Psychological Prices at Retail Gasoline Stations: The Policies of 0-, 5-, and 9-Ending Prices

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This is an Accepted Manuscript of an article published by Taylor & Francis in Applied Economics on 2021-07-19, available online: http://www.tandfonline.com/https://doi.org/10.1080/00036846.2021.1925627.

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Abstract

Psychological prices are known to impact consumer behavior and to depend on retailers' characteristics. Less understood is last digit pricing, especially in the context of retail gasoline stations. We study price endings in the French gasoline market with 11,471 gas stations and 4,775,300 prices for oil companies, supermarkets, and independent retailers during five years. Raw data suggest that 0-ending prices are more expensive. Yet, these last digit effects do not survive careful scrutiny focusing on the individual behavior/distribution of each gas station. Plus, 9-, 0-, and 5-ending prices are over-represented. Our evidence better informs administrative authorities investigating market irregularities and consumers interested in better deals.

Keywords: Psychological price, price ending, last digit pricing, gasoline retailing

1 Introduction

We study psychological prices in gasoline using French retail data. *Psychological prices* are prices with a trailing digit that induces particular consumer behavior (Aalto-Setälä and Halonen, 2004; Chenavaz et al., 2018; Karoubi and Chenavaz, 2015; Kleinsasser and Wagner, 2011; Knotek, 2011; Levy et al., 2004; Macé, 2012; Manning and Sprott, 2009; Wieseke et al., 2016). One argument for psychological prices is that prices that end in whole numbers, 0, are more expensive than those that end is odd numbers, 5 or 9 (Aalto-Setälä and Halonen, 2004; Kleinsasser and Wagner, 2011; Manning and Sprott, 2009). As such, prices ending in odd numbers may be used to signal to consumers product value (Hoffman et al., 2002; Schindler, 2006). Round price, ending with 0, have the advantage to be more convenient for cash payments, expediting transactions (Chenavaz et al., 2018; Karoubi and Chenavaz, 2015; Knotek, 2011). Conceptually, psychological prices make sense; however, the literature is mixed, as discussed in Section 2. Yet, when comparing prices among retailers, some argue that a discount grocer may use prices to differentiate itself from a high-end grocer that may use signage instead of price (Heda et al., 2017). This may mean that inherently different pricing behaviors may not only be due to psychological prices but also to the type of retailer. For example, in the data we use, we have three types of retailers: an oil company (e.g., Shell, BP, etc.), a supermarket (e.g., Intermarché, Carrefour, etc.), and an independent retailer (e.g., "24h/24h CARBURANTS", independently owned, operated, and branded store(s)). Different pricing behaviors of retailers may be explained by the type of retailer or their location as opposed to some form of strategic prices, such as psychological prices, designed to induce consumer behavior.

Independent of the academic literature, the popular and trade literature suggests that psychological prices do indeed exist. For example, informal evidence suggests individuals purchase goods priced at \$0.99 at a higher frequency than goods priced at \$0.98 or \$1.00 (Adler, 2003). In France, the media identifies that there are inherent differences in gasoline (we only consider diesel in this study, as it represents over 80% of the gasoline sales volume) prices depending on the type of retailer. It is widely acknowledged that supermarkets use their gasoline station as a key *call product*, one used to incentivize store patronage (Lesaffre and Duteil, Europe1, 2018). As a call product, supermarkets may sell gasoline at cost resulting in lower prices (Schwab, France Television, 2020). One additional feature in the French gasoline retail sector is that gasoline is perceived to be more expensive on highways than elsewhere (Vosges Matin, 2015, LCI, 2019), and verified in our data.

On the one hand, some argue psychological prices occur in practice and anecdotal evidence suggests psychological prices do indeed work. On the other hand, price differences may be due to other exogenous factors not related to a strategic retailer inducing consumer behavior. In this research, we consider these seemingly opposing forces of retail pricing. Using real-world retail gas prices we determine if psychological prices indeed exist in practice, or if they may be explained using retailer characteristics. This means that we look if psychological prices are more often set and if they are more expensive than other prices. We consider, in this research, psychological prices with their right-most digit, that is we consider the last digit of a price (Coulter and Coulter, 2007; Coulter and Norberg, 2009). We look at round (Wieseke et al., 2016) and odds prices (Manning and Sprott, 2009; Schindler, 2001, 2006), and more precisely at prices ending in 0, 5, and 9, following Aalto-Setälä and Halonen (2004); Lewis (2015).

