The Proliferation of Unmanned Fuel Retailing and Cost Pass-Through: Empirical Evidence from The Netherlands*

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Abstract

In the last decade, many European countries have seen a sharp increase in the number of unmanned fueling stations. We study the effect of this market change on price levels at converted outlets and their competitors. Using detailed data on the retail market in the Netherlands, we find that this prices at converted sites have decreased with €0.03-0.04/liter, which is economically significant given an estimated gross retail margin of €0.19/liter. Moreover, we find evidence of positive spillover effects to neighboring sites, which indicates that the pass-through of realized cost reductions is the prime force driving the observed lower price levels at re-branded stations, not a deterioration in perceived product quality. In one of the first applications of event study analysis to non-financial price data, we show that the timing of this pass through to consumers is immediate.

Keywords: retail gasoline, pricing, competition, event study analysis
JEL classification: C8, D4, L13, L81

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1 Introduction

In the last decade, unmanned retail fuel stations have proliferated across Europe. According to one large study on the functioning of the vehicle fuels market in Europe, 7.7% of all service stations in the European Union were unmanned in 2012, but with large cross-country differences. The market for unmanned stations has matured in Scandinavian countries such as Denmark and Sweden where the share of unmanned stations is over 60%, but in other countries such as Italy and Hungary it is still less than 1%.[1] Four regions in Spain have recently stalled the rise of unmanned 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.[2]

Declining fuel volumes and a desire to cut fixed staffing cost seems to drive the increased activity of converting service stations into unmanned sites.[3] At converted sites, this may lead to lower price levels for two reasons. First, realized reductions in unit cost may be partially or fully passed onto consumers in the form of lower retail prices. Second, replacing a full service station by an unmanned site where motorists can only use automated payment technology may lower product quality and thereby prices. On the other hand, manned-to-unmanned conversions in markets where most stations are still manned increases product differentiation in one dimension. This may soften price competition and lead to higher local retail prices. An evaluation of the social benefits of the pan-European trend towards more unmanned stations therefore necessitates an assessment of how this development impacts prices via the respective channels of changes in cost base, quality perception and competition intensity. This study provides such an assessment by focusing not only on observed price changes at converted outlets but also considering the spillover effects on prices charged by their direct competitors. If products are substitutes and firms compete in prices, theory predicts positive competitive effects if the prices at converted sites decrease because of lower unit cost; prices at local competitors should instead increase when price levels at converted stations are lowered due to lower product quality. When competition is softened because of the conversion, equilibrium price levels at converted and their competitors should instead both increase.

In our empirical application, we use 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

[1] *Source:* Civic Consulting (2014).

[2] `http://economia.elpais.com/economia/2015/02/06/actualidad/1423251729_289297.html`.

[3] See CBRE (2012).

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 but sufficiently small not to be considered a mature unmanned fuel retailing market that has already reached a new steady state equilibrium.[4] With the proportion of unmanned sites at 12.4% in November 2005, the Dutch market has witnessed a doubling of in the proportion of unmanned outlets in the period we consider.

Our sample of 3,820 individual sites with on average more than 1,000 price quotes per station allows us to conclude day fixed effects in all our regressions. These pick up all 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. The regression analysis in Section 4 is followed by an event study analysis (Brown and Warner, 1985; MacKinlay, 1997) in Section 5 which exploits the high-frequency characteristic of our data. Our object of interest is the cumulative abnormal price movement after the event of a conversion to an unmanned station. The fact that new price quotes arrive almost daily enables the identification of abnormal post-event price movements which inform us whether unit cost reductions are passed through to consumers immediately or with a lag.

Our main empirical findings are the following. First, our regression results show that off-highway, stations that convert from manned to unmanned reduce pre-tax prices with 2.6 eurocents per liter (cpl); for highway sites, this number is 3.8 cpl. For off-highway stations these conversions lead to significant competitive effect with a doubling of the number of unmanned stations in one's direct neighborhood causing a statistically significant average price decrease of 0.18 cpl. This supports the view that the lower prices at converted stations are primarily caused by the pass-through of realized cost efficiencies and not by a reduction of the product quality; no indication is found that the conversion have softened competition.[5] Consistent with the regression estimates, the event study analysis uncovers sharp non-transitory price drops at the day a station converts to an unmanned station and competitive effects of 0.2 cpl for off-highway sites that neighbor (2 km radius) a site that experienced a conversion. The latter are however not significant at the 5-percent level.

Throughout our analysis, we contrast the direct and competitive effect of manned/unmanned

[4]Table 2 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.

[5]Our findings are in contrast to results from the cross-country analysis Civic (2014, p. 289-293). Using a panel of 16 EU member states, this study finds a positive relationship between the share of unmanned stations and prices. This finding surprises the authors of this study as well and they suggest that it may be because "unmanned stations are more strongly represented in EU15 Member States" (p. 290), the on average richer states that acceded to the EU before 2004.

conversions with the impact of another station transformation that is often observed in our data: the event of rebranding a station from a major non-major brand (or vice versa). Rebranding from one of the six major brands to a minor brand leads to prices that are on average 1.4-2.2 cpl lower. For highway stations, we find a competitive effect from nearby off-highway competitors as well: when the number of nearby off-highway competitors serving a major brand doubles, prices increase with on average 0.5 cpl. So we tentatively conclude that the pass-through of realized cost reductions is the prime force driving the observed lower price levels at re-branded stations, not a reduction in perceived product quality. The event study approach reveals that this pass-through to consumers is however much slower than for manned-to-unmanned conversions, with the adjustment to the lower equilibrium price level taking one to two months.

The empirical literature so far has not addressed the effect of unmanned fueling on retail price levels.[6] Other researchers have used conversions at the station level to identify the causal relations between market characteristics and price levels. Hastings (2004) uses the quasi-experimental variation caused by the event of the conversion of 260 independent Thrifty gasoline stations to ARCO stations to analyze the effect on competitors' prices. She finds that not the share of vertically integrated stations but the decrease in independent retailers results in higher equilibrium prices. Other researchers before us have estimated the pass through of cost changes. The difference with our case is that in most of these studies, it is a priori clear that the events studied affect cost but have no impact in the quality dimension. For example, Doyle and Samphantharak (2008) use daily prices to determine short-term pass-through of taxes by comparing two days before and two days after the tax change.

The application of event study techniques has so far been limited to the field of finance, where it has been used to measure e.g. the impact of earning announcements on a firm's stock price by estimating abnormal ex post returns in the stock's performance. In the field of industrial economics, event study analysis has been applied to estimate the impact of EU merger control decisions on consumer surplus (Duso et al., 2007), but again by considering the stock market prices of the firms involved in the decision.[7] We extend the use of event study analysis to non-financial price data and believe that this is approach has potential in studying other retail markets characterized by frequent price changes and consumer search, such as the markets for groceries, financial products and online markets.

The paper continues as follows. Section 2 presents the theoretical results that motivate our em-

[6]The empirical literature on retail gasoline markets is vast and we refer the reader to Eckert (2013) for an extensive overview.

[7]We have found one study using an event study for non-financial data: McKenzie and Thomsen (2001) studying the impact of recalls on wholesale beef prices.

pirical approach. Section 3 introduces the data. Sections 4 and 5 contain the results of the empirical analysis. Section 6 concludes.

