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The Impact of Process Innovation on Prices: Evidence from Automated Fuel Retailing in The Netherlands

Adriaan R. Soetevent[1]
Tadas Bruzikas[2]

[1] *University of Groningen and Tinbergen Institute*
[2] *University of Groningen*

The Impact of Process Innovation on Prices:

Evidence from Automated Fuel Retailing in The Netherlands*

Adriaan R. Soetevent†
University of Groningen
Tinbergen Institute

Tadas Bružikas‡
University of Groningen

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Abstract

In the last decade, many European countries have seen a sharp increase in the number of automated fueling stations. We study the effect of this process innovation on prices at stations that are automated and their competitors using a difference-in-differences matching strategy. Our estimates show that prices at automated stations drop by 1.0 to 2.1% immediately after conversion and stabilize at this lower level. We find no indication of competitive spillover effects to neighboring sites at the conventional significance levels. Other than previous studies, our estimates do not reveal a difference in impact between early and later adopters of automation.

Keywords: technology adoption, retail gasoline, pricing, competition
JEL classification: C22, D4, L13, L81

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†Corresponding author: University of Groningen, Faculty of Economics and Business, Nettelbosje 2, 9747 AE Groningen, The Netherlands, a.r.soetevent@rug.nl.

‡University of Groningen, Faculty of Economics and Business, Nettelbosje 2, 9747 AE Groningen, The Netherlands, tadas.bruzikas@gmail.com.

1 Introduction

In the last decade, unmanned or automated fueling stations have proliferated across Europe. Automated fueling sites are completely unstaffed and payment is by debit or credit card at the pump only. According to one large study, 7.7% of all service stations in the European Union were unstaffed in 2012, but with large cross-country differences.[1] In Scandinavian countries such as Denmark and Sweden the share of unmanned stations was found to be over 60% in 2012 while in other countries such as Italy and Hungary it was less than 1%.

Declining fuel volumes and a desire to cut fixed staffing cost seems to drive the increased activity of converting service stations into unstaffed sites.[2] At converted sites, this may lead to lower price levels if realized cost reductions are partially or fully passed onto consumers. There may also be competitive spillovers in the form of lower prices at nearby competitors. The aim of this study is to empirically estimate the extent to which these direct and competitive effects on prices are statistically and substantially significant.

The literature on technology evolution distinguishes between product and process innovations. Whereas in the early stage of a product technology's life cycle product innovation is the most important mode of innovation, in the later stages when the product design stabilizes, process innovations that enable firms to produce the same output using less input take over as the dominant innovation mode (Adner and Levinthal, 2001). The transition to automated fuel retailing is a good example of a process innovation in an industry in the later stages of its technology cycle. In the Netherlands, full service stations where an attendant at the forecourt delivers fuel into the customers car disappeared in the 1970s and 1980s. Nowadays, all staffed stations are self service stations where customers pump their own gas.[3]

Given the rise of non-cash debit and credit card payments in everyday transactions, the adoption of automats that allow for payment at the pump instead of at a cashier only is a natural next step. Automation lowers a firm's cost while leaving the physical product that consumers receive unaltered. Moreover, whereas the impact of process innovations on prices

[1] Civic Consulting (2014, Table 89). Four regions in Spain have recently stalled the rise of unstaffed stations by adopting legislation that requires all service stations to have at least one employee present during opening hours. This happened on instigation of an alliance of employers, unions and consumers that cited potential safety risks, job losses and barriers to people with disabilities. `http://economia.elpais.com/economia/2015/02/06/actualidad/1423251729_289297.html`.

[2] See CBRE (2012).

[3] The same development has happened in many other countries. Basker et al. (2017) study the adoption of self service pumps in the U.S between 1977-1992 and show how this shifting of work to customers biases upward conventional measures of labor productivity.

is mostly hard to measure because either the innovations themselves are invisible and/or price data are not easily available, retail gasoline markets are instead very favorable to studying this question empirically. First, automation is a visible event which allows us to pin down the date of automation rather precisely. Second, fuel prices are readily available at the station-level and cleanly measured. This allows us to use stations as the unit of observation in our analysis. Third, because oil companies already frequently adjust their retail prices to reflect fluctuations in the price of inputs (notably the oil spot price), changing prices due to automation does not involve any additional menu cost. The absence of menu cost increases the likelihood that price effects, if any, become apparent shortly after the event of automation. Despite these advantages, we are the first to address the impact of automated fuel retailing on prices.

Our paper is related to other papers on technology adoption in retail markets, such as Foster, Haltiwanger and Krizan (2006), Basker (2012, 2015) and Carranza, Clark and Houde (2015). Foster *et al.* (2006) compare the productivity gains across multiple retail sectors. They find that most of gains in labor productivity are due to the entry of more productive firms that replace less productive ones. As in the current study, Carranza *et al.* (2015) turn to gasoline markets and study the effect of price floor regulations on technology adoption. They find that such regulations reduce efficiency by barring the entry of low-cost retailers but do not increase prices. Basker (2012) studies the effects of introducing barcode scanners on labor productivity and prices. Basker (2012) finds that the introduction of scanning reduces the wage bill with 4.5%.

Most related to our work is Basker (2015), in which she considers the impact of scanners on the prices of various grocery products. She estimates that these prices have decreased by at least 1.4% because of the introduction of scanners. As with the introduction of scanners, the event of fuel station automation speeds up the checkout process and there is no impact on the physical product received by consumers, which Basker (2015) calls a "pure" process innovation.[4] Also, similar to the introduction of scanning in the U.S. retail sector, the diffusion of automation in the Netherlands happened gradually. This phase-in feature makes it possible to identify the price effect of automation by comparing the price levels before and after automation of treated sites with those of a suitably selected set of control stations that did not experience automation. The

[4]Basker (2015) notices that next to a faster checkout, scanning may save on labor cost because the technology eliminates the need to place price stickers on each item in stock. As a consequence scanning stores are able to change prices more frequently than non-scanning stores. Such a difference does not apply to automated and non-automated fuel stations.

detection of treatment effects is possible as long as the price effects of automation materialize quickly enough relative to time for the phase-in to complete (Duflo, Glennerster and Kremer, 2007). The empirical estimates show that this condition holds in our case.

We employ an extensive data set that contains price quotes of over 80% of all outlets in the Netherlands for the time period 10/2005-04/2011. The Dutch market is an interesting market to consider because with a market share for unmanned stations of 25.1% in March 2011, it can be classified as a market in transition: The share of unmanned stations is sufficiently large for its economic impact to be estimable. At the same time, the share is sufficiently small not to be considered a mature unmanned fuel retailing market that has already reached a new steady state equilibrium. As a consequence, our study focuses on the short-run effects of automation, i.e. the price effects in the stage of development where adoption of automated fuel retailing at about 25% at the end of the sample period. Table 1 shows that the share of unmanned stations has steadily increased in the period considered with no signs of this trend leveling off near the end. With the proportion of unmanned sites at 12.4% in November 2005, the Dutch market has witnessed a doubling of the proportion of unmanned stations in the period we consider.

Our estimation sample of 2,973 individual off-highway stations with on average more than 1,000 price quotes per station allows us to include day fixed effects in all our regressions. These pick up time-variant shocks common to all sites, such as price fluctuations due to developments in the international oil market. Next to that, station-level fixed effects are included such that identification of our key parameters is based on within-site variation. This is a notable difference with Basker (2015) who is constrained in her analysis by the fact that the scanner installation mostly happened in the 1970s and 1980s, a period for which only quarterly city-level average price data are available. As a result, she cannot make pre- and post-installation price comparisons at the store level nor study the competitive spillovers to nearby stores. The high-frequency nature of our price data allows us to match the automation events to pre- and post-automation price data at the site level and to investigate the presence of competitive spillovers.

We use a difference-in-difference matching strategy that creates balance between the treatment group of stations that are automated and a control group of stations that do not experience automation. We match treated and control units using the propensity score. The fact that new price quotes arrive almost daily enables a precise identification of post-event price movements in the weeks following automation. This informs us whether unit cost reductions are passed through to consumers immediately or with a lag.

Our main empirical findings are the following. First, our difference-in-difference matching estimates show that automation reduces the prices with on average 1.2-2.6 eurocents per liter (cpl) before taxes. This corresponds to a decrease of 1.0 to 2.1% in the price paid by consumers.[5] Second, the price adjustment happens instantly in the week of automation and the prices stay at these lower levels in the months following. Third, although the coefficient plots of lagged price responses suggest some competitive spillovers to neighboring service stations within 1 km and especially 2 km radius, these effects are very small and not significant. Finally, in contrast to Basker (2015), who shows that early adopters of scanning infrastructure contribute disproportionately to the observed price decreases, we find that the impact of automation is similar for service stations that were automated in different points of time. A main reason for this difference in finding is provided by the different nature of the innovation. Whereas the introduction of scanning opens up possibilities for grocery stores to adopt complementary processes that help to optimize the use of inputs, such as tracking sales and changing worker schedules, automation of fuel stations offers much less scope for such complementary innovations.

The paper continues as follows. Section 2 provides a classification of retail fueling services to elucidate the differences between staffed and unstaffed stations. Section 3 introduces the data. Section 4 outlines our estimation strategy and Section 5 gives the main results. Section 6 concludes.

2 Retail Fueling Services

Three main forms of fueling services can be distinguished. At full service stations, an attendant is present at the forecourt who delivers fuel into the customer's car. Next to that, the attendant may offer other services such as cleaning the windows, checking oil, tyres etc. At self-service stations, there is no such attendant and customers pump their own fuel. Payment is to a cashier sitting in a shop or booth. For security reasons, it is forbidden for this employee to leave the shop which rules out the performance of services at the forecourt similar to those of attendants at full service stations. The defining characteristic of unmanned or automated stations is that payment in the shop or booth is not possible. Instead, automats are installed at each pump (or pair of pumps) that enable customers to pay by credit or debit card immediately without visiting the shop or booth.

[5] Including the VAT of 19%, the reduction is 1.5-3.1 cpl or, compared to the average retail price of €1.45 in the period considered, 1.0 to. 2.1%. For the introduction of scanners, Basker (2015) finds an average price decrease of at least 1.4%.

This classification into self service stations and automated service stations does not strictly delineate stations with and without a shop or stations with and without the possibility to pay at the pump. Especially larger self service stations may have a limited number of one or two pumps equipped with an automat for credit and debit card payments that can be used either 24/7 or only outside the staffed opening hours. A shop may be present at automated stations. In some cases, this shop is operated by the same company that operates the forecourt, in other cases, the shop and forecourt are operated by different companies. In all these cases, shop and fuel sales are however strictly separated in that customers cannot pay for fuel in the shop. At some automated stations without a shop, basic food and non-food items (such as soft drinks, candy bars and cigarettes) can nevertheless be bought at vending machines.