Our first results confirm the claim of the French press that highway stations post higher prices, charging about 10¢ more per liter (vs non-highway stations) and that supermarkets, for which oil is a call product, are cheaper, about 4¢, than an oil-company gas station. Focusing on the last digits, raw data, and even after preliminary analysis, results seem to indicate that some digits (especially 0) are more expensive. Controlling further the characteristics of each station (like the type of retailer, competition, type of road), these last-digit effects on the price level do not hold. In a nutshell, there is no last digit effect at the price level, even though gas stations use some last digits more often. Indeed, 9-, 0-, 5-ending prices are over-represented. More precisely, at the individual level (station per station), the distribution of last digits may be highly diverse (sometimes highly asymmetric, focusing on a single last digit).

In the remainder of the paper, we highlight the related contributions in psychological and gasoline pricing in Section 2. In Section 3 we present the data. Section 4 details the empirical results We summarize our results and conclude in Section 5.

2 Related Work

We now present the work related to our research. Our work spans two streams of literature: 1) Psychological prices and 2) Gasoline prices. We now discuss each stream in turn and show our contribution to each stream.

The psychological prices literature falls into two main categories: 1) psychological prices are effective and 2) psychological prices exist. The first category, the effect of psychological prices on consumer demand is widely studied. Results consistently show that price digits act as signals and consumers indeed change their purchasing behavior depending on a product's price (Coulter and Coulter, 2007; Macé, 2012; Schindler, 2006; Schindler and Wiman, 1989). This purchasing behavior may be explained by the *level effect*, consumers truncate least significant digit(s), by the *image effect*, certain trailing digits, 9 most commonly, are associated with discounts (Gedenk and Sattler, 1999; Stiving and Winer, 1997), or by *price convenience*, which make cash payment easier (Chenavaz et al., 2018; Karoubi and Chenavaz, 2015; Knotek, 2011). However, the effect may be a function of the overall product price, and the effect tends to diminish as price increases (Coulter and Coulter, 2005; Coulter and Norberg, 2009; Hackl et al., 2014). As we do not have demand data, i.e., how much gasoline is consumed at each station, we are not able to speak as to the efficacy of each price in the French gasoline retail market. However, we contribute to this line of research by testing if indeed the *image effect* holds in practice. Particularly, we determine if the trailing digit of a price is indeed an indication of a lower price.

The second category "psychological prices exist" may partially be supported by the fact the last digit of retail prices is known to not be uniformly distributed across industries (Hackl et al., 2014; Lewis, 2015; Wagner and Jamsawang, 2012). However, this is not sufficient to claim psychological prices exist as prices ending in a specific digit must be lower than prices ending in other digits. Some evidence suggests that indeed psychological prices exist at least in e-tailing (Hackl et al., 2014), while other work suggests that psychological prices do not exist (Schindler, 2001). So far, only the work of Schindler (2001) tests for psychological prices and finds that they do not exist only for prices ending in 99, relative to prices ending in 00 and 98 for multiple products. However, in our study, we use a much larger data set and a single product. Besides, we test for more than prices ending in 99 and look at prices ending in x9, x5, and x0 where $\mathtt{x} \in \{0, \ldots, 9\}$. After careful scrutiny including fixed effects, our results suggest that the last digit does not affect the price level. The main difference between these results is the models and data used. Further, different results may be attributed to the application domain and missing variable bias resulting in spurious correlation results. We contribute to this literature by determining if certain price endings are more expensive than others, on average. Working with a wide range of data, with a focus on automobile and grocery markets, Aalto-Setälä and Halonen (2004) reveals that last (right-most) digits 0, 5, and 9, are more common in retailing for different goods. We provide empirical evidence that no last digit price appears more expensive in the French retail gas sector, when controlling for merchant type and location.

