structure is since long well documented (G.J Stigler, 1961)(P.A. Diamond, 1971). Within the context of pharmaceutical markets information among consumers also have proven to have a crucial effect on pricing. The effects going so far that just simply introduction of generic competition without adequate information have been known to in some cases increase the price of brand-name drugs (R.G Frank & D.S. Salkever, 1991). This suggests that there is good reason to expect a decrease in prices following the reform.

This reform has according to Granlund(2010) had positive effects on competition resulting in a average price drop of 10% mainly among brand-name products. Other studies however, concerning the introduction of such systems in other countries have presented results contrary to Granlunds findings, especially when considering brand-name drugs (Wiggins, S. N. & R. Maness, 2004)(Grabowski, H G & J M Vernon, 1992). These mixed conclusions demonstrates that the issue is in many respects complex, and no outcome is by any means guaranteed.

Furthermore a study by Granlund and Köksal(2011), argued that the mandatory substitution reform had a impact on prices trough competition. Among products facing therapeutic competition the prices are expected to be 1.5% lower. The reform proved however to be a poor amplifier to the effect of competition from parallel imports. In excess of these studies Buzzelli et al 2006 argued that in the context of all OECD countries the introduction of mandatory substitution has resulted in a decrease in prices.

Since the reform in 2002 it has become apparent that even after the introduction of mandatory substitution the cheapest products on the market held a relatively low share of the total sales, 41% according to the Dental and Pharmaceutical Benefits Agency, Swedish acronym. (TLV, 2011). These findings should be unexpected in a market where

the competing products are close to identical. Though could be a result of the subsidy effectively decreasing consumer price sensitivity, making consumers less likely to consider price when filling a prescription. Nevertheless this served as an indication that there are opportunities to further increase competition, thereby lessening the cost put on the government. The need for increased price sensitivity among consumers was further increased with the proposed deregulation of the market. Since private pharmacist when considering their bottom line, would have no incentives to prioritise selling cheap products.

With this as background the system of mandatory substitution were, in connection with the deregulation of the pharmacy market, reformed again in 2009. The new reform brought new rules to how mandatory substitution was conducted in Swedish pharmacies. According to the new reform all pharmacies had a responsibility to acquire and keep a supply of the cheapest products on the market to be available to the consumer. Aside from increasing the consumer information about the price relations on the market this also made the cheapest product on the market available everywhere. The hopes were that these factors would further increase the level of competition in the pharmaceutical market.

In order to continuously determine which product is cheapest, a monthly auction is held at the Dental and Pharmaceutical Benefits Agency (TLV). The competing manufacturers of every pharmaceutical products regularly submit their prices and the agency determine what product is to be the stocked by Swedish pharmacies. The chosen product is referred to as “Product of the Period”. From this follows that producers must compete by underbidding each other to be chosen to deliver the “Product of the Period”. This would supposedly force down the price on the products included in the governmental coverage.

2. Method, assumptions and data

2.1. The data

The data used in this thesis is all available trough the "The Dental and Pharmaceutical Benefits Agency" (TLV). The time series have been constructed from historical prices available from 2002 to 2012 observed through rulings by the agency. The rulings ranges from price changes to introductions of new product as well as exits. In total 178881 observations are available for the analysis, containing price information on every drug that is subsidized in Sweden.

From these observations it is possible to construct individual time series for every drug and ultimately create panel data. Beyond price information the data contain information on the name of the manufacturer, the "Anatomical Therapeutic Chemical"(ATC) code, NPL identification as well as package NPL. The ATC code is a system of classification among pharmaceutical product. The NPL identification is kept by the Swedish Medical product agency makes it possible to distinguish a specific product and package from the mass. From these variables it is possible to apart from the price series calculate the number of different manufacturers within an ATC code at a given time. This is considered to be the number of competitors of a given product on the Swedish pharmaceutical market[2].

All rearrangements and transposes necessary to achieve this are available in Appendix 1. The total amount of pharmaceuticals used in the final analysis exceeds 8000.

Making use of a dataset of this size opens up additional aspects to consider when making inference. Due to the shear size of the dataset any difference in the data will most likely prove to be statistically significant. This statistical significance is distinctly different from economic significant, as discussed by McCloskey and Ziliak (1996). The core of their argument is that statistical significance does not translate into economic importance. A parameter could prove to be statically different from zero but so insignificant in magnitude as to carry no economic importance. This very point has been argued in other applications as well, in statistics in general (T. Wonnacott, 1987) and in medicine (M.J. Gardner & D.J. Altman 1986).

[2] Any competition between different active substances commonly referred to as Therapeutic Competition, is not accounted for in this paper.