In the Netherlands, full service stations have long given way to stations that operate under either a self service or automated service concept.[6] Unstaffed retailing started in 2000 when the company Tango opened the first unstaffed station of the country. Tango – the brand name is a combination of the words "tank" and "go" – was explicitly founded on the premise that enabling customers to pay directly at the pump would reduce the time to complete a transaction because customers no longer have to queue for payment in the shop or booth. In turn, the high degree of automation lowers cost which the company promises "to return to the customer in the form of a discount."[7]

The possibility and need to pay at the pump has been the defining characteristic that distinguishes all automated fuel stations that have established since then (Section 3.2 gives exact numbers on how many stations had been automated in the period we consider). The change in payment method at the day of automation may be accompanied with other changes such as a change in brand name or a change in shop activities. In the analysis, we account for any brand name changes. Unfortunately, we lack station-level information on changes that happen to the layout or operation of the shop at the time of automation. The most commonly observed change is that small shops up to 15m^2 where shop sales are secondary to handling fuel payments are closed after automation. In the empirical analysis, we will account for this by presenting

[6] At the end of 2011, outside the period considered in this paper, Shell announced a local test to re-introduce the attendant at one of its stations. (`https://www.tankpro.nl/pompshop/2011/10/07/pompbediende-gaat-weer-helpen-bij-tanken/`). This results did have not lead to a wider introduction of this concept. In fact, station owners commonly talk of "full service stations" when referring to self-service stations with a shop that sells a wide assortment of items that may include evening meals, snacks, premium coffee, fresh vegetables, etc.

[7] See `https://www.tango.nl/overtango` (visited April 29, 2017) for a short history of Tango and their business concept. In 2004, Tango has been taken over by Kuwait Petroleum.

estimates that condition on the presence or absence of a shop in the pre-automation period.

3 Data

3.1 Data collection and sample selection

For our empirical analysis, we use fleet-card data provided by Athlon Car Lease (Athlon, hereafter), the leading car leasing company in the Netherlands with a fleet of over 125,000 cars.[8] Every day, Athlon captures station-specific retail gasoline prices using information retrieved from fleet-card users who frequent these stations. Athlon's methodology of using card data is very similar to the one used by OPIS, an agency that provides detailed information on gasoline retail prices for the US market.[9] The scope of the data in terms of coverage and frequency of price quotes is also very similar. In total, price quotes of 3,826 different sites are collected which implies a coverage of about 85 percent of all outlets in the country. This number is comparable to the coverage by OPIS of around 90 per cent (Chandra and Tappata, 2011).[10]

Although price information is collected for all grades of gasoline, diesel, and liquefied petroleum gas (LPG), we limit attention in this paper to the sales of regular unleaded 95 octane gasoline (known as Euro 95) at off-highway sites. Euro 95 is the most commonly used type of fuel in the Netherlands. The reason for focusing on off-highway sites is twofold. In two competition cases, the European Commission has argued that highway and off-highway stations constitute separate product markets.[11] Consistent with this, our data exhibits pointedly higher prices at highway sites.[12] Also, while off-highway the market share of unmanned fueling stations has steadily grown from 13.1% in October 2005 to 26.5% in April 2011, with 5.9% the market share of unmanned stations in the highway market is still modest at the end of the sample period.

Our sample covers the time period between October 1, 2005 to April 25, 2011. Besides the price observations of the 240 highway sites, we also drop the price quotes of all 613 sites that entered and/or exited the market in this time period. We drop these sites because our difference-

[8] Data from the same source have been used in Soetevent *et al.* (2014) and Heijnen *et al.* (2015).

[9] Data collected by the Oil Price Information Service (OPIS) have been widely used in applied papers on pricing and price strategies, examples include Taylor and Hosken (2007); Doyle and Samphantharak (2008), Chandra and Tappata (2011), Myers et al. (2011), Lewis (2012, 2014) and Tappata and Yan (2013)).

[10] According to TankPro.nl there were 4,206 gasoline stations in the Netherlands in June 2011, `http://www.tankpro.nl/brandstof/2011/11/30/aantal-tankstations-in-nederland-blijft-stabiel/`. Original source: PetrolView. We count 3,562 active sites in February 2011.

[11] See e.g. European Union (1999), where it is argued in the Exxon/Mobil case that 'in some countries, it is possible to consider fuel retailing on motorways as a separate product market' (point 436). The Dutch antitrust agency has also mentioned differences in regulations and policies on approval for highway and off-highway stations (NMa, 2004).

[12] See Figure B2 in Heijnen *et al.* (2015).

in-difference approach uses price quotes before and after automation and for stations that enter as an automated fueling station, pre-conversion price quotes are lacking by definition. We do include these sites in our calculations of a station's number of local highway and off-highway competitors.

This leaves us with a final sample of 3,558,679 price observations of 2,973 selected off-highway stations. With more than five years of data, our panel of station-level prices is longer than most daily-price panels that have been used in this literature.[13] Throughout we consider retail prices before excise and value-added taxes. The price data is supplemented with information about the geographic coordinates of the station and the (Euclidean) distances between all pairs of stations.[14] Information on a number of mostly time-invariant station characteristics has been obtained from Experian Catalist Ltd. (the type of ownership, availability of a car wash, the number of pumps etc.). These are used in calculating the propensity scores to find the appropriate control stations. Table 1 summarizes the main characteristics of our sample.

As for studies using OPIS data, one potential drawback is that prices are not reported for all stations for all days (Tappata and Yan, 2013, p. 6). For stations in our sample on average a price-quote is registered every 2.8 days. This again compares well to the widely used OPIS data.[15] This may potentially bias our estimates if the data are not missing at random. Although the missing-at-random assumption is not refutable using the data alone[16] there is reason to suspect that missing data do not impact our results. First, one potential source of non-randomness is that drivers structurally avoid visiting the higher-priced stations which would bias our sample of observed prices towards the lower-end of the price distribution. Although this may be a concern in data composed of transaction data of private drivers, this arguably is less of an issue with fleet card data. Lessees do not pay for the fuel themselves which makes them rather unresponsive to prices. Second, the inclusion of day-specific fixed effects accounts for any bias caused by lessees having a different pattern of frequenting fuel stations than other drivers (they may for example drive relatively less in the weekend). Furthermore, only one lessee per day has to visit a station for a price quote of that station to be recorded. With over 125,000 cars, this sufficient condition is likely to be easily met for most stations.

[13] One exception is Hosken, Silvia and Taylor (2011) who use six years of daily price data.

[14] These data were obtained using Google Earth.

[15] OPIS reports on its web site that prices of the majority of its stations are updated via a daily batch process similarly to ours with "transactions that are from 1-5 days old with the majority of prices being no older than 3 days." `http://www.opisnet.com/about/methodology.aspx#RetailGas`, visited 06/03/2015.

[16] See Manski (2007, section 2.5) for a thoughtful treatment of this issue.

3.2 Price levels and changes in local market structure

In the period considered, fuel prices in the Netherlands have fluctuated widely. Figure 1 shows that fluctuations in average retail prices follow the dynamics of the crude oil spot price: They move closely in line with the Amsterdam-Rotterdam-Antwerp (ARA) premium unleaded gasoline spot price. The ARA price gradually increased until the onset of the Great Recession in August 2008 initiated a sharp decline. In the two years following, prices recovered and reached their previous peaks in Spring 2011.

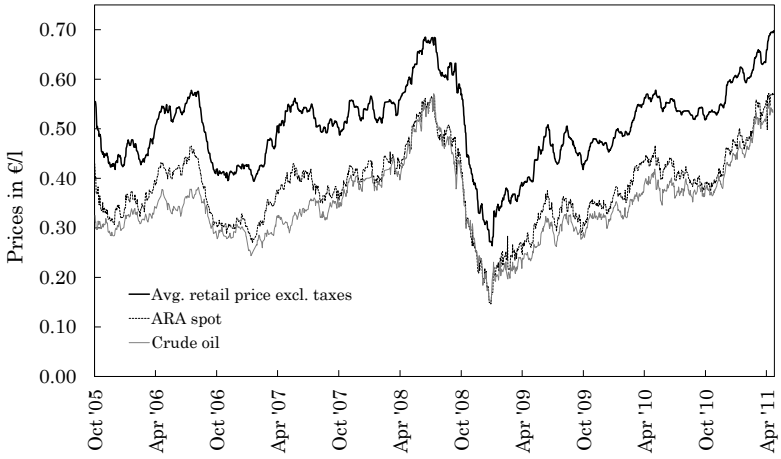


Figure 1: Average retail gasoline price, ARA spot price, and crude oil prices (Oct. 2005 – Apr. 2011).

Table 1 shows two main trends in the period of investigation: a steady increase in the number of automated stations and a decrease in the market share of the Major-6 brands (Shell, Esso, BP, Texaco, TOTAL or Q8) from 64.5% in 2005 to 54.1% in 2011.[17] With a market share over 14 percent, Shell is still the market leader in 2011 despite having lost 3 percentage points of its market share since January 2006. Table A.1 provides summary statistics of these trends at the regional level and shows that the share of unmanned stations has importantly increased in all regions.

Table 2 shows that per annum about 1.4 to 2.2 percent of all stations are automated. These conversions induce significant changes in the local market structure. Each year, 1.4-1.8% of all off-highway stations experience an increase in the number of unmanned off-highway competitors within a 1 km radius and these numbers increase to 3.9-6.5% and 12.6-21.1% for a 2 km and

[17]The market share of an individual firm is defined as the percentage of all gasoline stations operating under one of the firm's brand names.

Table 1: Development of the fraction of automated and Major-6 stations in the period 2005-2011.

	Oct-2005	Oct-2006	Oct-2007	Oct-2008	Oct-2009	Oct-2010	Apr-2011
Automated	0.129	0.157	0.194	0.214	0.236	0.249	0.266
Major-4	0.475	0.458	0.440	0.432	0.422	0.417	0.414
TOTAL	0.133	0.135	0.124	0.118	0.112	0.105	0.100
Q8	0.037	0.033	0.030	0.031	0.029	0.027	0.027

Notes: Statistics include entries and exits.
For historical reasons, the group of Shell, Esso, BP and Texaco is often referred to as the group of major firms. However, in terms of market share and brand premium, it is natural to consider Shell, Esso, BP, Texaco, TOTAL and Q8 as the set of major stations. To avoid confusion, we will talk of the Major-4 and Major-6 firms, respectively.

Table 2: Summary statistics on the annual percentage of stations (close to a station) that is automated.

	Percentage	A converted station within...			
year	converted	1km	2km	5km	10km
2006	1.8%	1.7%	6.0%	21.1%	43.6%
2007	2.2%	1.8%	6.5%	20.2%	48.3%
2008	1.6%	1.8%	5.5%	14.9%	38.5%
2009	1.6%	1.5%	4.6%	14.5%	39.8%
2010	1.4%	1.4%	3.9%	12.6%	37.8%
2006-2010	8.5%	8.0%	21.5%	53.0%	87.3%

5 km radius respectively. From 2006 to 2010, the majority of stations (53.0%) has witnessed an increase in the number of its unmanned competitors within a 5 km range. The totals for the entire period are lower than the sum of the percentages for individual years. This is because some sites see their number of unmanned competitors increase in more than one year. However, for the 2 km radius, this is only true for a total of 23 stations or 0.8% of the total number of stations.