2 Theoretical framework

Conditional on type, fuel itself is a fairly homogenous product despite the fact different oil companies may use slightly different additives. Still, the brand name and location of a station and the services and amenities it provides – such as the presence and size of a shop – lead to considerable product differentiation. For this reason, competition between gasoline stations is commonly modeled as price competition with differentiated products. We follow this approach to show the possible implications of manned-to-unmanned conversions on the prices of affected outlets and of their immediate competitors. We use the differentiated duopoly model introduced by Dixit (1979) that gives rise to the following inverse demand functions:[8]

$$p_1 = \alpha_1 - \beta_1 q_1 - \gamma q_2 \tag{1}$$

$$p_2 = \alpha_2 - \gamma q_1 - \beta_2 q_2, \tag{2}$$

with $\alpha_i, \beta_i > 0$, $\beta_1\beta_2 - \gamma^2 \equiv \delta > 0$ and $\alpha_i\beta_j - \alpha_j\gamma > 0$ $(i = 1, 2; j = 3 - i)$ to ensure well-behaved demand and positive prices. Given that we study the competition between different providers of fuel, we focus on the case where the goods are substitutes, $\gamma > 0$, with γ an inverse measure of product differentiation. The corresponding direct demand functions are

$$q_1 = a_1 - b_1 p_1 + c p_2 \tag{3}$$

$$q_2 = a_2 + c p_1 - b_2 p_2, \tag{4}$$

with $a_i = (\alpha_i\beta_j - \alpha_j\gamma)/\delta$, $b_i = \beta_j/\delta$ $(i = 1, 2; j = 3 - i)$, and $c = \gamma/\delta$. The assumptions made above imply that $a_i, b_i > 0$.[9]

The Bertrand-Nash equilibrium prices of this linear model are derived in Singh and Vives (1984). The equilibrium price p_i^B including marginal cost m_i for firm 1 is

$$p_i^B = m_i + \frac{2(a_i - b_i m_i + c m_j)b_j + (a_j - b_j m_j - c m_i)c}{D} \quad \text{for } i = 1, 2, j = 3 - i \tag{5}$$

[8] The results derived in Proposition 1 of this section are qualitatively the same when instead using Hotelling's location model (Hotelling, 1929) with firms located at the endpoints of the line. In that case, equilibrium prices are $p_i = t + (\alpha_i - \alpha_j + 2c_i + c_j)/3$ with α_i the willingness to pay for firm i's product, c_i the unit cost for firm i and t the degree of product differentiation.

[9] See Dixit (1979) for details.

with $D \equiv 4b_1b_2 - c^2$.[10]

For our purposes, we want to know the effect on equilibrium prices of a change in: *i*) the own unit cost; *ii*) the unit cost of the competitor; *iii*) the quality of one own's product; *iv*) the quality of product provided by one's rival, and *v*) the degree of product differentiation. With regard to *iii*) and *iv*), note that a higher value of the intercept α_i in (1) implies that firm i can sell the same quantity at a higher price, other things equal. We therefore take the change in equilibrium prices that follows a decrease of α_i as our measure of the impact of a reduction in product quality. Proposition 1 presents the results that will serve as the point of departure for our empirical analysis.

Proposition 1 *Consider the differentiated duopoly model with the linear inverse demand functions as in (1) and assume that two firms supply substitutes ($\gamma > 0$) and compete in prices, then the marginal effects on equilibrium prices p_i^B of a change in the own (m_i) or competitor's (m_j) unit cost are as follows:*

$$\frac{\partial p_i^B}{\partial m_i} > 0; \qquad \frac{\partial p_i^B}{\partial m_j} > 0; \qquad i = 1,2 \quad j = 3 - i. \tag{6}$$

The marginal effects of a change in the perceived quality of one's own or competitor's product are as follows:

$$\frac{\partial p_i^B}{\partial \alpha_i} > 0; \qquad \frac{\partial p_i^B}{\partial \alpha_j} < 0; \qquad i = 1,2 \quad j = 3 - i. \tag{7}$$

The marginal effects of changes in the level of product differentiation are as follows:

$$\frac{\partial p_i^B}{\partial \gamma} < 0; \qquad i = 1,2. \tag{8}$$

Proof: See Appendix A.

Proposition 1 thus shows that whereas a decrease in unit cost and quality both negatively affect own-prices, the impact on one's competitors' price is opposite; A decrease in unit cost puts a downward pressure on the competitor's equilibrium price, a decrease in quality instead gives competitors some leeway to increase prices. We will use this observation to interpret our empirical findings. When we observe that station that has converted from manned to unmanned charges lower prices after the fact, we take this as evidence that either the unit cost level of this station and/or the product quality has decreased. To gauge the relative importance of these unobserved causes, we will look at their net

[10] Singh and Vives (1984) give results for prices *net of* marginal cost. This amounts to subtracting m_1 (m_2, respectively) from both sides of equation (1). The left-hand side then becomes $\tilde{p}_i^B \equiv p_i^B - m_i$ and the constant α_i in the right-hand side is replaced by $\hat{\alpha}_i \equiv \alpha_i - m_i$. To ensure positive demand $q_i = (\alpha_i - m_i)/\beta_i$ when firm i sets price equal to marginal cost and firm j does not produce ($p_i = m_i; q_j = 0$), we throughout assume that $\alpha_i > m_i$, for $i = 1,2$. See Singh and Vives (1984) for further details.

effect on price levels at local competitors of a converted station: if price levels are importantly higher (lower) after the conversion, this indicates that the quality (unit cost) change has been significant; if we do not find an effect, this suggests that the spillovers of the quality and unit cost change cancel each other out on average.

If the conversions have the effect of increasing product differentiation (lowering γ) because of more variation in the service dimension, this would show up as higher price levels at converted stations and their local competitors because of softened competition. Indeed, when the conversions would intensify competition by lessening product differentiation, the observed effect on equilibrium prices would be similar to the predicted effect of lower unit cost. We however dismiss the possibility because in the period considered the large majority of stations was manned.

3 Data

For our empirical analysis, we use fleet-card data collected by Athlon Car Lease (Athlon, hereafter), the leading car leasing company in the Netherlands with a fleet of over 125,000 cars.[11] Every day, Athlon captures station-specific retail gasoline prices using information retrieved from fleet-card users who frequent these stations. This methodology is very similar to the one used by OPIS[12], an agency that provides detailed information on gasoline retail prices for the US market.[13] Our final sample contains price quotes of 3,820 sites which implies a coverage of about 85 percent of all outlets in the country, a number comparable to the coverage by OPIS which is around 90 per cent (Chandra and Tappata, 2011).[14]

Although price information is collected for all grades of gasoline, diesel, and liquefied petroleum gas (LPG), we limit attention in this paper to regular unleaded 95 octane gasoline (known as Euro 95) which is the most commonly used type of fuel in the Netherlands. Our sample covers the time period between October 1, 2005 to April 25, 2011 and contains a total number of 4,259,183 price observations. 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.[15] The price data is supplemented with information about the geographic coordinates of the station and the (Euclidean) distances between all pairs of stations.[16]

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

[12] The Oil Price Information Service.

[13] Numerous researchers have recently made use of OPIS data, including Taylor and Hosken (2007); Doyle and Samphantharak (2008); Chandra and Tappata (2011); Myers et al (2011); Lewis (2012, 2014); Tappata and Yan (2013).

[14] 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.

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

[16] These data were obtained using Google Earth.

Information on a number of mostly time-invariant station characteristics was obtained from Experian Catalist Ltd. (the type of ownership, availability of a car wash, the number of pumps etc.) but these do not play a role in our analysis because of the inclusion of station-level fixed effects.

Tables 1 and 2 summarize the main characteristics of our sample. As for studies using OPIS data one potential shortcoming is that prices are not reported for all stations for all days (Tappata and Yan, 2013, p. 6). Table 1 shows that for highway (off-highway) sites on average a price-quote is registered every 1.28 (3.70) days. This implies that for a randomly selected day, the most recent price quote is on average 0.64 (1.85) days old which is comparable to OPIS data.[17] This may potentially bias our estimates if the data are missing not at random. Although the missing-at-random assumption is not refutable using the data alone[18] there are some reasons 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. Another source of non-randomness is when the number of recorded price observations is systematically higher on some days than on others, for example because lessees drive less in the weekend. This however does not bias our estimates for we throughout include day-specific fixed effects which absorb the potential impact of this particular source of non-randomness. The empirical analysis contains further tests using sub-samples to gauge the potential impact of non-random missing data; none of them finds significant differences.

Table 2 clearly shows the two major trends in the period of investigation: a steady increase in the number of unmanned stations (both on- and off-highway) and a decrease in the off-highway market share of the Major-6 brands. Table B.2 provides summary statistics of these trends at the regional level. Table B.2 shows that the share of unmanned stations has importantly increased in all regions and that the number of events (manned-to-unmanned and major-to-minor conversions) has been geographically dispersed. For this reason, it is reasonable to take these events as exogenous in the local competitor's pricing decision, conditional on the inclusion of station-level and time fixed effects.

[17] To compare, 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.

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

Table 1: Sample statistics at the site level (3,820 observations).

	mean	std. dev.	min.	p_{10}	p_{25}	p_{50}	p_{75}	p_{90}	max.
# price quotes per year	210.89	93.90	1.46	62.75	134.32	239.14	298.15	306.77	362.25
# days between quotes	3.55	9.53	1.01	1.19	1.22	1.53	2.71	5.81	250.13
highway	0.06	0.24	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Highway sites (240 observations)									
# price quotes per year	293.91	34.52	70.84	260.23	300.23	304.69	308.30	309.92	340.53
# days between quotes	1.28	0.36	1.07	1.18	1.18	1.20	1.22	1.40	5.15
Off-highway sites (3,580 observations)									
# price quotes per year	205.32	93.99	1.46	58.35	127.70	229.85	293.71	305.69	362.25
# days between quotes	3.70	9.82	1.01	1.19	1.24	1.59	2.86	6.24	250.13

Note: p_x : x^{th} percentile sample.