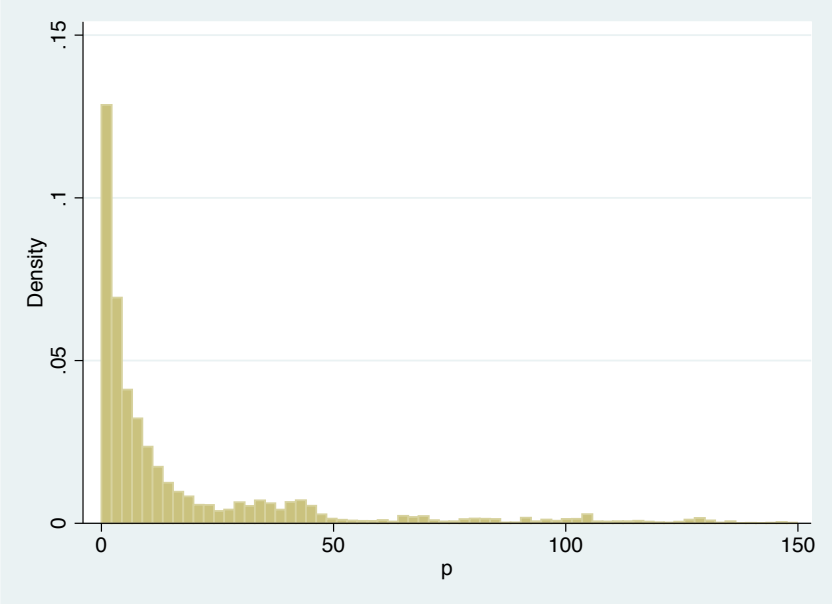
To focus the results in this thesis on economical significance more then the statistical the results will mainly be focused on the inference considering the parameters magnitude.

2.2. The price variable

The price of interest in this thesis is the pharmacy's purchasing price of a given pharmaceutical product (AIP). The first problem to arise when measuring how big effect the reform has had on price will be the unit of choice. The price of one unit of a product over time in the form it is observed in the dataset would not necessarily reflect changes in the cost of the product. A change in price could as an example also come about due to changes in concentration or size of one unit not affecting the actual cost of usage. It is an issue of nominal contra real price change. To correct for this risk all prices will be rewritten from price per unit to price per Defined Daily Dosage (DDD). The DDD of a substance is estimated by the WHO Collaborating Centre for Drug Statistics Methodology (WHOCC) and is should represent the average dose per day necessary for the drug to be effective in its main purpose when used by an adult.
The DDD of a product is tied to its ATC code and is established for every active substance used in pharmaceuticals that has an ATC code.

2.3. Distribution and measuring of central tendencies

In order to choose a model in which to estimate effect of the reform the distribution of the price variable must be considered. Analysing the distribution of the observed pharmaceutical prices in the histogram below it is apparent that the prices are clustered in the lower end of the distribution while also proving to have a long tail of extreme observations. This is problematic when measuring central tendencies in a sample.



Graph 2. Histogram of the observed prices (*p*).

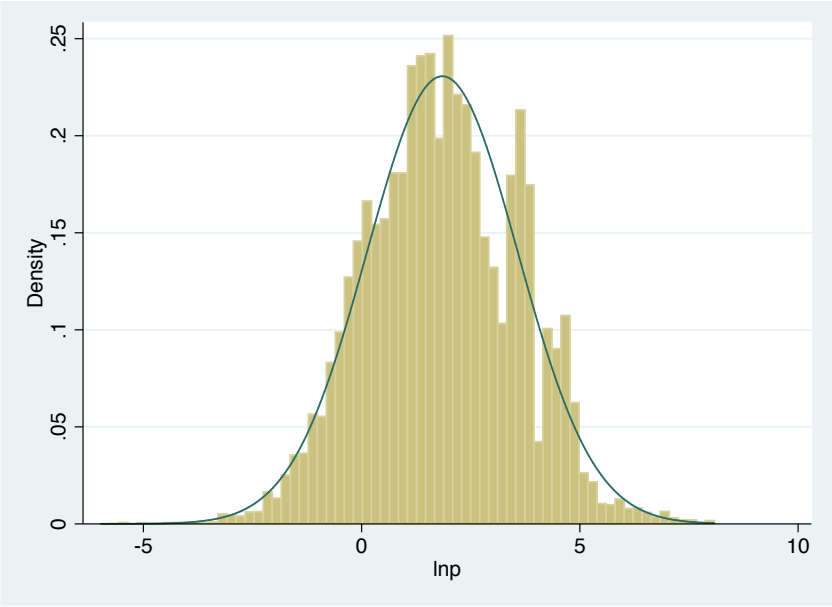
Percentiles	*p*
1%	0.130
5%	0.405
10%	0.720
25%	1.907
50%	6.139
75%	22.201
90%	63.367
95%	104.3
99%	368

Table 2. Percentiles of the observed price (*p*).

Considering the information provided in Table 1 it seems that the price data approximately follows a lognormal distribution. This distribution suggests that linear regression methods might be unsuitable for estimating the effect of the reform. This is because of the mean, the centre of gravitation, in the distribution is inadequate as a measurement of the central value. This results in the mean price being highly sensitive to changes in price among the more expensive pharmaceuticals compared to the cheaper products. A hypothetical drastic change in the mean price could simply be the result of relatively small changes among the most expensive products. Following this it is to be expected that the residuals, would not follow a symmetric pattern but be skewed in the same way the sample is[3]. Therefor some form of transformation is needed in order to satisfyingly make point estimations and inference concerning the effect. Assuming that the true distribution is indeed Log-normal the natural logarithm of the

[3] This violation does not invalidate linear models trough bias but it does undermine the possibility of extending the inference concerning the point estimations of the parameters.

data will be normally distributed. Such a distribution would suggest that a linear regression model is a good way of making point estimations. As seen below in Graph 2 applying the natural logarithm of the price data corrects for the previously observed skewness in a somewhat gratifying way.



Graph 3. Histogram of the logarithm of prices (*p*).