3.3 The price effects of automation: Descriptive statistics

Our panel covers a period of more than five years. In each year a considerable number of stations are automated but which stations are automated when is not determined by random assignment. In particular, firms may decide to convert specific stations in response to local market developments, some of which may be unobserved by the researcher. This endogeneity leads to two potential problems. First, the set of stations that is automated may not be representative for the full sample of stations. Second, because of selection effects, the set of stations automated in later years may show a different price response to automation when they operate in a different market context than sites automated earlier. Basker (2015) identifies larger price decreases for

early adopters of scanners. She ascribes this to the higher potential of these early adopters to complement the scanners with other process improvements that increase efficiency. To allow for a heterogeneous price response in different periods, we split our price data into three separate sub-samples: the years 2006/2007, 2008/2009 and 2010. Throughout descriptive statistics and estimates will be presented for each of these three sub-samples separately. The high number of automation-events per year combined with the high-frequency price data allows us to do this while retaining sufficient statistical power.

To address possible selection effects, Section 4 introduces a difference-in-difference matching (DDM) method that will, for each period considered, match the price quotes of stations that are automated in that period (the treatment group) with those of a comparable group of stations that do not experience automation in that period (the control group).

Table 3 provides a first glance at the price effect at stations that are automated themselves or that are in the proximity of a station that is automated. To take out price fluctuations due to (international oil) price developments common to all firms, we calculate in Table 3 for each day the nationwide average price and subtract this from the individual price quote to obtain the price residuals. A negative number means that the price at that day was below the national average. Per station, we compute the average of these price residuals before and after the station (or a station in its close proximity) was automated. Table 3 shows the average price residual across stations. The table suggests that there is a strong and highly significant direct effect on the prices of stations that experience automation ranging from an average drop of 2.6 cpl (cents per liter) of stations that convert in either 2006 or 2007 to 3.1 cpl for stations that convert in 2008 or 2009. However, these numbers do not correct for the fact that some of the stations also experiences other changes at the event-date, such as a change in brand name. The regression estimates that we will present later will take this into account. The tentative evidence in Table 3 does not lend much support to the presence of competitive spillovers: only for the years 2006/2007 we find that prices within a 1 km radius of an automated station experience a statistically significant drop of on average 0.3 cpl at the 5%-level.

The estimates in Table 3 however also suggest that the sample of automated stations is not representative because of selection effects. For all periods we observe that the average price in the neighborhood of stations being automated is already below the national average before the automation date. For distances up to 2 km, this deviation is almost always significant at the 1%-level. This suggests that stations are automated relatively more frequently in low-price

Table 3: Average price deviation (in €) from national average before and after conversion own station or station in neighborhood.

			Average price deviation		
Period	Conversion	#	before	after	Δ
2006/2007	self	118	-0.0036*	-0.0296***	-0.0260†††
	within 1km	102	-0.0068***	-0.0099***	-0.0031††
	within 2km	326	-0.0056***	-0.0066***	-0.0011
	within 5km	1047	-0.0011	-0.0017**	-0.0006
	within 10km	2019	-0.0008	-0.0007	0.0002
2008/2009	self	94	0.0008	-0.0303***	-0.0311†††
	within 1km	99	-0.0044*	-0.0054**	-0.0010
	within 2km	286	-0.0049***	-0.0049***	0.0000
	within 5km	792	-0.0027***	-0.0026***	0.0001
	within 10km	1739	-0.0022***	-0.0017***	0.0004
2010	self	41	-0.0012	-0.0309***	-0.0297†††
	within 1km	43	-0.0136***	-0.0136***	-0.0001
	within 2km	113	-0.0050*	-0.0037	0.0013
	within 5km	373	-0.0054***	-0.0039***	0.0014††
	within 10km	1122	-0.0028***	-0.0017**	0.0010†††

$^{***}(^{**},^{*})$: statistically different from zero at the 1%-level (5%-level, 10%-level).
$^{\dagger\dagger\dagger}(^{\dagger\dagger},^{\dagger})$: before-after difference is statistically different from zero at the 1%-level (5%-level, 10%-level).

areas. For the automated stations self, we find that stations automated in 2006/2007 but not in the years 2008-2010 price below the national average before automation. This suggests that the set of stations automated in 2006/2007 may differ from the set of sites automated in later years.

Table 4 explores the differences between converted and non-converted sites in more detail. This table reveals that compared to sites that do not experience a conversion, sites that are automated on average are significantly smaller in term of plot size, volume sold and shopping area. Also, stations in the more rural North and East of the country (zipcodes 7000s to 9000s) where the population density is lower and the road network less connected seems over-represented in the set of automated sites.[18] Looking at the variable Major-6, one observes that whereas in the initial years especially the minor brands are very active in automating their stations, the major six firms increasingly start automating as of 2008.

It is clear that without further correction these difference between automated and non-automated sites will bias our estimates of the effect of automation on prices. It is to this task of constructing a comparable set of automated and non-automated stations to which we turn next.

[18] Figure A.2 in the online Appendix maps the zip code areas in the Netherlands.

Table 4: Summary Statistics Characteristics Automated and Non-Automated Stations.

		Automated Sites						Non-automated Sites	
Time interval:		**2006/2007**		**2008/2009**		**2010**			
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
					Site characteristics				
Plotsize area		826.94***	(891.64)	993.01***	(868.32)	930.24**	(1,265.46)	1,437.19	(1,534.03)
No. pumps		2.41***	(0.91)	2.61	(1.02)	2.49	(1.05)	2.71	(1.11)
Estimated volume sold		1,578.17***	(911.28)	1,418.82***	(757.42)	1,416.46***	(745.44)	2,182.42	(1,305.38)
Shop area		43.33***	(25.78)	35.14***	(25.93)	39.93***	(23.51)	57.24	(28.30)
Company owned		0.45	(0.50)	0.23***,†††	(0.42)	0.27††	(0.45)	0.39	(0.49)
Major-6		0.28***	(0.45)	0.44***,††	(0.50)	0.61†††,‡	(0.49)	0.66	(0.48)
					Local market concentration				
# off-highway	$\leq$ *2 km*	4.43	(3.73)	4.66	(4.80)	3.95	(3.15)	4.35	(3.72)
sites at ...	$\leq$ *5 km*	16.93	(11.80)	14.54*	(12.06)	12.76**,†	(8.69)	17.04	(12.21)
	$\leq$ *10 km*	50.36	(29.07)	46.88*	(29.53)	42.83**	(27.05)	53.17	(31.67)
# highway	$\leq$ *2 km*	0.08	(0.37)	0.15	(0.44)	0.22†	(0.85)	0.11	(0.44)
sites at ...	$\leq$ *5 km*	0.64	(1.13)	0.68	(0.95)	0.76	(1.24)	0.81	(1.17)
	$\leq$ *10 km*	2.80	(2.01)	2.44**	(2.00)	2.78	(2.48)	2.98	(2.14)
					Geographical characteristics				
Zipcode...	*1000s*	0.20***	(0.40)	0.04**,†††	(0.20)	0.15‡	(0.36)	0.11	(0.32)
	2000s	0.09	(0.29)	0.09	(0.28)	0.05	(0.22)	0.11	(0.31)
	3000s	0.14	(0.34)	0.09	(0.28)	0.10	(0.30)	0.14	(0.35)
	4000s	0.02***	(0.13)	0.06	(0.25)	0.02*	(0.16)	0.11	(0.31)
	5000s	0.08**	(0.27)	0.12	(0.32)	0.07	(0.26)	0.14	(0.35)
	6000s	0.07	(0.25)	0.07	(0.26)	0.12	(0.33)	0.11	(0.32)
	7000s	0.20**	(0.40)	0.25***	(0.43)	0.20	(0.40)	0.12	(0.33)
	8000s	0.16***	(0.37)	0.12	(0.32)	0.20***	(0.40)	0.08	(0.26)
	9000s	0.05	(0.22)	0.17***,†††	(0.38)	0.10	(0.30)	0.07	(0.26)
German border		0.02	(0.13)	0.03	(0.18)	0.00	(0.00)	0.03	(0.18)
Belgian border		0.01	(0.09)	0.00	(0.00)	0.07**,††,‡‡‡	(0.26)	0.02	(0.15)
# priv. owned cars $\leq$ 20km		280.31	(191.65)	232.92***,†	(177.50)	237.34*	(181.72)	297.47	(197.80)
# sites		118		94		41		2693	

Standard deviations in parentheses; Data on site characteristics provided by Catalist Ltd. Plotsize area and shop area in sq. m; volume in '000s litres per annum; shop sales in €'000s per annum; privately owned cars in '000s.

[a] Gives the total number of stations per group. Sample sizes vary across rows of the table due to missing values.

***(**,*) : statistically different from the non-automated stations at the 1%-level (5%-level, 10%-level).

†††(††,†) : statistically different from the stations automated in 2006/2007 at the 1%-level (5%-level, 10%-level);

‡‡‡(‡‡,‡) : statistically different from the stations automated in 2008/2009 at the 1%-level (5%-level, 10%-level).

4 Empirical Strategy and Estimation Results

4.1 Propensity Score Matching

The previous section established that the set of stations that has experienced the 'event' of automation cannot be considered a random draw from the set of all stations. To obtain a set of automated and a set of non-automated stations that are comparable in terms of observable characteristics, we calculate for each station its propensity score: the predicted probability of being automated given the observed site characteristics (Rosenbaum and Rubin, 1983). We distinguish the three time periods 2006/2007, 2008/2009 and 2010. Thus for each station three different propensity scores – one for each time period – are calculated.[19] We use single nearest neighbor matching without replacement: For every treated station that is automated, the matched control station is determined to be the station with the propensity score closest to the score of the treated station. We set the maximum distance between the propensity score of a treated unit and its closest control match at 0.10. Treated units without a control within this distance are dropped to prevent that matched stations are in fact substantially different.[20]

To avoid interference with other events, the pool of potential control stations is limited to those stations that, in the given time bracket ±180-days, were not automated themselves and that are not within a 5 km range of a station that is automated. This is not a severe limitation as this leaves us with a set of potential controls of 1,800 to 2,400 stations per period. Some of the treated stations possibly also experience an indirect effect in the time period considered because they are within a 5 km range of another station that is automated. In order to isolate the direct effect of becoming automated from the indirect effect, we drop these sites from the analysis. For this reason, the number of automated stations in Table 5 is smaller than in Table 4.[21] Table 5 shows that the matching procedure leads to a selected sample of treatment (automated) and control (non-automated) stations that is similar in terms of observables. In fact, for none of the characteristics we find statistical significant differences at the 10%-level for any of the periods.

[19] Table A.2 of the Online Appendix presents for each period the results of this probit regression. For each time period, an automation-dummy is regressed on the same set of explanatory variables as in Table 4. For site variables such as 'Estimated volume sold' pre-2006 values are used to avoid *ex post* matching: matching on variables whose values may have changed due to the automation process studied.

[20] Only two units were eliminated because of this threshold.