The second stream of literature our work relates to is that in gasoline prices. There is a wealth of literature relating gasoline prices and crude oil prices (Balke et al., 1998; Borenstein et al., 1997; Karrenbrock et al., 1991). We do not consider this relationship and instead only focus on retail gasoline sales. From a retail perspective, some researchers use data to identify Edgeworth cycles as predicted by the literature (Maskin and Tirole, 1988) relating to competition (Anderson, 2011; Castanias and Johnson, 1993). In recent work, Byrne and de Roos (2019) find that dominant firms create focal points gradually to increase margins. We do not consider the equilibrium price aspect of the data we analyze. Instead, we determine if the last digit in the posted price is an indication of value. Our study is most similar to the work of Lewis (2015), which focuses on the US gasoline market; we consider French gasoline stations. We find that the distribution of last digit prices differs in France (our work) from the US (Lewis, 2015) (cf. Figure 1 in this paper and Lewis 2015, Figure 1, p. 670). Lewis (2015) focuses on American metropolitan areas, and we examine continental France, including both metropolitan and rural areas. Further, as we consider an entire country, we account for border and highway effects (tolls) while Lewis (2015) does not. We also want to verify if psychological prices exist, while Lewis (2015) finds *price rigidity,* prices do not often change when they have an odd last digit. Following the above literature, we use ordinary least squares (OLS) and fixed effects models, as the individual component of each station is a key issue. Similar to Aalto-Setälä and Halonen (2004); Lewis (2015), we focus on 0, 5, and 9 as the last digits of interest, as they found that retailers set them more often than other last digit prices.

3 Data

Table 1 presents some descriptive statistics about the dataset. Data about gasoline retail prices are gathered from the French government website `www.prix-carburants.gouv.fr/rubrique/opendata/`, following the open data policy described in `www.data.gouv.fr`. The data concern both general information on the point of sale, that is, address, geographic coordinate, services, access type (road or highway),[1]

[1] In France, as in most other countries, a road network consists of roadways of different capacities. The highest capacity roads we refer to as *highways*, and in France, motorists access gasoline stations directly from highways, without going on different types of roads. All other types of

Table 1: Descriptive Statistics

	Nb of Stations	Average Price	Stations within 5 km	Nb of Observations
All	11,471	1.242	18.2	4,775,300
Road	10,857	1.236	18.6	4,538,553
Highway	614	1.344	9.8	236,747
Oil Company	5,509	1.250	26.8	2,112,964
Road	4,934	1.241	28.5	1,910,672
Highway	575	1.338	10.5	202,292
Supermarkets	5,356	1.232	11.4	2,560,295
Road	5,336	1.232	11.4	2,544,765
Highway	20	1.381	6.4	15,530
Independents	606	1.304	8.9	102,041
Road	587	1.286	9.7	83,116
Highway	19	1.384	5.5	18,925

as well as the prices of gasoline. Using geographic coordinate, we calculate the number of retailers within a 5 km radius for each retailer, to estimate competition. We also look if a retailer is located in a county (called "département" in France) at a border with another country (Spain, Italy, Switzerland, Germany, Luxembourg, and Belgium) to control for border effects, as prices may be impacted by prices in neighboring foreign countries.

The governmental website does not directly provide the name or the brand of the retailer in the available dataset. However, we can match the name and brand via a secondary database available through the government. We gathered such data using web-scraping tools. Such additional data allows us to define the kind of retailer, namely oil company, supermarket, and independent. To obtain a homogeneous dataset, we consider only the diesel fuel, as it represents 80.7% of the volume of gasoline during the dataset period reference from `www.ufip.fr` (UFIP, 2016).