Percentiles	*ln(p)*
1%	-2.040
5%	-0.904
10%	-0.329
25%	0.646
50%	1.815
75%	3.100
90%	4.149
95%	4.647
99%	5.908

Table 3. Percentiles of the logarithm price (*p*).

Even thought the new form might not be strictly normally distributed it validates a linear regression as a viable method for estimating the effect of the reform. Assuming the true distribution of the variable *p* to be log-normally distributed implies that the true model is multiplicative.

2.4. Difference in Difference

In order to estimate the effect of the reform, a difference in difference regression will be conducted. The Difference in Difference regression (DiD) uses a control group not affected by the reform in order to separate the theoretical case of "no reform" from the actual case in the affected group, the test group. In this study the control group are products not facing generic competition.

Accounting for the permanent difference between the groups and the common trend, i.e. a time specific effect, renders it possible to isolate the effect of the reform. This is illustrated graphically with hypothetical data in Graph 4. In the graph a fictive reform takes place when *t* is 100.

Graph 4. Difference in Difference estimation of treatment effects.

Krueger and Card first popularized this method in economics in 1993 when they applied this to unemployment data from New Jersey and Pennsylvania in order to estimate effects of reforms concerning the minimum wages in New Jersey. Since then the method has been widely applied to evaluate reforms and policy.

Several concerns and criticisms have been raised concerning this method. One of the reoccurring issues is concerning the often-present autocorrelation. This leads possibly to underestimation of the size of the standard errors associated with the point estimations. When Bertrand et al brought this forward in 2002, they argued that many studies failed to properly account for this problem and thereby suffering from biased standard errors. In this paper this problem is dealt with by collapsing the data into two periods, pre and post reform.

The regression analysis will be carried out using the products protected by patent as a control group to the products that are subject to generic competition. The test group will be denoted as *Generics*, assuming values one or zero. To ensure that the two groups are completely separated no protected product whose patent expires within the estimation period will be included in the analysis.
The regression model will be defined as:

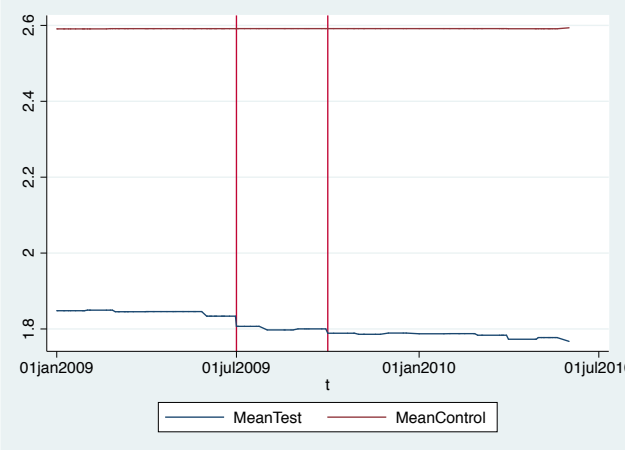
$$ln(p) = \alpha_0 + \beta_1 Generics + \beta_2 Agreement + \beta_3 Reform + \beta_4 (Generics * Reform) + \varepsilon,$$
$$where\ E(\varepsilon) = 0\ and\ V(\varepsilon) = {\sigma_\varepsilon}^2$$

This model will be referred to as equation 1.
Point estimation of the parameters will be conducted on the prices observed between January 2009, and June 2010, using OLS. The first exogenous shock accounted for is the agreement between the Swedish government and brand-drug manufacturers to set prices on brand-name products to 35% of the price one year prior to the patent expiration. This agreement took effect on the first of July 2009 and will be accounted for as the dummy variable $Agreement$. The variable *Reform* is a dummy variable signalling for a time period in which the new rules concerning the mandatory substation is in effect. Assuming the model is correctly specified the parameter β_4 of the interaction term $Generics * Reform$ constitutes the true casual effect of the reform on the pharmaceuticals subject to generic competition.
A common problem with linear OLS regression is heteroskedasticity. This refers to the situation when the variance of a response variable is dependent on the explanatory variables. In this context this would be the case if the reform resulted in higher price volatility then was the case before. This phenomenon does not affect the estimator's quality as of biasness. It does however damage the efficiency of the estimators. To avoid any problems of this kind the OLS regression will be conducted using robust standard errors. The Huber-White sandwich estimators will estimate the regressions robust errors.

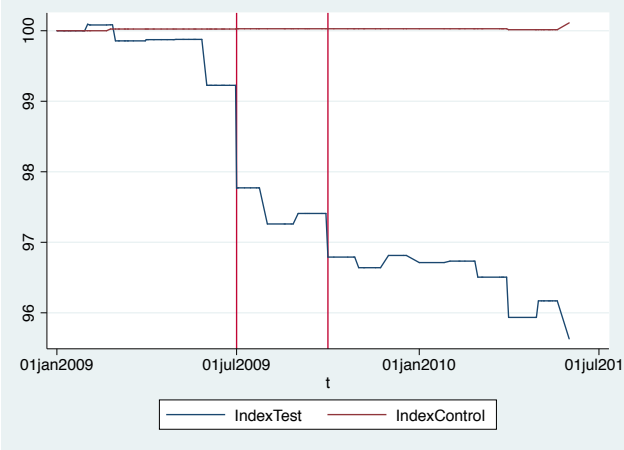
2.5. The parallel trend assumption

A pivotal assumption concerning the control group's suitability to estimate the causal effect of the reform is the assumption that the price development of pharmaceuticals in the two groups would have been similar if the reform would not have taken place[4]. The two groups, test and control, need to be subject to a common trend. This assumption is called the "parallel trend assumption". The DiD regression relies heavily on this assumption and if it were to be violated the estimated treatment parameter would be biased.