[21] Of course, part of the estimated treatment effect picks up the indirect feedback effects caused by neighboring stations decreasing their prices in response to the lower prices of of their automated competitor. Competitors that respond by adopting automation themselves arguably have more leeway to reduce prices. In dropping sites within 5 km range that both experience automation in the same period, we ignore the latter effect. For this reason, our estimates of the treatment effect can be considered a conservative estimate of the total price effect (direct plus indirect effect) of automation.

Table 5: Summary Statistics Characteristics Treated and Control Stations

		Automated Sites						Non-automated Sites					
Time interval:		**2006/2007**		**2008/2009**		**2010**		**2006/2007**		**2008/2009**		**2010**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
						Site characteristics							
Plotsize area		929.00	(1,049.97)	973.96	(824.11)	742.22	(811.32)	908.18	(1,003.15)	1,002.88	(1,121.64)	724.31	(616.03)
No. pumps		2.34	(0.86)	2.58	(1.00)	2.50	(1.08)	2.41	(1.07)	2.56	(0.99)	2.28	(0.82)
Estimated volume sold		1,573.08	(937.96)	1,365.97	(764.88)	1,499.31	(755.14)	1,731.64	(1,255.00)	1,433.56	(867.19)	1,561.11	(1,008.61)
Shop area		40.16	(23.55)	34.08	(22.42)	39.93	(23.51)	47.41	(23.02)	33.22	(23.94)	36.21	(21.45)
Company owned		0.41	(0.50)	0.25	(0.44)	0.31	(0.47)	0.46	(0.50)	0.26	(0.44)	0.28	(0.45)
Major-6		0.30	(0.46)	0.44	(0.50)	0.67	(0.48)	0.33	(0.47)	0.51	(0.50)	0.67	(0.48)
						Local market concentration							
# off-highway	*≤ 2 km*	3.14	(3.02)	3.88	(4.08)	4.06	(3.23)	3.13	(3.18)	4.21	(3.64)	3.69	(3.12)
sites at ...	*≤ 5 km*	13.61	(11.92)	12.80	(11.76)	13.42	(8.89)	12.99	(10.01)	12.62	(10.36)	13.75	(10.67)
	≤ 10 km	47.07	(33.76)	44.55	(32.03)	46.22	(27.10)	47.30	(28.27)	45.40	(29.61)	50.53	(27.60)
# highway	*≤ 2 km*	0.07	(0.34)	0.18	(0.48)	0.11	(0.40)	0.04	(0.25)	0.12	(0.47)	0.06	(0.33)
sites at ...	*≤ 5 km*	0.53	(1.02)	0.60	(0.89)	0.72	(1.09)	0.58	(1.15)	0.41	(0.78)	0.97	(1.11)
	≤ 10 km	2.40	(1.96)	2.22	(1.87)	2.92	(2.53)	2.38	(2.21)	2.11	(2.12)	3.39	(1.89)
						Geographical characteristics							
Zipcode...	*1000s*	0.13	(0.34)	0.06	(0.23)	0.17	(0.38)	0.14	(0.35)	0.08	(0.28)	0.31	(0.47)
	2000s	0.07	(0.25)	0.11	(0.32)	0.06	(0.23)	0.08	(0.27)	0.11	(0.32)	0.00	(0.00)
	3000s	0.16	(0.37)	0.08	(0.28)	0.11	(0.32)	0.17	(0.38)	0.08	(0.28)	0.08	(0.28)
	4000s	0.03	(0.16)	0.06	(0.23)	0.03	(0.17)	0.00	(0.00)	0.04	(0.20)	0.03	(0.17)
	5000s	0.12	(0.32)	0.11	(0.32)	0.08	(0.28)	0.08	(0.27)	0.07	(0.25)	0.17	(0.38)
	6000s	0.10	(0.31)	0.06	(0.23)	0.11	(0.32)	0.10	(0.31)	0.04	(0.20)	0.11	(0.32)
	7000s	0.18	(0.39)	0.21	(0.41)	0.22	(0.42)	0.21	(0.41)	0.25	(0.43)	0.11	(0.32)
	8000s	0.14	(0.35)	0.15	(0.36)	0.11	(0.32)	0.14	(0.35)	0.12	(0.33)	0.06	(0.23)
	9000s	0.08	(0.27)	0.18	(0.39)	0.11	(0.32)	0.08	(0.27)	0.21	(0.41)	0.14	(0.35)
German border		0.03	(0.16)	0.03	(0.16)	0.00	(0.00)	0.03	(0.16)	0.03	(0.16)	0.00	(0.00)
Belgian border		0.01	(0.11)	0.00	(0.00)	0.06	(0.23)	0.01	(0.11)	0.00	(0.00)	0.03	(0.17)
# priv. owned cars ≤ 20km		252.76	(197.36)	239.90	(196.88)	258.16	(184.53)	255.01	(171.48)	250.21	(203.59)	286.88	(161.88)
# sites[b]		77		73		36		77		73		36	

Standard deviations in parentheses; Data on site characteristics provided by Catalist Ltd. Data on site characteristics provided by Catalist Ltd. Plotsize area and shop area in sq. m; volume in '000s litres per annum; shop sales in €'000s per annum; privately owned cars in '000s.

[a] Gives the total number of stations in the treatment or control group. Sample sizes vary across rows of the table due to missing values.

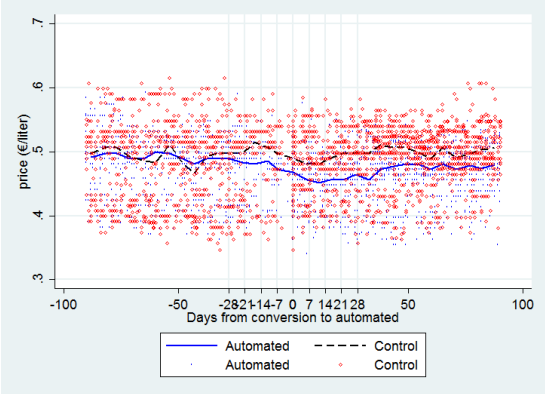
$^{***}(^{**},^{*})$: statistically different from Control at the 1%-level (5%-level, 10%-level).

4.1.1 Selection of price observations

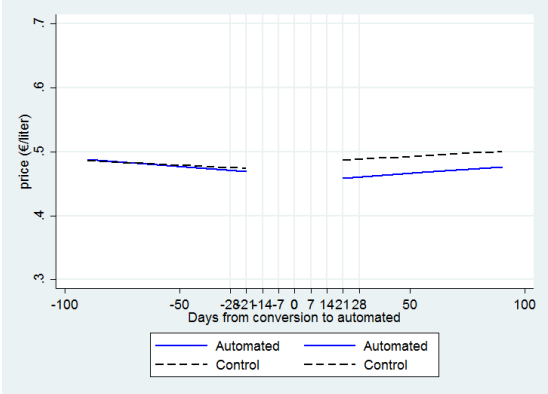
An important indicator of the similarity of the matched treatment and control stations – and thus for the success of matching – is whether price levels and price trends at matched treatment and control stations are similar in the pre-conversion period. However, such a comparison is not straightforward because stations convert at different calendar days. We address this as follows. For each treatment station i, we limit attention to the 180-day period around the date of conversion t_i. As pre-treatment price observations of station i we take the set of price quotes p_{it} with $t \in \{t : -90 \leq t - t_i < 0\}$. The post-treatment price observations is the set p_{it} with $t \in \{t : 0 \leq t - t_i \leq 90\}$. For the control station matched to station i, we similarly only include the price quotes observed within the 180-day window around the date of conversion t_i. It may happen that for a given day t, a price quote is observed for the treatment station but not for the matched control station, or vice versa. To prevent this unbalance from biasing our results, we only include days for which price quotes of both the treatment and matched control station are observed.

In the left panels of Figure 2, the individual dots present the matched individual price observations of treated (filled circles) and control (hollow diamonds) stations. The lines show the median value for treatment (solid) and control (dashed) group. Notice that within each period the pre-automation and post-automation price levels and trend are similar between the two groups. It is important that the prices in the two groups show parallel trends in the pre-automation period because the difference-in-differences estimator that we will apply only provides an unbiased estimate of the effect of automation if absent automation, the outcomes in the two groups would have followed parallel trends (Duflo *et al.*, 2007).

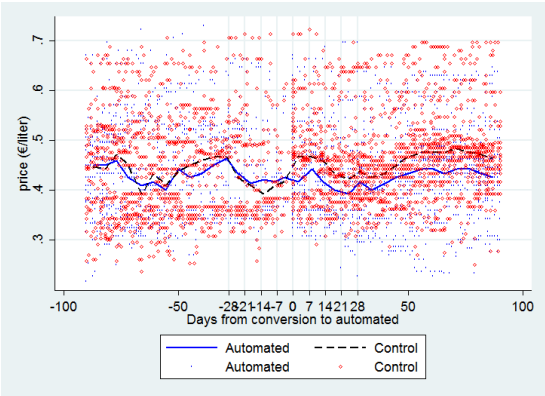
This empirical similarity in pre-treatment outcomes between the two groups is indicative of the "exogeneity" of the event of becoming automated to other station and regional characteristics that may correlate with price. However, in the final 28 and especially in the final 21 days before automation, this similarity seems less pronounced with the median price in the treatment group exhibiting a downward trend relative to the control group. This is driven by two anticipatory effects. First, some of the stations in the treatment group shut down a couple of days before being automated. The observation in Figure 2 that the cloud of price observations is noticeably less dense in the final 21 days before is proof of such an effect. This may generate some selection bias for this period. Second, the stations that continue to operate till the date of automation may anticipate the new price regime and already adjust their price level in the final days before



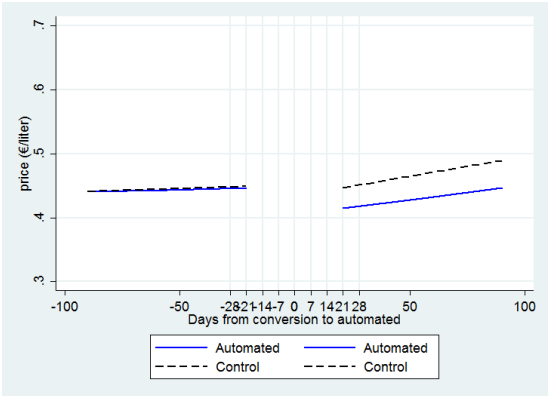
(a) 2006-07: Matched price quotes and median bands.



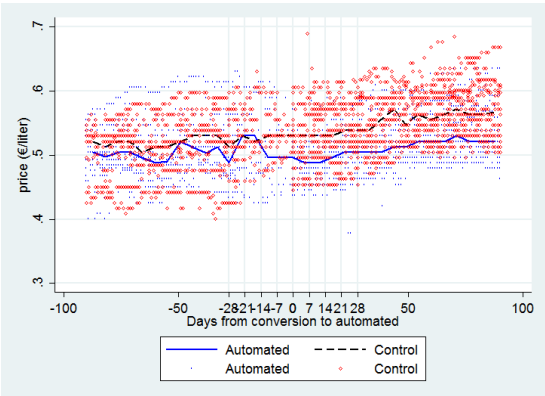
(b) 2006-07: Pre- and post conversion price trend.