To obtain a good quality of price reporting, we excluded stations that reported less than 100 prices during the period. That is we excluded 1,890 stations from the 13,361 initial stations (14.1% of the stations and less than 0.5% of the price observations). Prices below 50¢ and above €2 are also discarded, as such prices do not make sense in practice as the average price is €1.242 per liter and the standard error is €0.135. The study only considers Metropolitan France (mainland France, Corsica, and the closest islands) and excludes overseas France (DOM-TOM. e.g., French Guiana or Martinique). Eventually, the dataset contains 11,471 gasoline retailers, with price observations over the period 2012-2016, representing a total of 4,775,300 observations. Stations in the database have reported, on average, 416

roads we refer to as *roads* and include, but are not limited to arterial, access roads, collectors, and local roads.

prices during the 5 years ($416 = 4,775,300/11,471$, about 2 prices per week).

Prices per liter are numbers made of four digits. For instance, the most popular (the modal) price in the data set is €1.299 with 71,258 observations (1.5% of the observations). The first digit is before the decimal, and there are three digits after the decimal. In this study, we are interested in the last (or right-most) digit, that is the fourth digit. More precisely, for the popular price above 1.299, the last digit is 9.

Following Table 1, 94.6% (=10,857/11,471) of retailers are located on roads and 5.4% (=614/11,471) on highways. Further, oil companies, supermarkets, and independents represent 48.0% (=5,509/11,471), 46.7% (=5,356/11,471), and 5.3% (=606/11,471) of gasoline stations, suggesting the equal distribution of retailers between oil companies and supermarkets. Yet, oil companies dominate highway retailing with 93.6% (=575/614) of the gasoline retailers. Oil company retailers are placed where there is more competition (average of 26.8 other stations within a 5 km radius), followed by supermarket retailers (11.4 other stations in the radius), whereas independent retailers seem to experience less competition (8.9 other stations in the radius). An explanation may be that oil companies locate in areas with higher population density, and thus with more competition. In contrast, supermarkets are usually located in suburbs and independents in more remote places (with less population density), facing less competition. This location strategy explains why independents charge the higher price (€1.304 per liter) and oil companies a moderate one (€1.250 per liter), based on raw (uncontrolled) data. Supermarkets propose the lowest price (€1.232 per liter) because gasoline represents a call product.

Table 2: Average Price per Year

Year	Average Price
2012	1.400
2013	1.353
2014	1.277
2015	1.153
2016	1.116

Table 2 shows the average price from 2012 to 2016. We will take into account this price evolution in our analysis. It informs that prices decrease monotonically over the period we consider in the study.

Figure 1 depicts the proportion of prices given the last price digit. Following Figure 1 top-left, 9-ending prices represent about one-third of the sample (34.9%). Then, 0- and 5-ending prices are slightly over-represented with 12.2 and 10.5%. 4-ending prices come close but are under-represented with 9.3%. This pattern is clearer on the road, where 9-, 5-, and 0-ending prices are more heavily being set (1 top-middle), but it is different on the highway where almost only 4-, 9-, and 0-ending prices are set. Oil companies and independents are more likely to