Making use of Graph 3 and 4 as rough illustrations of the price development, these two groups seems to follow a similar trend between the first of January and October when the effect of the agreement is excluded. The shocks are illustrated as vertical lines in the graph. The trend by this graph seems to not be different from zero.



Graph 5. The mean price in the test and control groups over time.



Graph 6. Index series of the mean price in the test and control groups over time.

The parallel trend assumption lacks a formal test. But one suggested method of controlling the validity of the assumption is by estimating the DiD regression during a period prior to the reform. This regression will be referred to as the placebo regression. By applying the same model to the periods preceding the reform t(-1,0) any effect significantly different from zero would be the result of a differing trend in the test group. The estimations are conducted by Ordinary least squares (OLS) and presented in full Appendix 3. Below are the point estimations and their corresponding standard errors.

[4] This implies that $\text{cov}(\varepsilon, Generics * Reform | Generics, Argreement, Reform) = 0$

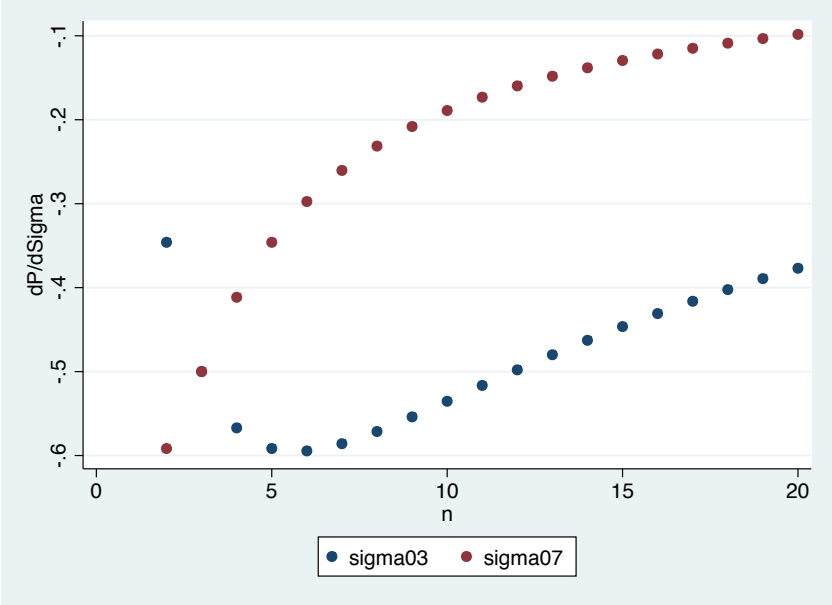
Placebo regression results		
	Estimate	**Std.Error**
Generics	-0.7427**	0.0256
Agreement	-0.0227	0.0195
Reform	0.0010	0.0267
Reform*Generics	-0.0180	0.0275
α	2.5908**	0.0248

Table 4. Placebo equation estimation results.
Notes: the asterisks **, * indicate significance at level 0.05 and 0.01 based on robust standard errors.

Since there was no significant treatment effect estimated in the placebo regression the parallel trend assumption is from here on considered valid. Had there been an effect different from zero there would have been an indication that the hypothetical case of "no reform" still would have yielded measurable differences between the groups.

2.6. The impact of competition

A Bertrand model extended to take into account product differentiation is applied in order to provide a theoretical background to the problem. The model predicts the marginal effect on price due to an increased rate of substitution to be dependent on the degree of substitution and number of competitors preceding the increase[5]. Rate of substitution is denoted σ and taking on values between zero and one, where one implies perfect substitution. This is illustrated below with *sigma03* signifying an initial level of substitution of 0.3, and *sigma07* a level of 0.7.



Graph 7. Derivative of Bertrand model with respect to σ at different values of n

The graph illustrates two distinguishable scenarios concerning the effect pattern. The first, decreasing effect with an increasing number of competitors. This pattern emerges when either the rate of substitution or the number of competitors are high, or both. This will be considered a high competition market. The second case, the effect increasing with the number of competitors emerges when both factors are low. Essentially this situation refers in a Bertrand model to a low competition market. The pattern of the reform's effect at an increasing number of firms therefore depends on the initial level of competition in the market.

To investigate what the case best describes this market a second regression will be conducted estimating the effect of reform as a function of different competition groups

[5] The derivate of the Bertrand model is presented in full in Appendix 2.

referred to as $Comp_i$. The number of competitors at a given time determines what group a product will be part of. In this study there will be six groups considered, ranging from the duopoly case to the case of a product facing competition from more than fifteen firms within their active substance. The first cluster will only contain the duopoly case since this is a case of special interest when competition is concerning. The second will be composed of products facing two to three competitors, third is four to five, fourth six to ten, the fifth is eleven to fifth teen and the sixth is containing all product facing from more that fifteen firms. The regression will estimate the effect by the interaction term between $Comp_i$ and dummy *Reform*Generics* as defined in the previous section as the treatment effect.