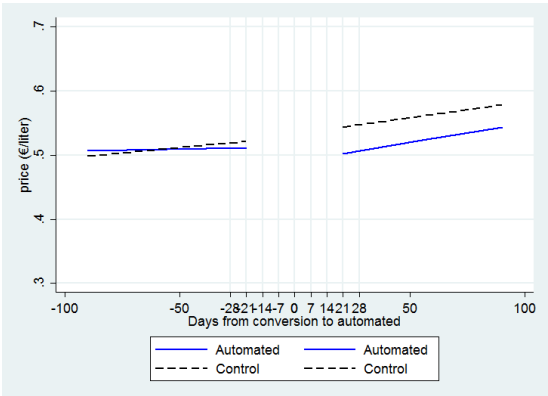
(c) 2008-09: Matched price quotes and median bands.



(d) 2008-09: Pre- and post conversion price trend.



(e) 2010: Matched price quotes and median bands.



(f) 2010: Pre- and post conversion price trend.

Figure 2: Prices, pre- and post conversion price levels and trends for Treatment and Control groups.

Note: In plotting the price trends, price quotes within 21 days of the conversion date have been excluded.

automation.

Panels (b), (d) and (f) plot for the treatment and control group the linear pre-conversion and post-conversion trend, excluding the transition period of 21 days before the conversion date till 21 days after that date. All three panels exhibit similar pre- and post-conversion price trends for treatment and control groups. For all three time periods, formal F-tests do not reject any of the null hypotheses that pre-automation price levels and trends are identical in treatment and control group at the 5% significance level.[22] The graphical analysis shows a clear and substantial post-automation increase in the price difference between the two groups.

4.2 Difference-in-Difference Matching Estimates

In this section we complement the visual evidence of the preceding section with statistical evidence by providing difference-in-difference matching (DDM) estimates. However, before presenting the results it is instructive to spell out the identifying assumptions. Let T be the set of stations in the treatment group. The set of control stations C consists of all stations $j = N(i)$ that have been matched to a station $i \in T$ by the nearest-neighbor matching procedure. We call $M_i \equiv \{i, N(i)\}$ a matched pair of stations. Let t_i denote the calendar date at which station i has been automated. For treatment stations i, the treatment dummy $D_{it} = 1$ for $t \geq t_i$ and 0 otherwise. We further define for each station $k \in M_i$ an index t'_k which denotes the number of days from the conversion date of treatment station in pair M_i. That is, $t'_k \equiv t - t_i$ for $k \in M_i$ $(\forall i, k, t)$, such that $S_k^{pre} \equiv \{t : -90 \leq t'_k < 0\}$ and $S_k^{post} \equiv \{t : 0 \leq t'_k \leq 90\}$ denote the 90-day pre- and post-treatment period of station k, respectively. In what follows, we suppress the subindex k in t' when the interpretation is clear from the context.

Define p_{1it} as potential price at station i at day t conditional on station i having been automated; similarly, p_{0it} is the potential price at station i at time t conditional on not having been automated. Under the assumption that the difference $E[p_{1it} - p_{0it}|i, t]$ is a constant, say γ, the observed price p_{it} can be written as:

$$p_{it} = c_i + c_t + \gamma D_{it} + \beta X_{it} + \epsilon_{it}, \tag{1}$$

with c_i and c_t site and calendar day fixed effects, X_{it} time variant station characteristics on which we have information, such as brand name changes and changes in the number of local competitors; $E[\epsilon_{it}|i, t] = 0$.

[22] For the 2010 period, the null hypothesis that the pre-automation price trend is the same in the treatment and control group is rejected at the 10%-level ($p = 0.051$).

Our DDM estimates use the difference in average pre- and post-treatment prices at treatment and control sites:

$$\bar{p}_{i,Pre} = \frac{1}{N_{i,Pre}} \sum_{t \in S_i^{pre}} p_{it} \text{ and } \bar{p}_{i,Post} = \frac{1}{N_{i,Post}} \sum_{t \in S_i^{post}} p_{it},$$

with $N_{i,Pre}$ ($N_{i,Post}$) the number of pre-treatment (post-treatment) price quotes of station i. From (1), we get that

$$\bar{p}_{i,s} = c_i + \bar{c}_s + \delta \bar{D}_{i,s} + \beta \bar{X}_{i,s} + \bar{\epsilon}_{i,s} \qquad s \in \{Pre, Post\}, \tag{2}$$

where $\bar{c}_s = \sum_{t \in S_i^s} c_t / N_{i,s}$, $\bar{X}_{i,s} = \sum_{t \in S_i^s} X_{i,t} / N_{i,s}$ and $\bar{\epsilon}_{i,s} = \sum_{t \in S_i^s} \epsilon_{i,t} / N_{i,s}$. Note that $\bar{D}_{i,s} = 1$ if $i \in T$ and $s = Post$ and 0 otherwise.

We have that

$$E[\bar{p}_{i,Post} | i \in C] - E[\bar{p}_{i,Pre} | i \in C] = \bar{c}_{Post} - \bar{c}_{Pre} + \beta[\bar{X}_{i,Post} - \bar{X}_{i,Pre}]$$

and

$$E[\bar{p}_{i,Post} | i \in T] - E[\bar{p}_{i,Pre} | i \in T] = \bar{c}_{Post} - \bar{c}_{Pre} + \gamma + \beta[\bar{X}_{i,Post} - \bar{X}_{i,Pre}].$$

The causal effect of interest is the population difference-in-differences

$$\begin{aligned} E[\bar{p}_{i,Post} | i \in T] - E[\bar{p}_{i,Pre} | i \in T] - \{E[\bar{p}_{i,Post} | i \in C] - E[\bar{p}_{i,Pre} | i \in C]\} \quad = \\ \gamma + \beta \left\{ [\bar{X}_{i,Post|i \in T} - \bar{X}_{i,Pre|i \in T}] - [\bar{X}_{i,Post|i \in C} - \bar{X}_{i,Pre|i \in C}] \right\} \end{aligned}$$

which is the joint price effect of all changes that happen at the station level at the date of automation: the effect of the automation itself, γ, plus the effect caused by changes in other station characteristics, β, for example a change in brand name that accompanies automation.

We will estimate the treatment effect using the sample analog of this difference in population means. As before, a price quote p_{it} of a treatment (control) site i is only included if the price p_{jt} of the matched control (treatment) site j is also observed at day t. This implies that $N_{i,s} = N_{j,s}$, $s \in \{Pre, Post\}$, for any pair matched pair of stations. Importantly, without this restriction $\bar{c}_s$ in equation (2) may be different for matched treatment and control sites if they are observed at different dates. That would potentially bias our estimates of the treatment effect.

As mentioned in the previous section, another bias arises if treatment stations already adjust prices in the pre-treatment period in anticipation of the upcoming conversion. If part of the effect already materializes in the pre-treatment period, this will lead to a downward bias of our

estimates. We check for this by testing for Granger causality (Granger, 1969) in the following way. We regress prices on a sequence of weekly lags and leads plus time and station fixed effects c_t and c_i:

$$p_{it} = c_i + c_t + \delta_0 D_{it} + \sum_{\tau=0}^{13} \delta_{-(\tau+1)} D_{i,t-7\tau} + \sum_{\tau=1}^{12} \delta_\tau D_{i,t+7\tau} + \beta X_{it} + \epsilon_{it}. \tag{3}$$

At the right-hand side of the equation, the coefficient δ_0 gives the effect on the day of conversion, the lags in the first sum the effects in the first 13 weeks post-treatment ($\delta_{-1}, \dots \delta_{-13}$) and the leads in the second sum the anticipatory effects in the 12 weeks preceding treatment ($\delta_1, \dots \delta_{12}$). In the absence of anticipatory effects, the sum of lead effects, $\sum_{\tau=1}^{12} \delta_\tau$, should equal 0. As before, we will estimate (3) separately for the time periods 2006/2007, 2008/2009 and 2010 to check whether the effect of conversion is similar across years.

5 Estimation results

5.1 Direct effects

We next separately estimate the regression difference-in-difference equation (1) for each time period, including for each station $k \in M_i$ the price quotes p_{kt} within the 180-day window around the conversion date t_i. Table 6 presents the estimates in the row labeled "none". For all periods, we find strongly significant effects of automation on the price levels at automated sites with the estimated effect ranging from 1.3 cpl in 2010 to 2.6 cpl in 2008/2009.

However these estimates may be biased if stations adjust their prices in anticipation of the upcoming conversion. We test for the presence of such anticipatory effects by estimating equation (3), clustering the errors at the treatment pair level. Figure 3 plots the estimated δ-coefficients. For all periods, the plots show a clear treatment effect. Prices at treated stations drops immediately at the event date $t' = 0$ and robustly stay at this lower level in the weeks following. The bottom line of Table 6 shows that the null hypothesis of the sum of lagged effects being equal to zero is firmly rejected ($p < 0.01$) for all periods. Table 6 also gives p-values for tests of the null hypothesis that the sum of leads equals zero. At the 5%-level, these tests cannot reject the null of no anticipatory effects. However, the p-values of 0.0870 and 0.0665 for the test $\sum_{\tau=1}^{12} \delta_\tau = 0$ in 2006/2007 and 2010, respectively, together with the significant estimate of the coefficients $\delta_{-3} \cdots \delta_{-1}$ for these periods in Figure 3a and 3c suggest some anticipatory effect. To assess how possible anticipatory effects influence our estimates, Table 6 also reports the estimated treatment effects for sub-samples of the data that take into account a transition

period by excluding price quotes within 14, 28 or 42 days of the conversion date.[23] In all cases, the estimates are very similar to those without a transition period which leads us to conclude that anticipatory effects do not importantly bias the estimated treatment effects.

The effect of automation is comparable across the years considered. This result differs from Basker (2015) who finds that early adopters of scanning contribute disproportionately to the price decreases. There are some natural explanations for this difference. The first is simply that we consider a shorter time period than Basker: *ceteris paribus*, firms that adopt the same process innovation within five years from each other are likely to be less heterogeneous than when the time of adoption is up to twelve years apart. Another in our view more important reason can be found in the different nature of the innovation. Scanner quality increased over time and prices fell, such that over time also smaller sized stores increasingly installed scanners. This makes selection effects more probable. Basker (2015, p. 358) argues that the earlier adopters had probably more to gain from scanning because they could combine them with the adoption of complementary technologies and processes, enabling larger price reductions. The scope for such efficiency enhancing complementary innovations however seems limited for the process innovation of automating service stations.