3.1 Prices

Gasoline prices in the Netherlands have varied widely over the last few years. Figure 1 shows that fluctuations in average retail prices reflect 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.

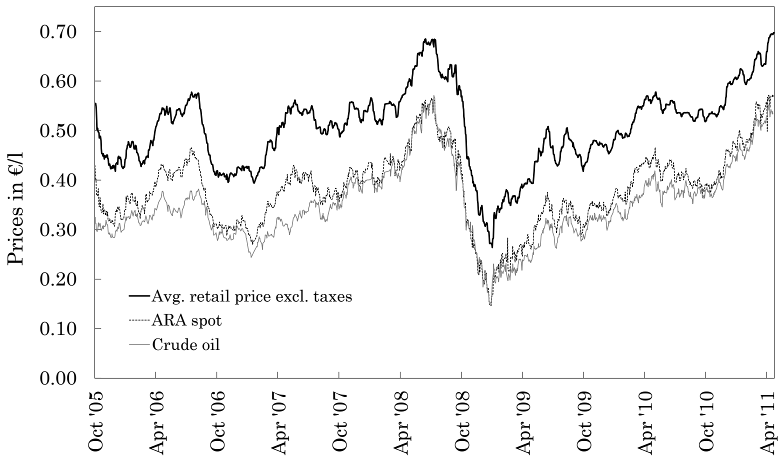


Figure 1: Average retail gasoline price, ARA spot price, and crude oil prices (Oct. 2005 – April 2011).

3.2 Within-station differences and changes in local market structure

Part A of Table 3 summarizes the changes at the station level in our data. The table shows that the most pronounced trend has been the conversion of manned to unmanned sites, with many more such conversions off-highway than on-highway. Off-highway, the number of unmanned fueling stations has

Table 2: Development of the shares of unmanned and Major-6 stations in 2005-2011.

	Oct-2005	Oct-2006	Oct-2007	Oct-2008	Oct-2009	Oct-2010	Apr-2011
unmanned	0.121	0.149	0.184	0.203	0.223	0.237	0.252
Major-4	0.494	0.477	0.459	0.451	0.442	0.437	0.435
TOTAL	0.131	0.132	0.122	0.117	0.111	0.105	0.100
Q8	0.039	0.035	0.032	0.033	0.031	0.029	0.029
Highway sites							
unmanned	0.021	0.042	0.050	0.050	0.050	0.055	0.059
Major-4	0.751	0.733	0.717	0.711	0.720	0.727	0.730
TOTAL	0.103	0.097	0.104	0.109	0.105	0.101	0.097
Q8	0.064	0.059	0.058	0.059	0.054	0.055	0.055
Off-highway sites							
unmanned	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

Note: 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.

steadily grown from a market share of 13.1% in October 2005 to 26.5% in April 2011.[19] The market share of unmanned stations in the highway market has almost tripled in the same period, but is with 5.9% still modest. We also observe a considerable drop in the number of off-highway sites carrying one of the Major-6 brands (Shell, Esso, BP, Texaco, TOTAL or Q8). In total, 247 off-highway (12 highway) sites of the Major-6 have been re-branded to another brand, 68 (6) stations have made a change in the opposite direction. With a market share over 14 percent, Shell is the market leader in 2011 despite having lost 3 percentage points of its market share since January 2006. TOTAL has experienced the largest decrease in market share with a fall of nearly 4 percentage points.[20] Whereas the off-highway market has a significant share of other players, the Major-6 still own 88 percent of all highway sites at the end of the sample period. Including off-highway stations, the total market share of the Major-6 decreased with 10 percentage points to 56 percent during the sample period.

These changes at the station level have induced significant changes in the local market context in which highway and off-highway stations operate. Part B of Table 3 shows that 951 (135) off-highway (highway) stations experienced an increase in the number of off-highway competitors within a 2 km (5 km) radius and 713 (102) a decrease. In other words, both for highway and off-highway

[19]That is, 874 out of 3303 stations. The number of 874 is higher than the 713 (=424+291-2) that one would derive from Table 3 because it also includes the unmanned stations that entered the market between 2005 and 2011.

[20]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 B.1 in Appendix B gives further details.

Table 3: Number of sites that experienced changes in site characteristics and local market characteristics.

A. Site characteristics				
	Unmanned		Major-6	
	Highway	Off-highway	Highway	Off-highway
31.12.2005	5	424	215	1997
NO $\rightarrow$ YES	7	291	6	68
YES $\rightarrow$ NO	0	2	12	247
	Total number of sites			
2005	233	3118		
2011	237	3303		

B. Local market characteristics		
# off-highway sites	Increase	Decrease
$\leq$5 km from highway site	135 [224]	102 [156]
$\leq$2 km from off-highway site	951 [1221]	713 [837]
# unmanned off-highway sites	Increase	Decrease
$\leq$5 km from highway site	159 [320]	46 [51]
$\leq$2 km from off-highway site	1207 [1742]	270 [295]
# Major-6 off-highway sites	Increase	Decrease
$\leq$5 km from highway site	109 [171]	146 [278]
$\leq$2 km from off-highway site	647 [802]	1070 [1466]
# highway sites	Increase	Decrease
$\leq$5 km from highway site	3 [3]	0 [0]
$\leq$2 km from off-highway site	4 [4]	2 [2]
# unmanned highway sites	Increase	Decrease
$\leq$5 km from highway site	5 [5]	0 [0]
$\leq$2 km from off-highway site	7 [10]	0 [0]
# Major-6 highway sites	Increase	Decrease
$\leq$5 km from highway site	14 [14]	16 [16]
$\leq$2 km from off-highway site	20 [20]	21 [21]

Notes: Figures in brackets indicate the total number of events with double counts (some sites experienced multiple events).

stations competition by off-highway stations intensified, at least when measured by the number of neighboring off-highway stations. One caveat is that part of these entries may not be genuine but an artifact of gradual improvements in market coverage.[21] Using the same 2 km (5 km) radius, there were 1,207 off-highway (159 highway) sites that experienced an increase in the number of off-highway unmanned sites in their neighborhood, resulting from either conversion or entry. Some sites experienced multiple changes in their local environment: The numbers in brackets reflect these double

[21] Table 3 also shows the corresponding numbers for changes in neighboring highway stations. These numbers are much smaller and for this reason not discussed in the text.

counts. Even though we observe only two sites converting from unmanned to manned, there is a significant number of highway and off-highway sites that saw the number of unmanned off-highway sites in their neighborhood decrease at some point. This is because a number of unmanned off-highway stations exited the market. A total of 1,070 off-highway (146 highway) stations saw at some point the number of off-highway Major-4, Total or Q8 within a 2 km (5 km) radius decrease, while 647 (109) stations saw an increase.[22]

3.3 Unmanned stations and price levels

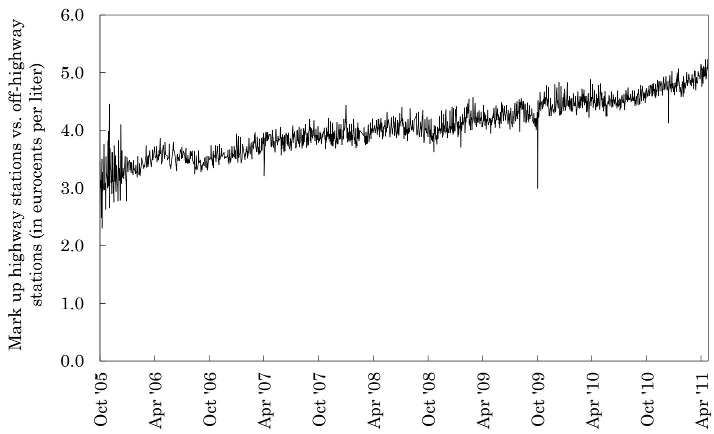


Figure 2: Absolute mark up highway vs. off-highway sites (01/10/2005–25/04/2011).
Note: Dates with less than 20 price quotes for highway sites and/or less than 30 price quotes in total have been excluded.