This model is defined as:

$$ln(p) = \alpha_0 + \theta_1 Agreement + \theta_2 Reform + \sum_{i=1}^{n} \alpha_i Comp_i + \sum_{i=1}^{n} \beta_i (Comp_i * (Reform * Generics)) + \varepsilon,$$

$$where\ E(\varepsilon) = 0\ and\ V(\varepsilon) = {\sigma_\varepsilon}^2$$

This will be referred to as equation 2.

The estimated parameters β_i will be the estimated average effect of the reform in the different competition groups. Compering these different estimations will give us a clearer picture of what role competition has played on the effect of the reform.

	Pre Reform					*Post Reform*			
	Mean	**Std. Dev.**	**Min**	**Max**		**Mean**	**Std. Dev.**	**Min**	**Max**
ln(p)	1.884	1.778	-5.530	8.309		1.838	1.776	-5.416	8.309
Generics	0.932	0.251	0	1		0.932	0.251	0	1
$Comp_N$	8.415	5.925	0	21		8.415	5.925	0	21
$Comp_1$	0.071	0.256	0	1		0.071	0.256	0	1
$Comp_2$	0.147	0.354	0	1		0.147	0.354	0	1
$Comp_3$	0.090	0.286	0	1		0.090	0.286	0	1
$Comp_4$	0.211	0.408	0	1		0.211	0.408	0	1
$Comp_5$	0.251	0.434	0	1		0.251	0.434	0	1
$Comp_6$	0.164	0.370	0	1		0.164	0.370	0	1

Table 5. Pre & Post Reform basic measurements

The control group, products not facing any competitor, account for 6.8% of the data set. This amounts to a total of approximately 600 control products in the regression. The number of competitors a product faces is calculated by every time a new ruling has come into place. In total the products at most face competition from 21 firms at a specific time, the distribution of the number of competitors are presented in Appendix 4. The first group, the duopoly case, contain 7.1% of the total number of observations. The second represents 14.7%, the third 9.0%. The two following, fourth and fifth contain 21% and 25% and the last accounted for 16.4% of the observations.

3. Results

3.1. DiD regression results

Estimating equation 1 using OLS estimators yields the results presented below in table 6.

	Estimation Results	
	Estimate	**Std.Error**
Generics	-0.7583**	0.0094
Agreement	-0.0249	0.0195
Reform	-0.0002	0.0150
Reform*Generics	-0.0502**	0.0155
$\boldsymbol{\alpha}$	2.5917**	0.0091

Table 6. Equation 1 estimation results.
Notes: the asterisks **, * indicate significance at level 0.05 and 0.01 based on robust standard errors.

The coefficient of the interaction term is estimated to -0.502 with a standard error associated to it of 0.0155. The statistical significance of this result is tested through a t-test under a normality assumption based on the Gauss-Markov assumptions and the Central Limit Theorem (CLT) (Casella G. & Berger R. L., 2002). This test is successful in rejecting the hypothesis that the coefficient is equal to zero at a significance level of 0.01. In order to study the magnitude of this treatment effect a confidence interval is constructed. The interval is based on the same assumptions as in the t-test and a significance level of 0.05. Both boundaries and the point estimation are transformed in order to be interpreted in relevant terms[6]. The intervals are constructed through inverting the t-statistic (Casella G. & Berger R. L., 2002). The result is defined below:

$$\left(\hat{\beta}_i - t_{\frac{\alpha}{2},df} * s_{\widehat{\beta_i}}\right) \leq \beta_i \leq \left(\hat{\beta}_i + t_{\frac{\alpha}{2},df} * s_{\widehat{\beta_i}}\right)$$

Confidence Interval Estimation (α=0.05)		
Lower Boundery	**Upper Boundery**	**Point Estimate**
-7.74	-1.97	-4.90

Table 7. Interval estimation of the point estimation $\boldsymbol{\beta_4}$.

[6] The transformation is: $\left(e^{\beta_i} - 1\right) * 100$

The point estimation suggests that the reform has resulted in a drop in price among the effected substances of 4.90%. According to the confidence interval there is a 95% probability that the interval [-7.74. -1.97] is covering the true treatment effect in the population.

The group specific effect is estimated to -0.7583, a result also significant at a 0.01 significance level. The effect of the variable included to account for the agreement reached between the government and the manufacturers were estimated to -0.0249, although not significantly different from zero. The full regression results are presented in Appendix 5.

3.2. The effect of competition

Equation 2 was introduced as to estimate what role the number of competitors played. The model was estimated using OLS and the results are presented below.

	Estimation Results	
	Estimate	**Std.Error**
Agreement	-0.0249	0.0192
Reform	-0.0002	0.0150
$\boldsymbol{Comp_1}$	-0.9210**	0.0122
$\boldsymbol{Comp_2}$	-0.5208**	0.0110
$\boldsymbol{Comp_3}$	-0.6859**	0.0107
$\boldsymbol{Comp_4}$	-0.3413**	0.0101
$\boldsymbol{Comp_5}$	-1.1185**	0.0101
$\boldsymbol{Comp_6}$	-0.9248**	0.0106
$\boldsymbol{Comp_1 * Reform}$	0.0018	0.0203
$\boldsymbol{Comp_2 * Reform}$	-0.0190	0.0183
$\boldsymbol{Comp_3 * Reform}$	-0.0430*	0.0177
$\boldsymbol{Comp_4 * Reform}$	-0.0499**	0.0168
$\boldsymbol{Comp_5 * Reform}$	-0.0606**	0.0167
$\boldsymbol{Comp_6 * Reform}$	-0.0892**	0.0177
$\boldsymbol{\alpha}$	2.5917**	0.0091

Table 8. Equation 2 estimation results.
Notes: the asterisks **, * indicate significance at level 0.05 and 0.01 based on robust standard errors.