The estimated direct price effect is not only statistically significant but also economically important. A 1 to 2 percentage point drop is non-negligible compared to a gross retail margin that in the Netherlands is estimated to be about 12%.[24] Also, with 5.5 billion liters of Euro95 being annually sold in the Netherlands, potential savings in fuel by consumers amount to millions of euro per annum. Of course, extrapolating the price effect out of sample is problematic because in the longer run automation may cause for example changes in market concentration.[25]

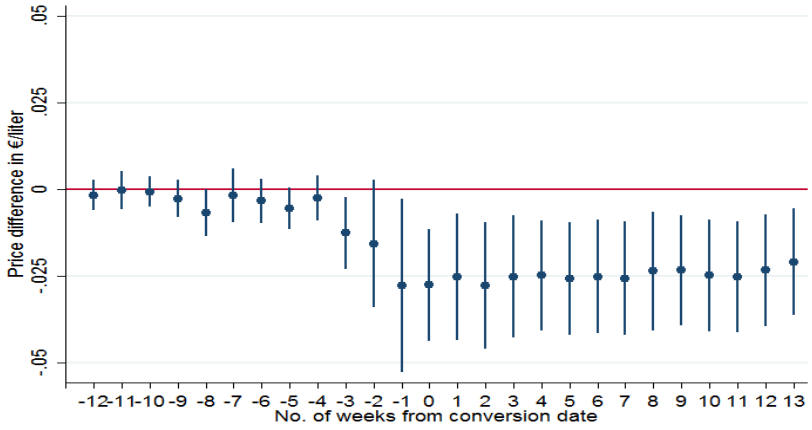
5.2 Unobserved Changes in Shop Operations

The regression estimates in the previous section account for brand name changes that coincide with the conversion of a self service station to an automated service station. It is however possible that next to changes in payment infrastructure and brand name, a conversion is also combined with a change in shop operations. In the most extreme case, the shop will be closed.

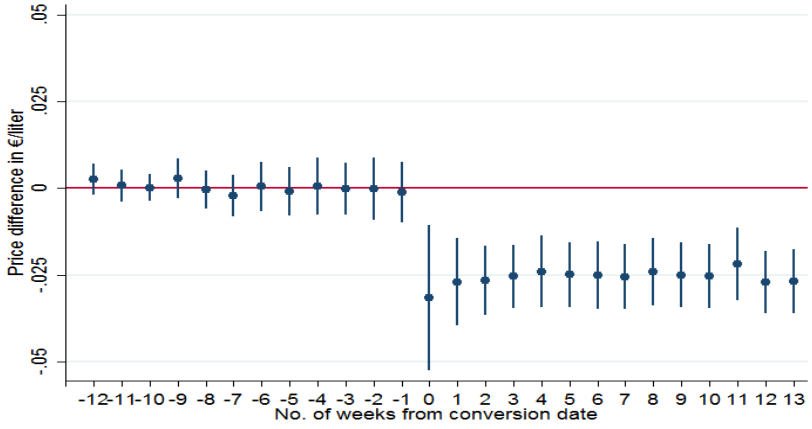
[23] Similar to the 21 days around the conversion date not being considered in Figure 2b, d, and f.

[24] Reported for August 2011 by BOVAG (2011, p. 25, Fig. 3.3), the Dutch trade organization for employers in mobility. Hosken et al. (2008) also report an estimate of 12% for the average gross retail margin in the U.S.

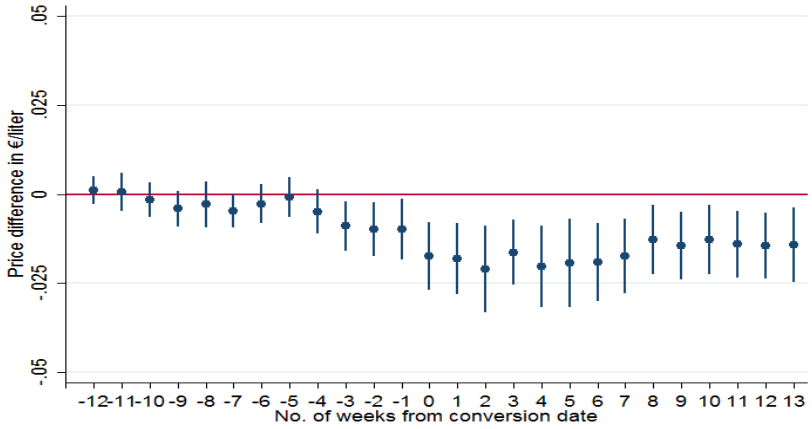
[25] Articles in the magazine for station owners support the view that the impact of automation on price levels that we identify in this paper for the period 2007-2010 has continued in the out-of-sample years that followed: "However, the overall growth of the unmanned segment increasingly forces staffed locations to give higher price discounts" (TankPro, 2016).



(a) 2006-07.



(b) 2008-09.



(c) 2010.

Figure 3: Temporal effects conversion on price level automated sites.

Note: Price difference between treatment and control stations in the weeks before and after conversion. The vertical spikes indicate 95% confidence intervals. Each graph plots for one of the time periods considered (2006/07, 2008/09 and 2010) the regression coefficients of the weekly lead and lag dummy variables. Standard errors clustered at the treatment-group level.

Table 6: Price effect of conversion on automated sites.

Time period:		2006/2007 (1)	2008/2009 (2)	2010 (3)
Transition period:	None	-0.019***	-0.026***	-0.013***
		(0.005)	(0.004)	(0.005)
	14 days	-0.021***	-0.025***	-0.014***
		(0.006)	(0.004)	(0.004)
	28 days	-0.021***	-0.025***	-0.013***
		(0.007)	(0.004)	(0.005)
	42 days	-0.021***	-0.025***	-0.012**
		(0.007)	(0.004)	(0.005)
Station FE		YES	YES	YES
Day FE		YES	YES	YES
Time variant characteristics		YES	YES	YES
p-values F-tests:				
$\delta_{-12} + .. + \delta_{-1} = 0$		0.0870	0.9420	0.0665
$\delta_{-12} + .. + \delta_{-3} = 0$		0.1773	0.8860	0.1836
$\delta_{-12} + .. + \delta_{-5} = 0$		0.2708	0.8591	0.3802
$\delta_{-12} + .. + \delta_{-7} = 0$		0.3496	0.7705	0.3546
$\delta_1 + .. + \delta_{13} = 0$		0.0035	0.0000	0.0014

DID regression estimates of equation (1). Robust standard errrors in parentheses; errors are clustered at the matched treatment pair level. $^{***}(^{**},^{*})$: statistically significant from zero at the 1%-level (5%-level, 10%-level).

As mentioned previously, we unfortunately lack station-level information on such changes at the time of automation. As a result, the estimates in Table 6 may present the combined effect on prices of the payment innovation and unobserved shop changes not accounted for by the time variant brand dummies.

To assess the extent to which these unobserved changes bias our results, we divide our treatment group into two sub-samples based on whether or not a shop was present in the period before automation and perform the analysis for both groups separately. The idea is that stations without a shop pre-automation are very unlikely to experience a change in their shop operations at the time of automation. The estimates for this subgroup would thus isolate the effect of the change in payment infrastructure, whereas the estimates for the second subgroup would present the joint effect.

Table 7: Price effect of conversion on automated sites with/without a shop in the pre-automation period.

Time period:		2006/2007		2008/2009		2010	
		Pre-treatment		Pre-treatment		Pre-treatment	
		No Shop	Shop	No Shop	Shop	No Shop	Shop
		(1)	(2)	(3)	(4)	(5)	(6)
Transition period:	None	-0.017***	-0.023**	-0.020***	-0.029***	-0.012*	-0.015**
		(0.005)	(0.009)	(0.005)	(0.006)	(0.007)	(0.006)
	14 days	-0.018***	-0.025**	-0.019***	-0.028***	-0.011*	-0.016**
		(0.005)	(0.010)	(0.005)	(0.005)	(0.006)	(0.006)
	28 days	-0.019***	-0.025**	-0.019***	-0.028***	-0.010*	-0.016**
		(0.005)	(0.011)	(0.006)	(0.006)	(0.006)	(0.006)
	42 days	-0.019***	-0.024**	-0.019***	-0.028***	-0.008	-0.014**
		(0.006)	(0.011)	(0.006)	(0.006)	(0.006)	(0.006)
Station FE		YES		YES		YES	
Day FE		YES		YES		YES	
Time variant characteristics		YES		YES		YES	

DID regression estimates of equation (1). Robust standard errrors in parentheses; errors are clustered at the matched treatment pair level. ***(**,*) : statistically significant from zero at the 1%-level (5%-level, 10%-level).

Table 7 gives the results. A comparison of columns (1), (3) and (5) with the corresponding entries in Table 6 shows that the estimates for the years 2006/2007 and 2010 are very similar. For the years 2008/2009 however, the estimates for the group of no-shop station are notably smaller in absolute sense than the corresponding estimates reported in Table 6. Together with the observation that we previously found the biggest price impact for 2008/2009, this suggests that the estimates in column (2) of Table 6 at least partly reflect the effect of unobserved changes in shop operations.

That said, the estimates presented in Table 7 do not qualitatively change our main findings: independent of the presence of a shop before conversion, automation has a very significant and consistent negative impact on prices. For all years, the price decrease is somewhat larger for the group of stations with a shop before automation. Although this difference of 0.3-0.9cpl is not statistically significant, it again suggests that part of the estimated effect in Table 6 is not caused by innovations in the payment process but should be ascribed to unobserved changes in shop operations.

5.3 Competitive Effects

Next we consider whether the lower prices at converted stations lead to price changes at local competitors. In estimating these indirect or spillover effects, we use a procedure similar to the one used to estimate the direct effect. First we identify for all periods the stations within a range of 1 km (2 km) of a station that was automated in this period. We consider the 1 and 2 km range for two reasons. First, the before/after price deviations in Table 3 do not suggest an indirect treatment effect at wider ranges. Second, for wider ranges, the majority of the stations will be in the treatment group (see Table 2) leaving the set from which we can draw the set of controls correspondingly small. We limit the pool of stations considered to off-highway stations that were not automated themselves in the given time period or half a year before or after.[26] We also exclude the 23 stations that experienced multiple automation within a 2 km range in the period 2006-2011.

Again, nearest neighbor propensity score estimation is used to match a station experiencing a conversion within a 1 km (2 km) range with a control station.[27] We subsequently use this selected sample to estimate a regression equivalent to equation (3) but with the dummy variable D_{it} now reflecting "being within 1 km (2 km) range of a station that has been automated."

Plots of the estimated δ-coefficients are plotted in Figure 4. Note that the scale of the vertical axis is one-tenth the scale of Figure 2. The plots do not reveal a competitive effect. The point estimates for the 2 km range suggest a slightly downward jump after the event date but the precision is insufficient for this effect to be statistically significant. The non-significance of this difference is confirmed in Table 8 which shows that none of the null hypotheses on the joint insignificance of the lagged δ-coefficients is rejected at the 10%-level. The null hypothesis that

[26] For example, for the period 2006/2007, stations automated between July 1, 2005 and June 30, 2008 excluded.

[27] Tables A.3 and A.4 in the Online Appendix summarize the characteristics of the selected sample of treatment and control stations. None of the characeristics is significantly different between the treatment and control group at the 10%-level for any of the periods.

the sum of the leads equals zero is not rejected at the 5%-level for any range and time period.