The introduction of unmanned stations is an obvious route to cut cost. Figure 2 shows that the sharp increase of the number of unmanned stations in the off-highway market has been accompanied by a similar sharp increase in the highway/off-highway price differential. This differential has increased from 3 cpl in October 2005 to 5 cpl in April 2011.[23] At first sight a 2-cent change may look benign, but realizing that the average retail price in this period excluding excise duty and VAT has been 50.7 cpl makes clear that 2 cents constitutes a big chunk of the companies' profit margin.[24] On the surface this lends support to the view propagated by oil companies[25] that competition off-highway has become stronger because of the emergence of unmanned stations. However, without further analysis of the spillovers, one cannot tell whether the lower off-highway prices are primarily caused by the pass-through of realized cost efficiencies, a reduction of the off-highway product quality or a combi-

[22]Note that both sets are not mutually exclusive.
[23]Excluding the 19% VAT.
[24]Hosken et al. (2008) report an average gross retail margin in the U.S. of 12%, translated to the Netherlands, this would amount to about 19 cpl.
[25]`http://www.tankpro.nl/brandstof/2014/01/03/prijsverschillen-snelweg-en-onderliggend-wegennet-groeien/`.

nation of the two. Section 2 showed that increased cost efficiency at converted stations may intensify competition, manifesting itself in lower price levels at the converted station's local competitors. The effect of a decrease in product quality will give local competitors room to increase prices instead. The next section will use this opposite effect on competitors' prices to identify the relative importance of cost efficiency and the quality dimension in driving down off-highway price levels.

4 Regression Analysis

The large N large T panel data set we employ ($N = 3,820$, $T = 1,977$) allows for a statistical model that includes both day-specific fixed effects and station-specific fixed effects. The time fixed effects capture the time-varying price components common to all highway and off-highway firms. The station-specific fixed effects absorb all unobserved variables at the station level that may be correlated with the other regressors. Including such a rich set of fixed effects implies that in a reduced-form regression of prices on a number of explanatory variables, only the coefficients of the time-varying regressors will be identified. Fortunately, as we saw in Section 3.2, a considerable number of such changes have taken place. Next to (time-variant) site characteristics such as unmanned and brand name dummy variables, we include as explanatory variables for off-highway (highway) stations local market characteristics such as the log of the number of highway and off-highway sites within 2 km (5 km), the log of the number of sites of a Major-6 brand within 2 km (5 km) and the log of the number of unmanned sites within 2 km (5 km).[26]

We estimate the following two-way fixed effect model:

$$p_{it} = \begin{cases} c_i + c_t^{H_1} + \boldsymbol{\beta^{H_1}} \mathbf{x}_{it} + \varepsilon_{it} & \text{if} \quad H_i = 1 \\ c_i + c_t^{H_0} + \boldsymbol{\beta^{H_0}} \mathbf{x}_{it} + \varepsilon_{it} & \text{if} \quad H_i = 0 \end{cases}$$

where H_i is a dummy variable equal to 1 if station i is located on a highway. The dependent variable is the price p_{it} at station i at day t (measured in eurocents per liter excluding taxes, i.e. excise duty and VAT). On the right-hand side, c_i and $c_t^{H_1}/c_t^{H_0}$ denote station-level and time fixed effects, respectively. The time fixed effects capture the time-varying price components common to all stations, such as variation in the price of crude oil and we expect this effect to differ for highway ($c_t^{H_1}$) and off-highway ($c_t^{H_0}$) stations. The vector $\mathbf{x}_{it} = (x_{it}^1, x_{it}^2, \ldots, x_{it}^K)'$ comprises the time varying explanatory variables. We allow these to have a different effect on highway ($\boldsymbol{\beta^{H_1}}$) and off-highway ($\boldsymbol{\beta^{H_0}}$) price levels. Throughout, we cluster the errors ε_{it} at the *location* level to account for the fact that, despite

[26]We use the natural logarithm of the number of neighbors (plus 1) because the price effects of the 1st and the 10th neighbor will in general not be the same. The implicit assumption in this specification is that new competitors will have a larger impact on prices the lower the initial number of local competitors.

the inclusion of station-level and daily time fixed effects, price observations at a given station may be characterized by serial correlation or heteroskedasticity.[27]

Statistical tests clearly favor the above specification with station- and time-fixed effects over a model with random station-specific effects. A Sargan-Hansen test for overidentifying restrictions in the random effects specification indicates that our specification with fixed effects is strongly preferred ($\chi^2(41) = 208.45$, $p < 0.001$).[28] We also test for the time fixed effects and conclude that we should include them ($F(64, 3819) = 1.7 \cdot 10^5$, $p < 0.001$).[29]

4.1 Estimates

Table 4 presents the estimates. We find that both on- and off-highway stations are cheaper when unmanned. The size of the effect is 3.8 cpl and 2.6 cpl, respectively, both significant at the 5% and 1% level.[30] This supports the view that stations will lower their price after they have converted into an unmanned station. We cannot reject the null hypothesis that this direct effect is the same for highway and off-highway sites.[31]

Pass-through of lower unit cost Next we consider whether the lower prices at converted stations lead to price changes at local competitors. The estimates in Table 4 detect significant ($p = 0.011$) competitive effects off-highway: Off-highway stations decrease their prices with on average 0.18 cpl when the number of off-highway unmanned competitors within a 2 km radius doubles. The identification of positive competitive effects points out that the pass-through of increased cost efficiency is the main force that drives prices at converted stations down, not a reduction of product quality due to less service.

For highway sites, we are not able to identify competitive effects from nearby on-highway or off-highway competitors converting into an unmanned station. For on-highway sites, one reason for this that only a small number of highway stations has converted, rendering relatively large standard errors. The circumstance that the share of unmanned sites is very low on-highway opens up the possibility

[27] A Wooldridge test (Wooldridge, 2002, 282-283) on the residuals from the first-differenced regression indeed finds significant ($p < 0.001$) serial correlation in the disturbances warranting the use of clustering. We cluster at the location level because there are different firms that may operate the same site at different points in time. Therefore, it is reasonable to assume that price observations are correlated not only at each station (firm), but at the location level as well.

[28] We use the user-written Stata command `xtoverid`.

[29] The null of no time fixed effects is also firmly rejected in a joint test for common and highway-specific (monthly) time fixed effects ($F(128, 3819) = 1.4 \cdot 10^5$, $p < 0.001$). The F-statistics are very large because the average daily price level has varied widely over the sample period.

[30] For the consumers, this translates to 4.5 cpl and 3.1 cpl, respectively due to the VAT. Consistent with this, Soetevent *et al.* 2014 have estimated in previous work that off-highway, gasoline sold at unmanned stations is on average 2.6% cheaper.

[31] $F(1, 3819) = 0.65$, $p = 0.420$.

Table 4: Fixed-effects regression of p_{it} on explanatory variables.

	Highway		**Off-highway**	
	coeff.	**s.e.**	**coeff.**	**s.e.**
Local market characteristics				
ln(# hw. sites + 1)	1.8903***	(0.6459)	1.2007	(1.0257)
ln(# hw. unmanned sites + 1)	-0.2959	(0.5185)	-0.3914	(0.9980)
ln(# hw. Major-6 sites + 1)	0.9822	(0.6028)	-0.2802	(0.6782)
ln(# off-hw. sites + 1)	-0.7560**	(0.3335)	-0.7362***	(0.1542)
ln(# off-hw. unmanned sites + 1)	0.1616	(0.0990)	-0.1820**	(0.0719)
ln(# off-hw. Major-6 sites + 1)	0.5070**	(0.2311)	0.1740	(0.1123)
Site characteristics				
Unmanned	-3.8115**	(1.4927)	-2.6008***	(0.1605)
Major-4	1.1623***	(0.4195)	1.6826***	(0.1808)
TOTAL	0.8506	(0.5815)	2.2433***	(0.3279)
Q8	1.3708***	(0.4508)	1.4237***	(0.2407)
Station fixed effects	YES			
Day fixed effects	YES			
Obs.	4,153,898			
R^2 within	0.1055			

Standard errors are clustered at the site level. *** p<0.01, ** p<0.05, * p<0.1

that the events have softened competition due to increased product differentiation but the negative coefficient does not bear out this explanation. While the coefficient on the number of local unmanned highway sites is not significantly different from zero, a formal test cannot reject the null of equality of the indirect effects for highway and off-highway stations ($F(1, 3819) = 0.05$, $p = 0.828$). So we find that the sharp increase in the number of unmanned stations off-highway has led to significant competitive effects off-highway but not on-highway. This is consistent with the view that the increased highway/off-highway price differential is at least partly caused by the high number of conversions off-highway.