Based on the same assumptions as in the previous section, t-tests are conducted to make inference of the probability of the parameters being equal to zero. Result of these test are presented in full in Appendix 5. Notable results are that the effect of the reform

among the lower stratum, the duopoly case and stratum 1, failed to display any effect significantly different from zero. The group containing substances facing competition from 3 or 4 different firms displayed an effect estimated to -0.0430 significant at significance level 0.05. From there on the effect seems to increase with the number of competitors, all point estimations significantly differ from zero at the significance level of 0.01.

To interpret the results in exact percentages the results are transformed back into there multiplicative form. The following table presents the all point estimation along with the upper and lower boundary levels of the confidence interval.

Confidence Interval Estimation (α=0.05)			
Group	**Lower Boundary**	**Upper Boundary**	**Point Estimate**
$Comp_1$	-3.72	4.24	0.18
$Comp_2$	-5.33	1.70	-1.88
$Comp_3$	-7.47	-0.83	-4.21
$Comp_4$	-7.95	-1.68	-4.86
$Comp_5$	-8.92	-2.74	-5.88
$Comp_6$	-11.65	-5.30	-8.53

Table 9. Interval estimation of the point estimations β_1 to β_6.

The estimated effect of the reform among the products facing the largest number of competitors are estimated to be -8.53%, and when considering the standard error the true effect is expected to lay between -11.65% and -5.30%. This result is vastly different from the estimated effect among products facing duopoly competition. Among these products the effect is estimated to 0.18%, virtually zero. The effect in the third and fourth group was -4.21% and -4.81% with both estimates being significantly different from zero. The fifth group displayed an observed effect of -5.88% also significantly different from zero at the significance level of 0.01. Except for the duopoly case only the second group, product facing 2-3 competitors within their active substance failed to produce an estimate significantly different from zero. The average effect in this group is with 95% probability covered in the closed interval [-5.33,1.70].

3.3. Concluding remarks

This paper was made possible trough the data publicly available through TLV. But therein lays also the limitations. In order to further expand the analysis of the effects of the new mode of procedure concerning mandatory substitution in Sweden more in-depth data is needed e.g. data on sale quantities would have made the effect on cost possible to estimate. Further, observations on what product was a generic copy and which was brand-name product would have made it possible to separate the effect between them, which has been the focus of many previous studies. But most important are the limitations in the timeframe, which are imposed on this study. Even though the data from TLV stretched from 2002 to 2012 the control group could not be made to hold the parallel trend assumption for that long a time period. Thereby limiting the effect to be estimated only in the following eight months, the result is therefore limited to be interpreted as somewhat of an initial effect. When writing, it seems that a control group consisting of products that are not included in the coverage of the government but yet faces competition, would open up the possibility of expanding the analysis into a long-term evaluation.