In sum, although some of the plots in Figure 4 suggest some competitive spillover effects to the prices of stations within a 1 to 2 km range of a site that is automated, these differences are statistically insignificant and never amount to a price decrease higher than 0.2 cpl.

Table 8: Indirect Treatment Effect of conversion on stations within 1 and 2 km range.

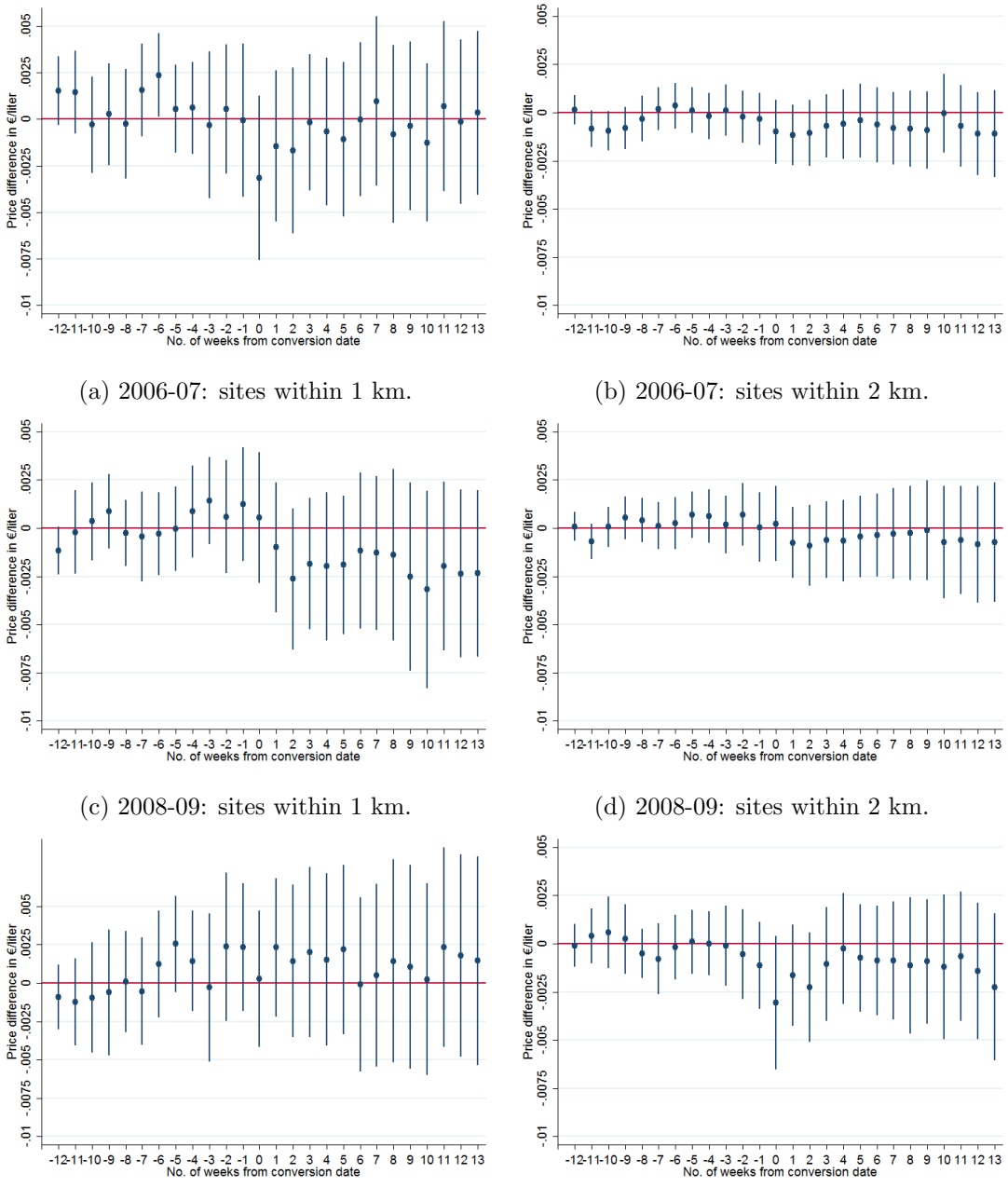
ITE:	within 1 km			within 2 km		
Time period:	2006/2007	2008/2009	2010	2006/2007	2008/2009	2010
Transition period:						
None	-0.001	-0.002*	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
14 days	-0.001	-0.002	0.001	0.000	-0.001	-0.001
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
28 days	0.000	-0.002	0.000	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
42 days	0.000	-0.003	0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Station FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
p-values F-tests:						
$\delta_{-12} + .. + \delta_{-1} = 0$	0.5419	0.7611	0.7614	0.6347	0.6183	0.8013
$\delta_{-12} + .. + \delta_{-3} = 0$	0.4518	0.8813	0.9582	0.6411	0.6227	0.9621
$\delta_{-12} + .. + \delta_{-5} = 0$	0.3583	0.8411	0.9736	0.5568	0.6749	0.9675
$\delta_{-12} + .. + \delta_{-7} = 0$	0.4916	0.8416	0.6250	0.3204	0.8311	0.9713
$\delta_1 + .. + \delta_{13} = 0$	0.8037	0.2969	0.6124	0.4007	0.6289	0.4652

Robust standard errors in parentheses; errors are clustered at the matched treatment pair level. ***(**,*) : statistically significant at the 1%-level (5%-level, 10%-level).

6 Conclusions

This paper has investigated the consequences of the sharp increase in automated fuel retailing that has been observed in several European countries. One market where these developments have played out is the Dutch retail gasoline market in the years from 2005 to 2011. This market is the focus of our empirical analysis.

Using a difference-in-differences matching method to estimate the effect of automation on prices, we find that automated stations reduce pre-tax prices with on average 1.0 to 2.1% instantly after the implementation of this process innovation and stabilize at this lower level in the months following. Following Basker (2015), we empirically allow for the possibility that the early adopters of automation have a larger impact on price levels than the later adopters. Basker



(a) 2006-07: sites within 1 km.

(b) 2006-07: sites within 2 km.

(c) 2008-09: sites within 1 km.

(d) 2008-09: sites within 2 km.

(e) 2010: sites within 1 km.

(f) 2010: sites within 2 km.

Figure 4: Competitive temporal effects of conversion on the price levels at sites within a 1 km (2 km) range of a converted site.

Note: Price difference between treatment and control stations in the weeks before and after a nearby conversion. The vertical spikes indicate 95% confidence intervals. Each graph plots for one of the time periods considered (2006/07, 2008/09 and 2010) the regression coefficients of the weekly lead and lag dummy variables. Standard errors clustered at the treatment-group level.

(2015) has identified such a heterogeneous effect for the adoption of scanning technology by US grocery stores, but our estimates for automated fuel retailing indicate that the price impact is similar-sized across years. The high-frequency nature of our price data at the station-level also enables the investigation of competitive spillovers to neighboring stations. The coefficients plots suggest a small but insignificant drop in prices at competing stations within 2 km after the date of automation.

In view of the billions liters of fuel annually sold and an estimated gross retail margin of about 12%, our estimates are not only a statistically significant but also economically important. We hope our results will fuel the public debate in some European countries on whether or not automated stations should be prohibited through legislation.

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A Online Appendix: Additional figures and tables

(a) Staffed station.

(b) Unmanned station.

Figure A.1: Examples of staffed (a) and unmanned (b) stations.

Table A.1: Sample statistics at the regional level.

	Oct-2005	Oct-2006	Oct-2007	Oct-2008	Oct-2009	Oct-2010	Apr-2011	
	Number of stations							**Change**
Highway	233	236	240	239	239	238	237	4
Off-highway	3054	3181	3225	3258	3291	3339	3280	226
North	436	483	480	485	497	501	485	49
Mid	802	832	862	865	870	884	861	59
West	1136	1164	1179	1196	1203	1220	1213	77
South	913	938	944	951	960	972	958	45
	Share of unmanned stations							**Change**
North	0.140	0.174	0.208	0.252	0.298	0.315	0.334	0.194
Mid	0.106	0.136	0.195	0.217	0.238	0.249	0.269	0.163
West	0.121	0.155	0.187	0.201	0.214	0.229	0.240	0.118
South	0.125	0.142	0.159	0.167	0.183	0.194	0.209	0.084
	Annual conversions to automated							**Mean**
North	-	2.0	1.7	3.1	2.9	1.6	-	2.3
Mid	-	1.5	3.3	1.7	2.0	1.1	-	1.9
West	-	2.2	2.2	1.0	0.8	0.8	-	1.4
South	-	0.3	1.1	0.7	1.4	0.7	-	0.8
	Percentage of major-to-minor conversions							**Mean**
North	-	1.1	1.7	1.2	2.6	1.4	-	1.6
Mid	-	0.7	3.1	0.8	0.6	0.9	-	1.2
West	-	0.9	1.3	0.7	1.1	0.8	-	1.0
South	-	0.8	1.5	0.8	1.4	1.1	-	1.1
	Percentage of minor-to-major conversions							**Mean**
North	-	0.0	0.0	0.4	0.0	0.8	-	0.2
Mid	-	0.0	0.1	0.5	0.1	0.1	-	0.2
West	-	0.0	0.0	0.2	0.3	0.2	-	0.1
South	-	0.1	0.1	0.3	0.3	0.3	-	0.2

Note: Percentages: conversions in preceding twelve months as percentage of the total number of stations in the sample.

Figure A.2: Four-digit zip-code areas in the Netherlands.

Table A.2: Probit Regression of Automation Dummy on Explanatory Variables.

Time interval:		**2006/2007**		**2008/2009**		**2010**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
				Site characteristics			
Plotsize area		0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
No. pumps		-0.059	(0.065)	0.019	(0.061)	0.031	(0.076)
Estimated volume sold		0.000	(0.000)	0.000***	(0.000)	0.000**	(0.000)
shop area		0.183	(0.141)	-0.046	(0.142)	0.099	(0.167)
Company owned		-0.009***	(0.004)	-0.011***	(0.003)	-0.005	(0.004)
Major-6		-0.518***	(0.130)	-0.308**	(0.123)	0.180	(0.160)
				Local market concentration			
# off-highway	$\leq$ *2 km*	-0.038	(0.026)	0.052**	(0.024)	0.034	(0.027)
sites at ...	$\leq$ *5 km*	0.021*	(0.012)	0.003	(0.011)	-0.016	(0.013)
	$\leq$ *10 km*	0.003	(0.006)	0.002	(0.005)	0.002	(0.006)
# highway	$\leq$ *2 km*	-0.024	(0.183)	0.211	(0.129)	0.007	(0.184)
sites at ...	$\leq$ *5 km*	-0.091	(0.074)	-0.028	(0.070)	-0.016	(0.077)
	$\leq$ *10 km*	-0.010	(0.038)	-0.035	(0.036)	0.030	(0.041)
				Geographical characteristics			
Zipcode...	*1000s*	0.309	(0.299)	-0.850***	(0.309)	0.092	(0.339)
	2000s	-0.188	(0.394)	-0.513	(0.364)	-0.539	(0.462)
	3000s	0.308	(0.306)	-0.738**	(0.309)	-0.285	(0.364)
	4000s	-0.911**	(0.363)	-0.882***	(0.272)	-0.725*	(0.419)
	5000s	-0.063	(0.276)	-0.543**	(0.248)	-0.320	(0.341)
	6000s	-0.103	(0.282)	-0.819***	(0.283)	-0.118	(0.321)
	7000s	0.128	(0.250)	-0.201	(0.220)	0.158	(0.276)
	8000s	0.410	(0.264)	-0.281	(0.231)	-0.054	(0.304)
	9000s	-	(-)	-	(-)	-	(-)
German border		-0.327	(0.374)	-0.232	(0.348)	-	(-)
Belgian border		-0.024	(0.470)	-	(-)	0.657*	(0.377)
# priv. owned cars $\leq$ 20km		0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
constant		-1.110***	(0.309)	-0.347	(0.267)	-1.669***	(0.352)
Pseudo R^2		0.1967		0.1664		0.1006	
# sites		1811		2027		2450	

Standard deviations in parentheses; Controls for missing site characteristics have been included in all regressions
[a] Gives the sum of the number of stations in the treatment group and the number of stations eligible to be in the control group.
***(**,*) : statistically different at the 1%-level (5%-level, 10%-level).