Rebranding, entry and exit Table 4 further shows that off-highway, rebranding from one of the Major-6 brands to a minor leads to price levels that are on average 1.4-2.2 cpl lower; for highway stations this effect is 0.9-1.4 cpl. For off-highway sites, we do not identify significant competitive effects of rebrandings. For highway stations, we observe that when the number of nearby off-highway competitors serving a major brand doubles, prices increase with on average 0.5 cpl. Panel B of Table 3 shows that identification of this coefficient is mostly driven by events where a highway station experienced an increase in the number of minor-brand nearby off-highway stations.

As for the manned-to-unmanned conversions, we conclude that reductions in perceived product quality are of minor importance and do not lower firm-level demand. The direct and competitive effects of major-to-minor conversions seem determined by the pass-through of realized cost reductions. A possible alternative explanation is that the price decreases are the result from intensified competition due to decreased product differentiation, as argued by Hastings (2004) in her empirical analysis of the conversion of 260 independent unbranded retailers.

The competitive effects of entry and exit are as follows. A doubling of the number of nearby off-highway competitors leads to prices that are 0.7 cpl lower. This number is similar for highway and off-highway stations (apart from the fact that for highway stations we take a 5 km and for off-highway stations a 2 km circumference).[32] This suggests that highway sites do compete with off-highway sites conditional on being located sufficiently close to the smaller roads.[33] Finally we note that prices at highway sites increase with the number of highway competitors within 5 km distance. This result is probably due to the fact that entry in the highway market is highly regulated and almost exclusively permitted at places where the road network expands. Therefore, the estimate is likely to reflect increases in local highway traffic, allowing stations to increase their highway premium.

Robustness checks We have tested the robustness of our estimates by using different sub-samples for estimation. For example, we dropped days if we observe less than one half of the maximum number of daily price quotes ($\frac{1}{2}\max(N_t)$), because highly-frequented stations may be over-represented on these days. In another test, we also excluded the bottom 10% of stations in terms of the number of price quotes. Finally, because of our data collection method, we observe less price quotes on Wednesdays and Thursdays in the first two years of our sample.[34] The data set is sufficiently long to allow us to drop the first years of observations without losing precision. None of these modifications changed our results either quantitatively or qualitatively. The only notable change is that for highway sites, the number of highway competitors within 5 km distance is only significant at the 10% level.

5 Event study approach

The regression analysis in the previous section primarily considered the average direct and competitive price effects of a change in one of the station characteristics. The aim of this section is to look more in detail what happens to prices in the time period surrounding a change in local market constellation

[32]For the highway sites that experience local entry (exit) off-highway, the median number of off-highway sites within 5 km is 9 (13) prior to entry (exit).

[33]We have noticed that some off-highway sites have placed big signs on roofs of farms next to a highway-exit to direct drivers to their premises.

[34]The reason is that until February 2007, we were not collecting the data during weekends. When we started to do so, the average number of price quotes per day jumped from roughly 1,400 to more than 2,000.

and whether the impact of a change is the same independent of the direction of the change, as the model in Section 2 suggests and the regressions of the previous section assume. The high frequency with which our price data arrive allows us to apply event study analysis to this end.

Next to shedding light on possible asymmetries in the effects of manned/unmanned conversions, re-branding from and to a major, and entry and exits, event study analysis enables one to see how quickly prices react to the change and whether prices show any change *prior to* the event. The latter is a real possibility. For example, competitors may anticipate the entry by a new competitor by lowering their prices in advance. Also, the decision to convert a manned station into an unmanned one may be related to particular negative price developments in the local market of that station. In these cases, a simple comparison of price levels before and after the change would underestimate the direct effect of converting into an unmanned station and the competitive effect of entry, respectively.

5.1 Analytical setup

The empirical setup of our event study analysis is derived from MacKinlay (1997). Retail gasoline prices are almost perfectly correlated with highly volatile crude oil prices. For any event study, we have to isolate the influence of all factors except the event itself. Hence, we consider price deviations from the average highway or off-highway market price, whichever is relevant:

$$\tilde{p}_{it} = \begin{cases} p_{it} - \bar{p}_t^{H_1} & \text{if} \quad H_i = 1 \\ p_{it} - \bar{p}_t^{H_0} & \text{if} \quad H_i = 0 \end{cases}$$

As before, this transformation accounts for all possible time fixed effects such as taxes, seasonal trends, or weekday-specific effects specific to the set of highway or off-highway stations. In event studies on financial data, the interest is in detecting abnormal returns in stock prices. Given our context, we redefine returns as follows. The first difference of $\tilde{p}_{it}$ is taken as the 'return' of station i on day t. That is,

$$R_{it} = \Delta\tilde{p}_{it} = \tilde{p}_{it} - \tilde{p}_{i,t-1} = \mu_i + \zeta_{it} \tag{9}$$

where ζ_{it} is a disturbance term with a mean zero and variance $\sigma^2_{\zeta_i}$. In the terminology of MacKinlay (1997), this specification has the form of a market model with the imposed constraint that prices at individual stations will move with the general market and therefore show the same volatility.[35] Other than in a financial market context where μ_i measures a stock's excess return (as compensation for the risk borne), we have reason not to expect individual μ's to significantly differ from zero.[36] We have a

[35] The specification is identical to MacKinlay (1997, p. 18) equation (3) with $\beta_i = 1$ for all stations i.

[36] We indeed do not find any stations with a μ_i significantly different from zero at $p = 0.10$.

couple of reasons for selecting this model specification.[37] Firstly, the time series of prices at individual outlets reveal that for most stations, the difference between the station's price and the national average price is very stable over time. Due to inflation, this difference will automatically grow somewhat in time, but this effect is negligible in our case because the periods considered are relatively short (up to a couple of months) and inflation has been modest in the period 2005-2011. Secondly, even though we observe a considerable number of changes in local markets, individual stations are not very often exposed to an event with subsequent events in most cases sufficiently separated in time for their effects on price returns not to interfere, apart from cases were events happen simultaneously, e.g. a brand name change and a manned-to-unmanned conversion.[38]

Our interest is in estimating abnormal price changes in the periods surrounding the event. To that end, we define an 80-days event window as the time period $[-10, 70)$, containing the price observations from 10 days before to 70 days after the event. In order to identify whether an observed price change in the event window is "abnormal", we have to specify what price changes we would normally expect. To do this, we employ the period $[-90, -10)$ prior to the event as an estimation window. In this configuration, the estimation window is of the same length as the event window and long enough to obtain consistent estimates of normal returns; the event window is sufficiently wide to see the full adjustment of prices after the event day.

Having defined returns, the estimation and event window, abnormal returns at dates τ within the event window are calculated as a difference between the actual and predicted return:

$$AR_{i\tau} = R_{i\tau} - \hat{\mu}_i \tag{10}$$

The variance of $AR_{i\tau}$ is simply equal the variance $\sigma^2_{\zeta_i}$. For a period $[\tau_1, \tau_2]$ within the event window, we calculate the cumulative abnormal return (CAR) for station i by aggregating abnormal returns from τ_1 to τ_2:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{11}$$

Since in our setup the return is a price change, CAR_i can be interpreted as the *abnormal price level* of station i.

To estimate the price effect of a particular event-type (e.g. manned-to-unmanned conversion), we need to aggregate for this event all abnormal return observations for the event window and across

[37] The common alternative is the market model which assumes a stable linear relation between, in our case, national price changes and station-level price changes. For details, see MacKinlay (1997, pp. 18, 20-21).

[38] The maximum number of different events per station is 2 (at 5 sites only). Those events are at least 7 months (217 days) apart hence the estimation and the event windows do not overlap.

observations of the event. In doing this, we assume that the different events are independent. In other words, we rule out overlap between the different event windows at a given station and higher order spillovers. Due to the small number of events per station, this first assumption is not stringent. The second, slightly stronger assumption imposes that, for example, a station that sees one of its competitors convert into an unmanned site only responds to that event and not to the possible price response of the converted station's other competitors.