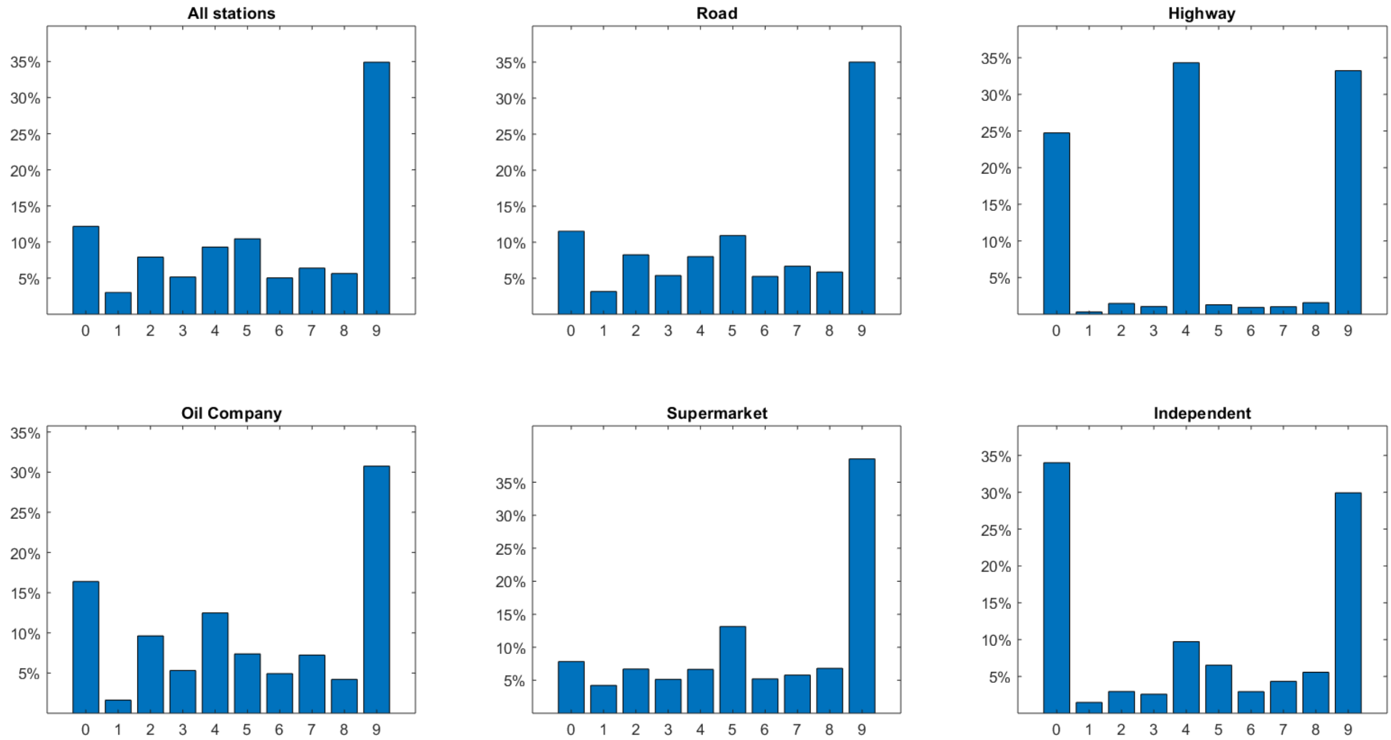

Figure 1: Last Digit Prices Proportion by Road and Retailer

set 9-, 0-, and 4-ending prices (Figure 1 bottom-left and bottom-right), whereas supermarkets are more likely to propose 9- and 5-ending prices (Figure 1 bottom-middle). In a nutshell, 9-ending prices are by far the most popular, followed by 0-ending prices. Then, 5- and 4-ending prices may also be set, depending on the kind of road and retailer. The distribution of last digit prices is very different from the one observed in the U.S. market (Lewis, 2015). For example, Lewis (2015) finds prices ending in a nine are the most common (about 30%) and odd numbers are more likely than even numbers. Even numbers are, for example, extremely rare in a city like Los Angeles.

Table 3 details the elements of Figure 1 over time. It represents the proportion of last-digit price in the sample for each year considered. Table 3 shows that prices ending with 9, 0, and 5 are over-represented, with 9-ending prices representing more than one-third of the prices. The proportion of 5- and 9-ending prices remains stable over time. Yet, the proportion of 0-ending prices decreases from 19.3% to 7.8% within four years. Therefore, 9-ending prices are over-represented and stable, 5-ending prices are only slightly over-represented and stable, whereas 0-ending prices move from over to under-representation over time. On the contrary, 4-

Table 3: Last-Digit Proportions per Year

Last-Digit	All years	2012	2013	2014	2015	2016
0	12.2%	19.3%	14.5%	11.8%	10.2%	7.8%
1	3.0%	3.9%	3.1%	2.9%	2.2%	3.1%
2	7.9%	6.2%	6.5%	7.5%	9.3%	9.1%
3	5.2%	4.4%	5.1%	5.3%	5.3%	5.6%
4	9.3%	6.1%	8.5%	9.0%	9.8%	11.8%
5	10.5%	9.3%	10.5%	11.0%	10.7%	10.6%
6	5.0%	4.5%	5.2%	5.3%	5.0%	5.1%
7	6.4%	5.0%	5.5%	5.8%	7.0%	7.8%
8	5.6%	5.6%	6.1%	6.1%	5.2%	5.4%
9	34.9%	35.9%	35.0%	35.2%	35.3%	33.7%

ending prices shift from under- to over-representation during the period. Appendix A.1 presents detailed information about last digit proportion over time-based on the kind of road and retailers.