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Appendices

Appendix 1 – Rearrangements and transformations in STATA

```
scalar start_dag=1
scalar start_manad=1
scalar start_ar=2008

destring Styrka, generate (Styrka2)
ignore("qwertyuiopåasdfghjköäzxcvbnm-QWRYOPÅASDFGHJKLÖÄZXCVBNM")
force
sort Styrka2, stable
drop if Gllerfrom<td(1,1,2000)
drop if Gllerfrom>td(1,1,2013)
drop if NPLpackid=="0"
drop if NPLpackid=="."
drop if NPLpackid=="2"
drop if NPLpackid=="1"
drop if NPLpackid=="11111111111113"
drop if Fretag==""
drop if Styrka2==.

replace ATCkod = subinstr(ATCkod," ","",.)
joinby ATCkod using
"/Users/rasmuslonn/Documents/Uppsats/NEK/Data/Index ATC:DDD.dta"
drop if Enhet== "ml" | Enhet== " " | Enhet== "TU" | Enhet== "tablet"
| Enhet== "U" | Enhet=="mmol"
replace Styrka = subinstr(Styrka, "1","",.)
replace Styrka = subinstr(Styrka, "2","",.)
replace Styrka = subinstr(Styrka, "3","",.)
replace Styrka = subinstr(Styrka, "4","",.)
replace Styrka = subinstr(Styrka, "5","",.)
replace Styrka = subinstr(Styrka, "6","",.)
replace Styrka = subinstr(Styrka, "7","",.)
replace Styrka = subinstr(Styrka, "8","",.)
replace Styrka = subinstr(Styrka, "9","",.)
replace Styrka = subinstr(Styrka, "0","",.)
replace Styrka = subinstr(Styrka, ".","",.)
replace Styrka = subinstr(Styrka, " ","",.)
drop if Styrka ==" "

replace Styrka2= Styrka2/1000 if Styrka=="mg" & Enhet=="g"
replace Styrka2= Styrka2*1000 if Styrka=="g" & Enhet=="mg"
replace Styrka2= Styrka2/1000 if Styrka=="mikrogram" & Enhet=="mg"
replace Styrka2= Styrka2/1000 if Styrka=="mikrog" & Enhet=="mg"
replace Styrka2= Styrka2*1000 if Styrka=="mg" & Enhet=="mcg"

replace NyttAIP=. if NyttAIP==0
replace TidigareAIP=. if TidigareAIP==0

replace NyttAIP= ((NyttAIP/Antal)/Styrka2)*DDD
replace TidigareAIP=((TidigareAIP/Antal)/Styrka2)*DDD
```

```
replace TidigareAIP=999 if TidigareAIP==.
replace NyttAIP=9999 if NyttAIP==.

qui duplicates tag NPLpackid Gllerfrom, gen(dup_id)
qui sort NPLpackid Gllerfrom, stable
qui gen n=1
qui replace n=sum(n)
qui egen N=max(n)
scalar obs=N
tsset n
qui gen dup=0
qui replace dup=1 if dup_id==1 & Gllerfrom==l.Gllerfrom
count if dup==1
drop if dup==1
drop dup_id dup n N

qui sort NPLpackid Gllerfrom, stable
qui gen n=1
qui replace n=sum(n)
qui egen N=max(n)
scalar obs=N
drop n N

sort ATCkod Fretag, stable
range obs 1 `=scalar(obs)' `=scalar(obs)'
tsset obs

drop if Styrka2==.
drop Fretag Antal Styrka2 ATCkod

gen NyttAIP2=NyttAIP

qui destring NPLpackid, ignore(" " | ".") replace
qui format %20.0g NPLpackid

qui destring NPLid, ignore(" " | ".") replace
qui format %20.0g NPLid

qui gen t=Gllerfrom
drop DDD Enhet Styrka NyttAIP obs NPLid
gen double NPLpackid2=NPLpackid
qui format %20.0g NPLpackid2
ren NyttAIP2 NyttAIP

timer off 2

/* Här börjar transponeringarna*/
timer on 3

qui reshape wide NyttAIP TidigareAIP t, i(NPLpackid) j(Gllerfrom)
qui format %25.0g NPLpackid

qui gen n=1
qui replace n=sum(n)
```

```
qui egen N=max(n)
qui scalar N=N
qui drop N n

qui xpose, clear promote

/* Här slutar transponeringarna*/

timer off 3
/* Fyll ut serierna så vi inte saknar några värden förutom vid
utträden*/
timer on 4

qui gen n=1
qui replace n=sum(n)
tsset n
egen N2=max(n)
scalar N2=N2

qui egen double t = rowmax(v1 - v`=scalar(N)')
qui replace t=. in 1
qui replace t=. if t<15000
qui replace t=. if f.t!=.
qui format t %td

forvalues i = 1/`=scalar(N)' {
qui replace v`i'=. if v`i'>15000 & _n!=1 & _n!=_N
}

qui format %20.0g v1 - v`=scalar(N)'

qui replace t=f.t
qui replace t=l.t if t==.
qui replace t=t[3] in 2

gen start=1 if
t>=td(`=scalar(start_dag)',`=scalar(start_manad)',`=scalar(start_ar)
') & t!=.
gen calibrering=n if start!=1
egen start_period=max(calibrering)
scalar start_t= start_period[1]

forvalues i = 1/`=scalar(N)'{
qui replace v`i'=l.v`i' if v`i'==. & l.v`i'<1000000 & l.v`i'!=999 &
l.v`i'!=9999
}
forvalues i = 1/`=scalar(N)' {
while v`i'[2]==. {
qui replace v`i'=f.v`i' if v`i'==.
}
}
forvalues i =1/`=scalar(N)'{
qui replace v`i'=9999 if l.v`i'==9999
}
```

```
forvalues i =1/`=scalar(N)'{
qui replace v`i'=. if v`i'==999 | v`i'==9999
}
forvalues i = 1/`=scalar(N)'{
qui replace v`i'=. if v`i'[_N]==.
}
forvalues i = 1/`=scalar(N)'{
qui replace v`i'=. if v`i'[`=scalar(start_t)']==.
}
forvalues i = 1/`=scalar(N)'{
qui replace v`i'=l.v`i' if v`i'==. & l.v`i'!=. & f.v`i'!=.
}

drop if _n==1
timer off 4

keep v1-v`=scalar(N)' t

drop if _n==_N-1
duplicates drop t, force
qui reshape long v, i(t) j(Produkt)

ren v p

bysort Produkt: egen double NPLpackid=max(p)
qui format %20.0g NPLpackid
qui replace NPLpackid=. if p==.

qui merge m:m NPLpackid using
"/Users/rasmuslonn/Documents/Uppsats/NEK/Data/ADV_NPL2.dta"

drop if p==.
drop if t>td(1,1,2015)
drop if p>10000000000
```

Appendix 2 – Derivate of Bertrand model

$$p = \frac{(1-\sigma)\alpha + [1+(n-2)\sigma]c}{2[1+(n-2)\sigma] - (n-1)\sigma}$$

Where c denotes marginal cost, α equals demand intercept and σ is rate of substitusion varying between 0 and 1. Assuming c< α.

$$\frac{\partial P}{\partial \sigma} = \frac{((-1+n)\,(c-\alpha))}{(2+(-3+n)\sigma)^2}$$

$$\frac{\partial^2 P}{\partial \sigma \partial n} = \frac{-((c-\alpha)\,(-2+\sigma+n\,\sigma))}{(2+(-3+n)\,\sigma)^3}$$

Appendix 3 – Placebo regression

The placebo regression is specified as:

$$ln(p) = \alpha + \beta_1 Ref + \beta_2 Agreement + \beta_3 Placebo + \beta_4 (Ref * Placebo) + \varepsilon,$$
$$where\ E(\varepsilon) = 0\ and\ V(\varepsilon) = \sigma_\varepsilon$$

The placebo variable, *Placebo*, is a dummy variable for the implementation of a fake reform. The fake reform is implemented in February 2009 and if the parallel trend assumption holds up the estimated effect of this reform wont be significantly different from zero.