Given M events of a given type, e.g. manned-to-unmanned or non-major-to-major, we compute the sample aggregated abnormal returns at day τ as:

$$\overline{AR}_\tau = \frac{1}{M_\tau} \sum_{i=1}^{M_\tau} AR_{i\tau} \tag{12}$$

In aggregating abnormal returns, we again assume that the events are independent such that the covariances across events equal zero. This is not unreasonable if events of a given type in a given region are sufficiently separated in calendar time or space.[39] The variance of average abnormal return depends on the length of the estimation period (MacKinlay, 1997). Since we have a reasonably wide estimation window, we can use the asymptotic variance estimate:

$$\mathrm{Var}(\overline{AR}_\tau) = \frac{1}{M_\tau^2} \sum_{i=1}^{M_\tau} \sigma^2_{\zeta_i} \tag{13}$$

Using equations (12) and (13) the cumulative (average) abnormal return and its variance for any interval in the event window are calculated as follows:

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \tag{14}$$

$$\mathrm{Var}(\overline{CAR}(\tau_1, \tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} \mathrm{Var}(\overline{AR}_\tau) \tag{15}$$

Finally, to test the significance of $\overline{CAR}(\tau_1, \tau_2)$ against the null hypothesis $\overline{CAR}(\tau_1, \tau_2) = 0$, MacKinlay (1997) derives the following test statistic

$$\theta_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{\mathrm{Var}(\overline{CAR}(\tau_1, \tau_2))}} \sim N(0, 1) \tag{16}$$

with the asymptotic distribution being the limiting distribution with respect to the number of gasoline stations experiencing a certain event and the length of the estimation window.

[39]None of the sites in our data experience multiple events of a given type. Taking the 80-day event window $[-10, 70)$ we have 24 instances (12.5% of the total) of overlap within a *5 km* distance for the event manned-to-unmanned; 6 (4.8%) for major-to-non-major, and 0 for non-major-to-major.

5.2 Results

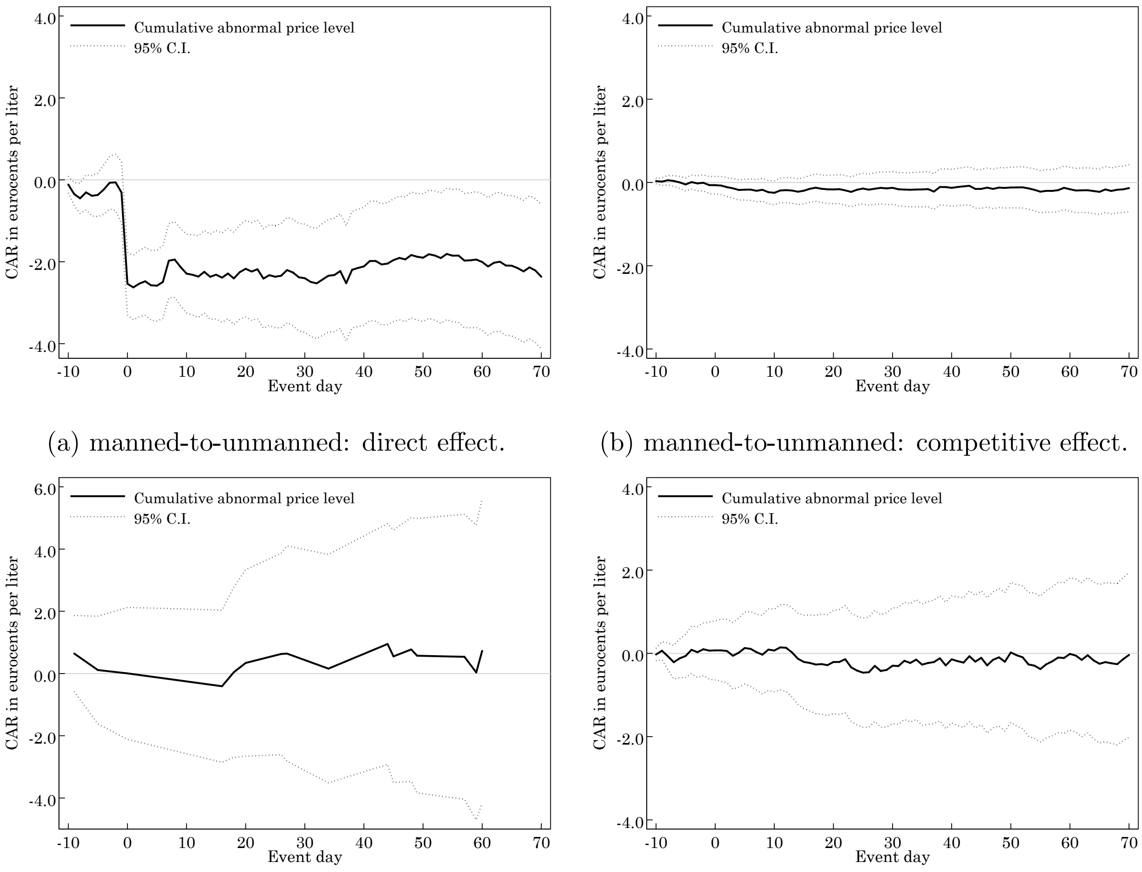
We calculate the cumulative abnormal return $\overline{CAR}(\tau_1, \tau_2)$ with $\tau_1 = -10$ and $\tau_2 \in [-10, 70)$. Setting τ_1 equal to the beginning of the event window yields wide confidence intervals and thus a conservative test of the significance of the cumulative abnormal returns.[40] Our main interest is in the events of manned/unmanned conversions and re-brandings from a Major-6 to a minor station (or *vice versa*). To disentangle the effects of different event-types, we exclude in our analysis all 99 (out of 457 in total) cases where these two events coincide at a site (e.g. sites that experience a manned/unmanned conversion combined with a re-branding). Another 60 sites are excluded because they have five or fewer observations in the estimation window. Finally we exclude all highway stations from our analysis because of a lack of events. Consequently, the number of events included in the sample is 151 for manned-to-unmanned, 1 for unmanned-to-manned, 37 for non-major-to-major, and 109 for major-to-non-major conversions.

Manned/unmanned conversions Figure 3 depicts the cumulative abnormal returns for the manned-to-unmanned conversions (and vice versa) for the sites that experience such a transformation (Figure 3a and c) and for their off-highway competitors (Figure 3b and d). Stations becoming unmanned reduce prices by roughly 2.2 cpl on the day of event.[41] For this abnormal return $\overline{AR}_0$, $\theta_1 = 27.71$ such that the null hypothesis of no impact on the day of conversion is firmly rejected. After the event date, prices consistently stay at this lower level, despite an upward jump at event day 7 (0.5 cpl, $\theta_1 = 5.47$), possibly because of the ending of first-week discounts. The chart shows that the part of the unit cost reduction that is passed through to consumers is transferred immediately following the conversion. In line with our regression estimates, panel (b) shows negative post-event cumulative abnormal returns of the order of -0.2 cpl for off-highway sites that neighbor (2 km radius) a site that experienced a conversion. However none of these spillover effects are significant at the 5-percent level. For completeness sake, panels (c) and (d) show the direct and competitive effects from unmanned-to-manned conversions. The small number of such events however prevents us to draw any definite conclusions.

Major/minor re-brandings Figure 4a shows that the impact of a major to non-major brand name change is approximately 1.2 cpl at the event date. However, in contrast to the direct impact of manned-to-unmanned conversions, this amounts to less than a half of the cumulative price decrease

[40] Recall from equation (15) that variance is accumulated day-by-day. Therefore, if any results are significant for this choice of τ_1, we can be sure that they will remain significant in different specifications of $\overline{CAR}(\tau_1^*, \tau_2)$ with $\tau_1^* \in (\tau_1, 0]$.

[41] Table B.3 in the Appendix shows per event date the abnormal returns for the different events.



(a) manned-to-unmanned: direct effect.

(b) manned-to-unmanned: competitive effect.

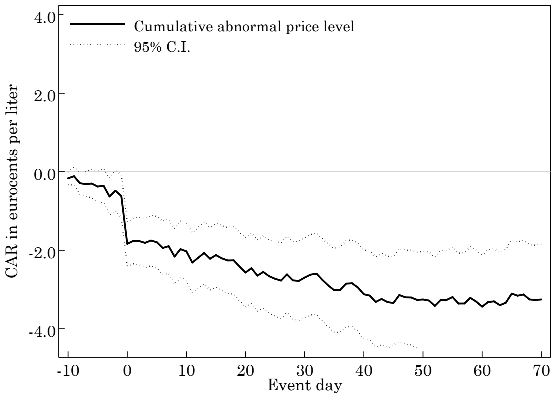
(c) unmanned-to-manned: direct effect.