Figure 2 represents the relative price level, by reporting the spread to the mean of the price, in line with the last price digit. Following Figure 2 top-left, 0-ending prices appear more expensive than other ending prices. This pattern appears on the road (2 top-middle), and is even more pronounced on the highway (2 top-right). Plus, larger 0-ending prices are especially set by oil companies (2 bottom-left), followed by independents (2 bottom-right), whereas supermarkets setting only a little more for 0-ending prices (2 bottom-middle). To summarize, 0-ending prices seem to be the most expensive, which motivates a deeper empirical analysis.

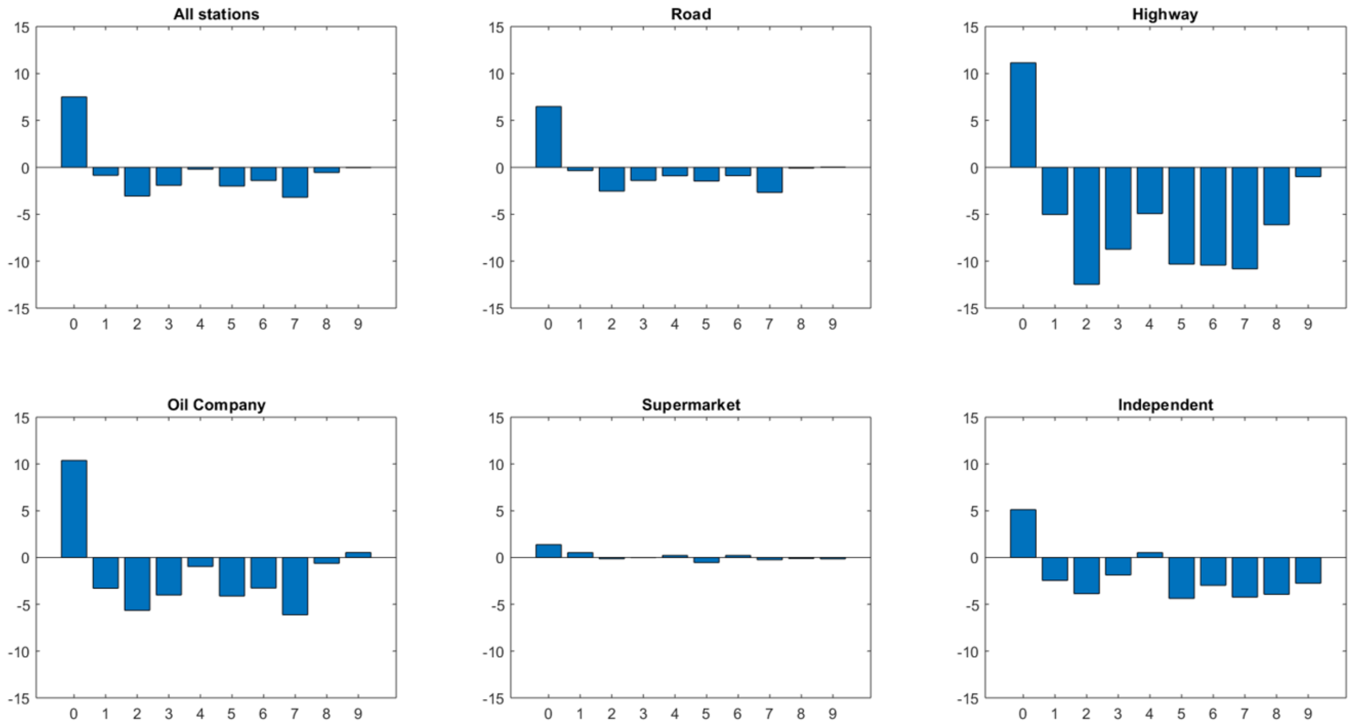

Figure 2: Spread to Mean Price (in cent) for Last Digit Price by Retailer and Type of Road