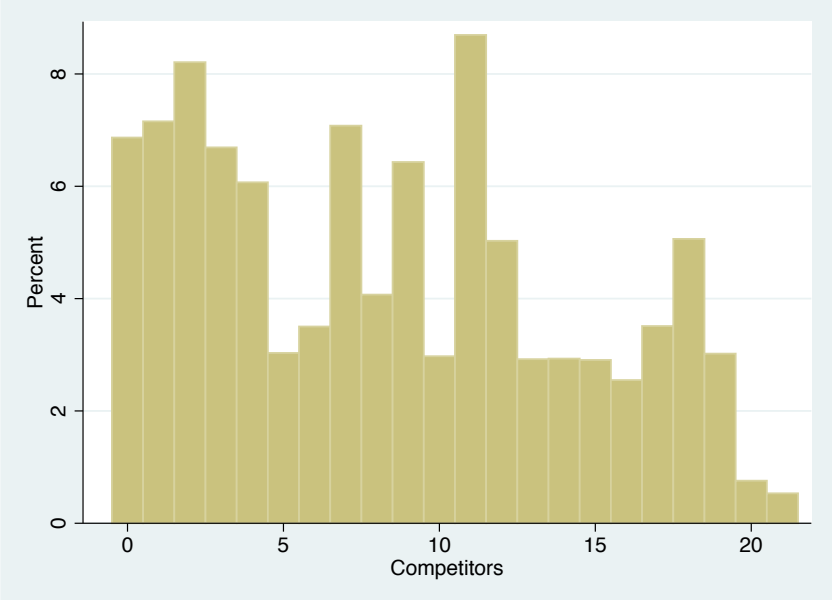
Linear regression

ln(p)	**Coef.**	**Robust Std. Err.**	**t**	**P>t**	
Generics	-.7427415	.0256223	-28.99	0.000	Number of obs = 629625
reform1	-.0227258	.0194846	-1.17	0.243	F(4,629620) = 1643.79
placebo_reform	.000966	.0266829	0.04	0.971	Prob > F = 0.0000
placebo_treatment	-.017909	.0275232	-0.65	0.515	R-squared = 0.0115
_cons	2.590808	.0248385	104.31	0.000	Root MSE = 1.7676

The regression renders it obvious that the placebo reform was insignificant. Therefore the parallel trend assumption is holding up.

Appendix 4 - Number of competitors

The distribution of the number of competitors in the data:



Appendix 5 – Regression results

The following tables are the results of equation 1 and 2.

Linear regression		Robust				
p	**Coef,**	**Std, Err,**	**t**	**P>t**	**[95% Conf,**	**Interval]**
Generics	-0,7582627	0,0093568	-81,04	0	-0,7766016	-0,7399237
reform1	-0,0248517	0,0194644	-1,28	0,202	-0,0630013	0,0132979
reform2	-0,0001938	0,015028	-0,01	0,99	-0,0296482	0,0292606
treatment2	-0,0502262	0,0154988	-3,24	0,001	-0,0806034	-0,019849
_cons	2,591674	0,0090742	285,61	0	2,573889	2,609459

Linear regression		Robust				
p	**Coef,**	**Std, Err,**	**t**	**P>t**	**[95% Conf,**	**Interval]**
reform1	-0,0248517	0,0191874	-1,3	0,195	-0,0624584	0,012755
reform2	-0,0001938	0,015028	-0,01	0,99	-0,0296482	0,0292606
stratum_1	-0,9210485	0,0122328	-75,29	0	-0,9450245	-0,8970725
stratum_2	-0,5207572	0,0110096	-47,3	0	-0,5423356	-0,4991788
stratum_3	-0,6859373	0,0106697	-64,29	0	-0,7068495	-0,6650251
stratum_4	-0,3412716	0,0101365	-33,67	0	-0,3611389	-0,3214044
stratum_5	-1,118464	0,0101122	-110,61	0	-1,138284	-1,098645
stratum_6	-0,9247634	0,0106879	-86,52	0	-0,9457113	-0,9038155
treat_strat1	0,0017689	0,0202666	0,09	0,93	-0,0379529	0,0414908
treat_strat2	-0,018956	0,0182516	-1,04	0,299	-0,0547286	0,0168166
treat_strat3	-0,0429932	0,0176711	-2,43	0,015	-0,0776279	-0,0083586
treat_strat4	-0,0498725	0,0167946	-2,97	0,003	-0,0827894	-0,0169556
treat_strat5	-0,0606044	0,0167214	-3,62	0	-0,0933778	-0,027831
treat_strat6	-0,0891534	0,0177065	-5,04	0	-0,1238575	-0,0544493
_cons	2,591674	0,0090741	285,61	0	2,573889	2,609459