(d) unmanned-to-manned: competitive effect.

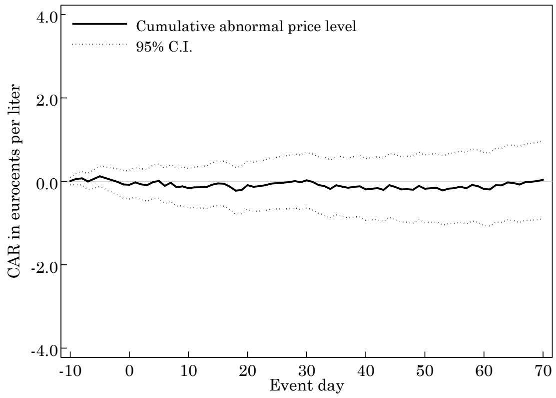
Figure 3: Panels *a* and *b*: The cumulative abnormal returns at off-highway sites (*a*) and at their neighboring off-highway competitors (*b*) following a manned-to-unmanned conversion; panels *c* and *d*: *idem* for unmanned-to-manned.

of about 3.2 cpl that is realized at the end of the event window. Indeed, in the 40 days following the event, we observe 6 days with significant price decreases in the range 0.15-0.3 cpl and only 1 day with a significant increase of the same order of magnitude.[42] Panel (c) shows that this effect is asymmetric: non-major to major re-brandings have no significant long-term price impact. There is a significant drop of 0.5 cpl at the event day ($\theta_1 = 5.81$), but this drop is only temporary. In other words, where both manned-to-unmanned conversions and the re-branding from to serving a major to a non-major brand lead to a significant decrease in a station's price level, the timing of the pass-through to consumers is very different. In case of a re-branding, the new price level is reached much more gradually. Panels (*b*) and (*d*) of Figure 4 reveal that we are not able to detect any significant competitive effects.

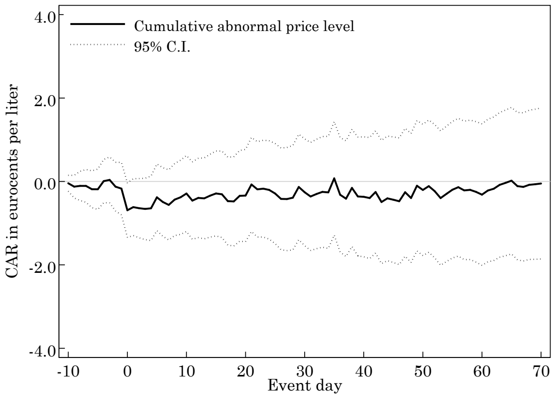
[42] At the 5% significance level. These days are event day 8, 11, 19, 22, 33, and 40, and 9, respectively.



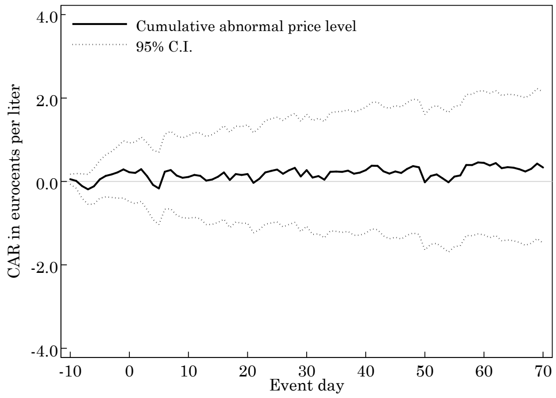
(a) major-to-non-major: direct effect.



(b) major-to-non-major: competitive effect.



(c) non-major-to-major: direct effect



(d) non-major-to-major: competitive effect.

Figure 4: Panels *a* and *b*: The cumulative abnormal returns at off-highway sites (*a*) and at their neighboring off-highway competitors (*b*) following a major-to-non-major conversion; panels *c* and *d*: *idem* for non-major-to-major.

6 Summary and conclusions

This paper has investigated the consequences of the sharp increase in unmanned 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 set of day and station fixed effects, we find that converted stations reduce pre-tax prices with on average 3.8 and 2.6 cpl on- and off-highways, respectively. Moreover, off-highway conversions generate significant competitive effects which is indicative of the price reductions at converted sites being the effect of pass-through of increased cost efficiency, not of worsened product quality. This evidence is important fuel for the public debate in some European countries on whether or not unmanned stations should be prohibited through legislation.

The application of event study analysis allowed us to consider in more detail the dynamics of the adjustment process towards the lower equilibrium price level. The main finding is that this adjustment is immediate. We contrast this with the price adjustment process following another frequently occurring event, i.e. the rebranding from a major to a non-major. This also leads to significantly lower prices at the rebranded location, but the adjustment towards the new price level is much more gradual and takes one to two months.

While the event study approach is widely used in finance to measure for example the effect of financial statements on a firm's stock market price, this is the first application of event study analysis to non-financial retail price data. Our results show the added value of this approach in increasing our understanding of pricing. Given the increased availability of detailed price data we envision an increased use of this tool. We hope that this study will stimulate the use of similar research approaches in empirical work on other retail markets that are characterized by frequent price changes and consumer search, such as the markets for groceries, financial products and online markets.

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A Appendix: Proof of Proposition 1

To find the effect on equilibrium price of a change in own marginal cost, take the derivative of the equilibrium price in equation (5) with respect to m_i:

$$\begin{aligned}\frac{\partial p_i^B}{\partial m_i} &= \frac{-2b_ib_j + c^2}{D} + 1 = \frac{-(2b_ib_j - c^2)}{4b_ib_j - c^2} + 1 \\ &= \frac{(4b_ib_j - c^2) - (2b_ib_j - c^2)}{4b_ib_j - c^2} = \frac{2b_ib_j}{D} > 0,\end{aligned}$$

where we have used that $D \equiv 4b_1b_2 - c^2 > 0$ and $b_1, b_2 > 0$.

Similarly,

$$\frac{\partial p_i^B}{\partial m_j} = \frac{2cb_j - cb_j}{D} = \frac{cb_j}{D} > 0,$$

because $b_j > 0$ and $c = \gamma/\delta > 0$ for goods that are substitutes ($\gamma > 0$).

Next we derive the comparative statics results of changes in the own or the competitor's intercept α_i.

$$\begin{aligned}\frac{\partial p_i^B}{\partial \alpha_i} &= \frac{\partial p_i^B}{\partial a_i}\frac{\partial a_i}{\partial \alpha_i} + \frac{\partial p_i^B}{\partial a_j}\frac{\partial a_j}{\partial \alpha_i} \\ &= \frac{2b_j}{D}\cdot\frac{\beta_j}{\delta} - \frac{c}{D}\cdot\frac{\gamma}{\delta} \\ &= \frac{1}{\delta D}\left[2b_j\beta_j - c\gamma\right] = \frac{1}{\delta^2 D}\left[2\beta_i\beta_j - \gamma^2\right] > 0.\end{aligned}$$

to arrive at the second line, note that it follows from (5) that

$$\frac{\partial p_i^B}{\partial a_i} = \frac{2b_j}{D} \text{ and } \frac{\partial p_i^B}{\partial a_j} = \frac{c}{D}, i = 1, 2, \quad j = 3 - i$$

$$\frac{\partial a_i}{\partial \alpha_i} = \frac{\beta_j}{\delta} \text{ and } \frac{\partial a_i}{\partial \alpha_j} = \frac{-\gamma}{\delta} i = 1, 2 \quad j = 3 - i.$$

In the final step, we insert $c = \gamma/\delta$ and $b_j = \beta_i/\delta$.

Similarly, it follows that

$$\begin{aligned}\frac{\partial p_i^B}{\partial \alpha_j} &= \frac{\partial p_i^B}{\partial a_i}\frac{\partial a_i}{\partial \alpha_j} + \frac{\partial p_i^B}{\partial a_j}\frac{\partial a_j}{\partial \alpha_j} \\ &= \frac{-2b_j}{D}\cdot\frac{\gamma}{\delta} + \frac{c}{D}\cdot\frac{\beta_i}{\delta} \\ &= \frac{1}{\delta D}\left[c\beta_i - 2b_j\gamma\right] = \frac{1}{\delta D}\left[\frac{\gamma\beta_i}{\delta} - \frac{2\beta_i\gamma}{\delta}\right] = -\frac{\gamma\beta_i}{\delta^2 D} < 0.\end{aligned}$$

In the penultimate step, c is replaced with γ/δ and b_j with β_1/δ. The inequality follows because $\beta_i > 0$ and we have assumed $\gamma > 0$.