Table A.3: Summary Statistics Treatment and Control Stations ITE (1 km range)

		Sites within 1 km automated site						Control sites					
Time interval:		**2006/2007**		**2008/2009**		**2010**		**2006/2007**		**2008/2009**		**2010**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
						Site characteristics							
Plotsize area		1,097.02	(1,765.22)	1,237.64	(1,133.30)	1,092.75	(1,142.50)	957.08	(1,033.26)	1,402.69	(1,796.19)	946.34	(876.12)
No. pumps		2.81	(1.22)	2.60	(1.15)	2.70	(1.42)	2.69	(1.04)	2.49	(0.92)	2.49	(0.87)
Estimated volume sold		2,559.05	(1,421.83)	1,989.33	(1,146.05)	2,166.25	(1,393.64)	2,463.63	(1,706.27)	1,871.91	(1,094.41)	2,155.61	(1,329.08)
shop area		52.76	(24.17)	58.75	(25.42)	55.67	(23.15)	47.86	(24.73)	54.44	(23.26)	60.32	(35.40)
Company owned		0.42	(0.50)	0.37	(0.49)	0.31	(0.47)	0.41	(0.49)	0.39	(0.49)	0.33	(0.47)
Major-6		0.69	(0.47)	0.59	(0.50)	0.49	(0.51)	0.67	(0.47)	0.54	(0.50)	0.61	(0.49)
						Local market concentration							
# off-highway	*≤ 2 km*	6.87	(3.15)	8.07	(4.16)	6.46	(3.00)	6.76	(4.39)	8.03	(4.28)	6.83	(4.04)
sites at ...	*≤ 5 km*	22.31	(10.43)	19.66	(11.73)	18.24	(8.91)	22.74	(13.91)	19.19	(10.84)	19.68	(11.90)
	≤ 10 km	57.33	(27.74)	57.78	(36.61)	53.39	(29.45)	57.01	(32.83)	56.90	(30.99)	51.63	(30.25)
# highway	*≤ 2 km*	0.21	(0.79)	0.16	(0.45)	0.34	(0.83)	0.21	(0.58)	0.16	(0.58)	0.46	(0.93)
sites at ...	*≤ 5 km*	0.93	(1.42)	0.88	(0.97)	0.66	(1.13)	0.87	(1.23)	0.67	(1.01)	0.81	(1.29)
	≤ 10 km	3.27	(2.03)	3.08	(1.82)	3.29	(2.49)	3.38	(2.20)	2.84	(2.13)	3.20	(2.02)
						Geographical characteristics							
Zipcode...	*1000s*	0.25	(0.44)	0.06	(0.23)	0.29	(0.46)	0.21	(0.41)	0.10	(0.30)	0.32	(0.47)
	2000s	0.12	(0.33)	0.16	(0.36)	0.07	(0.26)	0.13	(0.34)	0.17	(0.38)	0.07	(0.26)
	3000s	0.17	(0.38)	0.10	(0.30)	0.05	(0.22)	0.17	(0.38)	0.06	(0.23)	0.07	(0.26)
	4000s	0.00	(0.00)	0.09	(0.29)	0.15	(0.36)	0.00	(0.00)	0.08	(0.27)	0.07	(0.26)
	5000s	0.02	(0.15)	0.07	(0.25)	0.07	(0.26)	0.04	(0.19)	0.09	(0.29)	0.10	(0.30)
	6000s	0.01	(0.11)	0.09	(0.29)	0.12	(0.33)	0.01	(0.11)	0.04	(0.21)	0.10	(0.30)
	7000s	0.14	(0.35)	0.21	(0.41)	0.07	(0.26)	0.12	(0.33)	0.27	(0.45)	0.02	(0.16)
	8000s	0.21	(0.41)	0.16	(0.36)	0.15	(0.36)	0.23	(0.42)	0.16	(0.36)	0.15	(0.36)
	9000s	0.07	(0.26)	0.08	(0.27)	0.02	(0.16)	0.10	(0.30)	0.04	(0.21)	0.10	(0.30)
German border		0.00	(0.00)	0.01	(0.11)	0.02	(0.16)	0.00	(0.00)	0.01	(0.11)	0.05	(0.22)
Belgian border		0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
# priv. owned cars ≤ 20km		327.46	(198.30)	289.67	(228.42)	301.70	(204.59)	318.06	(212.33)	288.88	(223.60)	303.57	(209.61)
# sites[b]		84		90		41		84		90		41	

Standard deviations in parentheses; Data on site characteristics provided by Catalist Ltd. Data on site characteristics provided by Catalist Ltd. Plotsize area and shop area in sq. m; volume in '000s litres per annum; shop sales in €'000s per annum; privately owned cars in '000s.

[a] Gives the total number of stations in the treatment or control group. Sample sizes vary across rows of the table due to missing values.

$^{***}(^{**},^{*})$: statistically different from Control at the 1%-level (5%-level, 10%-level).

Table A.4: Summary Statistics Treatment and Control Stations ITE (2 km range)

		Sites within 1 km automated site						Control sites					
Time interval:		**2006/2007**		**2008/2009**		**2010**		**2006/2007**		**2008/2009**		**2010**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
							Site characteristics						
Plotsize area		1,299.87	(1,768.35)	1,313.24	(1,341.18)	1,233.91	(1,428.26)	1,353.72	(1,684.72)	1,312.00	(1,243.66)	1,186.91	(1,258.33)
No. pumps		2.89	(1.19)	2.74	(1.12)	2.84	(1.26)	2.98	(1.26)	2.68	(1.04)	2.65	(0.96)
Estimated volume sold		2,565.94	(1,449.99)	2,144.76	(1,063.15)	2,180.48	(1,367.28)	2,578.19	(1,679.14)	2,161.86	(1,185.04)	2,102.86	(1,323.00)
shop area		55.79	(26.85)	59.41	(25.23)	55.06	(26.59)	58.93	(25.60)	61.40	(26.11)	55.95	(29.73)
Company owned		0.48	(0.50)	0.43	(0.50)	0.43	(0.50)	0.50	(0.50)	0.46	(0.50)	0.42	(0.50)
Major-6		0.71	(0.45)	0.63	(0.49)	0.58	(0.50)	0.71	(0.46)	0.61	(0.49)	0.59	(0.50)
							Local market concentration						
# off-highway	*≤ 2 km*	7.38	(3.15)	7.84	(3.39)	6.75	(3.02)	7.64	(4.13)	7.75	(3.92)	7.23	(4.74)
sites at ...	*≤ 5 km*	24.11	(11.89)	23.15	(13.40)	18.51	(8.80)	24.31	(14.19)	22.13	(12.37)	20.97	(11.56)
	≤ 10 km	64.61	(34.34)	63.11	(36.48)	51.32	(25.39)	67.55	(38.49)	59.43	(33.40)	53.89	(23.73)
# highway	*≤ 2 km*	0.17	(0.59)	0.13	(0.44)	0.18	(0.57)	0.19	(0.55)	0.15	(0.53)	0.23	(0.68)
sites at ...	*≤ 5 km*	0.85	(1.26)	0.86	(1.14)	0.67*	(1.01)	0.87	(1.25)	0.90	(1.26)	0.93	(1.28)
	≤ 10 km	3.34	(2.06)	3.13	(1.93)	3.04	(2.26)	3.14	(2.10)	3.09	(2.11)	3.50	(2.08)
							Geographical characteristics						
Zipcode...	*1000s*	0.22	(0.41)	0.04	(0.21)	0.26	(0.44)	0.20	(0.40)	0.03	(0.16)	0.27	(0.45)
	2000s	0.16	(0.37)	0.19	(0.39)	0.07	(0.25)	0.20	(0.40)	0.17	(0.38)	0.04	(0.19)
	3000s	0.17	(0.38)	0.13	(0.33)	0.05	(0.21)	0.16	(0.37)	0.11	(0.31)	0.07	(0.25)
	4000s	0.00	(0.00)	0.10	(0.30)	0.10	(0.31)	0.00	(0.00)	0.12	(0.33)	0.08	(0.27)
	5000s	0.08	(0.27)	0.10	(0.30)	0.11	(0.32)	0.08	(0.28)	0.09	(0.28)	0.09	(0.28)
	6000s	0.03	(0.16)	0.06	(0.23)	0.10	(0.31)	0.03	(0.17)	0.06	(0.23)	0.08	(0.27)
	7000s	0.13	(0.34)	0.22	(0.42)	0.15	(0.36)	0.13	(0.34)	0.25	(0.44)	0.18	(0.39)
	8000s	0.15	(0.36)	0.10	(0.30)	0.09	(0.29)	0.16	(0.36)	0.10	(0.30)	0.09	(0.29)
	9000s	0.06	(0.23)	0.07	(0.26)	0.06	(0.23)	0.03	(0.18)	0.07	(0.26)	0.11	(0.32)
German border		0.00	(0.00)	0.02	(0.13)	0.01	(0.10)	0.00	(0.00)	0.02	(0.13)	0.00	(0.00)
Belgian border		0.00	(0.00)	0.00	(0.07)	0.03	(0.17)	0.00	(0.00)	0.01	(0.09)	0.02	(0.14)
# priv. owned cars ≤ 20km		366.99	(217.18)	317.96	(225.73)	278.70	(185.13)	379.10	(242.87)	296.99	(228.07)	278.05	(175.08)
# sites[b]		262		228		106		262		228		106	

Standard deviations in parentheses; Data on site characteristics provided by Catalist Ltd. Data on site characteristics provided by Catalist Ltd. Plotsize area and shop area in sq. m; volume in '000s litres per annum; shop sales in €'000s per annum; privately owned cars in '000s.

[a] Gives the total number of stations in the treatment or control group. Sample sizes vary across rows of the table due to missing values.

***(**,*) : statistically different from Control at the 1%-level (5%-level, 10%-level).