The proof that $\frac{\partial p_i^B}{\partial \gamma} < 0$ for $i = 1, 2$ if $\gamma > 0$ is straightforward. For $i = 1$, equation (5) can, after some manipulations, be rewritten as

$$p_1^B = m_1 + \frac{1}{\delta^2 D}\left[(2\beta_1\beta_2 - \gamma^2)(\alpha_1 - m_1) - \beta_1\gamma(\alpha_2 - m_2)\right].$$

Taking the derivative of p_1^B with respect to γ leads to an expression with $(\delta^2 D)^2 = (4\beta_1\beta_2 - \gamma^2)^2 > 0$ in the denominator and as nominator:

$$\begin{aligned}&\delta^2 D\left[2\gamma(m_1 - \alpha_1) + \beta_1(m_2 - \alpha_2)\right] + 2\gamma\left[(2\beta_1\beta_2 - \gamma^2)(\alpha_1 - m_1) - \beta_1\gamma(\alpha_2 - m_2)\right] \\ = \; & -4\beta_1\beta_2\gamma(\alpha_1 - m_1) - \beta_1(\gamma^2 + 4\beta_1\beta_2)(\alpha_2 - m_2) < 0,\end{aligned}$$

where the inequality follows from the condition $\alpha_i - m_i > 0$ for $i = 1, 2$. □

B Additional figures and tables

Table B.1: Comparison of the number of stations with BOVAG.

	Athlon 01-06-06	BOVAG June 2006	coverage	Athlon 01-05-11	BOVAG June 2011	coverage	Market share† 01-01-06	01-04-11
Shell	553	586	94.4%	520	528	98.5%	17.0%	14.7%
TOTAL	458	595	77.0%	355	419	84.7%	13.2%	10.0%
Texaco	438	562	77.9%	465	544	85.5%	12.7%	13.1%
BP	333	394	84.5%	318	374	85.0%	9.9%	9.0%
Esso	325	361	90.0%	321	349	92.0%	9.6%	9.1%
Q8	200	247	81.0%	226	259	87.3%	6.0%	6.4%
Other	1103	1590	69.4%	1335	1770	75.4%	31.7%	37.7%
Total	**3410**	**4335**	**78.7%**	**3540**	**4243**	**83.4%**		

Note: For the largest firms, this table reports for two points in time the number of stations in our sample and compares these two numbers as published by BOVAG (2010, 2011). BOVAG is the Dutch trade organization for employers in mobility.

†: Based on counts of the number of stations in the Athlon data.

Table B.2: 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
	Percentage manned-to-unmanned conversions							**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.

Table B.3: Abnormal returns (in eurocents per liter) for different event-types.

Event	manned to unmanned			non-major to major			major to non-major		
Event day (τ)	$\overline{AR}_\tau$	s.e.	θ_1	$\overline{AR}_\tau$	s.e.	θ_1	$\overline{AR}_\tau$	s.e.	θ_1
-10	-0.116	0.104	1.119	-0.044	0.098	0.446	-0.167**	0.083	2.015
-9	-0.233**	0.098	2.382	-0.081	0.098	0.819	0.053	0.079	0.672
-8	-0.102	0.123	0.827	0.017	0.113	0.155	-0.178**	0.089	1.998
-7	0.145	0.110	1.313	0.000	0.092	0.002	-0.023	0.073	0.312
-6	-0.083	0.125	0.668	-0.079	0.103	0.774	0.014	0.085	0.167
-5	0.021	0.098	0.213	-0.001	0.100	0.013	-0.077	0.091	0.847
-4	0.133	0.150	0.883	0.196**	0.097	2.027	0.021	0.086	0.246
-3	0.166	0.111	1.496	0.028	0.091	0.314	-0.274***	0.094	2.899
-2	0.009	0.124	0.070	-0.162	0.103	1.572	0.147	0.096	1.533
-1	-0.246	0.153	1.611	-0.046	0.116	0.395	-0.136	0.106	1.283
0	-2.229***	0.080	27.711	-0.519***	0.089	5.809	-1.218***	0.063	19.389
1	-0.089	0.092	0.972	0.075	0.101	0.744	0.072	0.076	0.950
2	0.090	0.101	0.898	-0.026	0.103	0.251	-0.001	0.085	0.006
3	0.058	0.082	0.714	-0.017	0.098	0.175	-0.047	0.081	0.580
4	-0.098	0.096	1.015	0.014	0.121	0.120	0.059	0.073	0.809
5	-0.009	0.092	0.102	0.264**	0.103	2.561	-0.043	0.079	0.549
6	0.091	0.090	1.010	-0.112	0.099	1.127	-0.146*	0.075	1.941
7	0.519***	0.095	5.466	-0.070	0.091	0.771	0.046	0.074	0.620
8	0.028	0.097	0.290	0.127	0.098	1.292	-0.265***	0.072	3.677
9	-0.185**	0.093	1.992	0.055	0.110	0.504	0.188**	0.077	2.451
10	-0.158	0.101	1.567	0.091	0.100	0.907	-0.056	0.081	0.693
11	-0.029	0.097	0.294	-0.170*	0.091	1.875	-0.285***	0.078	3.655
12	-0.045	0.088	0.510	0.065	0.108	0.601	0.122	0.076	1.600
13	0.117	0.081	1.443	-0.011	0.097	0.118	0.122	0.087	1.406
14	-0.122	0.131	0.928	0.065	0.109	0.596	-0.146**	0.071	2.068
15	0.052	0.142	0.370	0.053	0.112	0.474	0.091	0.075	1.208
16	-0.073	0.083	0.870	-0.020	0.098	0.202	-0.083	0.075	1.104
17	0.101	0.086	1.167	-0.164*	0.098	1.664	-0.053	0.083	0.636
18	-0.119	0.113	1.055	-0.008	0.094	0.084	0.004	0.083	0.043
19	0.153	0.126	1.215	0.134	0.101	1.325	-0.163**	0.077	2.110
20	0.081	0.121	0.674	0.007	0.102	0.065	-0.149*	0.078	1.911
21	-0.066	0.097	0.686	0.266**	0.111	2.396	0.110	0.072	1.523
22	0.055	0.081	0.681	-0.116	0.098	1.187	-0.189**	0.078	2.429
23	-0.227***	0.088	2.581	0.016	0.101	0.163	0.093	0.078	1.198
24	0.083	0.093	0.895	-0.030	0.111	0.276	-0.110	0.077	1.422
25	-0.038	0.106	0.360	-0.086	0.111	0.778	-0.064	0.079	0.808
26	0.025	0.136	0.183	-0.129	0.110	1.172	-0.046	0.083	0.551
27	0.137	0.095	1.442	-0.003	0.104	0.030	0.157*	0.084	1.884
28	-0.059	0.097	0.609	0.032	0.101	0.320	-0.152*	0.084	1.813
29	-0.117	0.087	1.339	0.257***	0.089	2.889	-0.014	0.085	0.163
30	-0.022	0.082	0.273	-0.126	0.102	1.241	0.085	0.077	1.108
31	-0.090	0.100	0.903	-0.102	0.100	1.015	0.074	0.078	0.951
32	-0.036	0.092	0.387	0.060	0.105	0.566	0.026	0.080	0.324
33	0.094	0.107	0.876	0.051	0.101	0.506	-0.161**	0.072	2.252
34	0.093	0.081	1.148	-0.012	0.111	0.110	-0.142*	0.086	1.657
35	0.017	0.093	0.186	0.336***	0.105	3.191	-0.120	0.077	1.560
36	0.097	0.098	0.989	-0.393***	0.098	4.014	0.010	0.081	0.122
37	-0.297***	0.090	3.303	-0.094	0.099	0.948	0.159*	0.095	1.684
38	0.327***	0.089	3.677	0.258**	0.113	2.284	0.009	0.077	0.119
39	0.045	0.084	0.533	-0.205*	0.120	1.717	-0.108	0.078	1.386
40	0.038	0.096	0.392	-0.008	0.104	0.081	-0.172**	0.082	2.100

Note: For the given event $\overline{AR}_\tau$ is the sample average abnormal return at event day τ.
*** p<0.01, ** p<0.05, * p<0.1