Table 4

	Model Estimates for Price Dependent Variable: Daily Prices 2012-2106						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) FE	(7) FE
0-Ending Price	9.1***	8.4***	8.5***	3.3***	0.7***	-0.1***	-0.1***
	(0.020)	(0.020)	(0.020)	(0.010)	(0.014)	(0.014)	(0.014)
5-Ending Price	-0.3***	0.1***	0.1***	0.01***	-0.1***	0.1***	0.1***
	(0.021)	(0.021)	(0.021)	(0.010)	(0.010)	(0.088)	(0.088)
9-Ending Prices	1.6***	1.6***	1.6***	0.7***	0.6***	0.3***	0.3***
	(0.014)	(0.014)	(0.014)	(0.007)	(0.007)	(0.006)	(0.006)
Road (=1) vs Highway Dummy		-9.3***	-9.5***	-10.0***	-9.9***		
		(0.028)	(0.028)	(0.014)	(0.014)		
Supermarket (=1) vs Oil Company		-0.3***	-0.2***	-4.0***	-3.4***		
Dummy		(0.012)	(0.013)	(0.007)	(0.007)		
Independent (=1) vs Oil Company		3.1***	3.3***	0.9***	2.1***		
Dummy		(0.042)	(0.042)	(0.021)	(0.021)		
$0\_Ending\_Price * Oil\_Company$					4.4***	0.5***	0.5***
Cross-Dummy					(0.018)	(0.023)	(0.023)
Competition	No	No	Yes	Yes	Yes	Yes	Yes
Border Dummy	No	No	Yes	Yes	Yes	Yes	Yes
Yearly Dummies	No	No	No	Yes	Yes	Yes	Yes
Day of the week dummies	No	No	No	No	No	No	Yes
R^2	0.046	0.071	0.072	0.775	0.778	0.841	0.841
Adjusted R^2	0.046	0.071	0.072	0.775	0.778	0.841	0.841

Notes. *p<0.1; **p<0.05; ***p<0.01. Number of observations: 4,775,300. Standard errors are in parentheses. The constant is not reported. Data are from the French government's open data policy for gasoline prices. Prices are in euro cent (€0.01 or 1¢). The dummy "Road vs Highway" equals one for a road and zero for a highway. The dummy "Supermarket vs Oil Company" equals one for a supermarket and zero for an oil company. The dummy "Independent vs Oil Company" equals one for an independent and zero for an oil company. The variable "Competition" counts the number of gasoline stations within a 5km radius. The dummy "Border" equals one if the stations belong to a county at the border and zero otherwise. There are four "Yearly Dummies," which equal one for 2013, 2014, 2015, and 2016 prices. The cross-dummy $0\_Ending\_Price * Oil\_Company$ equals one for 0-ending prices given by oil companies and zero otherwise. In regression 7, a potential day of week effect is controlled via the introduction of 6 dummies. None is economically significant. The R^2 and adjusted R^2 are very close because of the large number of observations.

4 Empirical Analysis

In the empirical section, we, step by step, present our main results. Additional data are provided in the Appendix. They include detailed figures at a yearly frequency and a deeper understanding (of the heterogeneity) of the last digits proportion posted by gas stations.

4.1 First insights: ordinary least squares regressions

At first, regressions (1) to (5) (Table 4) presents the coefficient estimates for each model with ordinary least squares (OLS) regressions. Due to the large volume of observations (4,775,300 observations/prices "P"), all effects are statistically significant at the 1% level; however, we look at the estimated effect when we discuss our findings. From our perspective, we deem an effect as economically significant only if it impacts prices by more than 1¢, as such a difference is "visible" to consumers.

The regression (5) writes as:

$P_i = constant + \beta_{(0-ending)} * LD0_i + \beta_{(5-ending)} * LD5_i + \beta_{(9-ending)} * LD9_i + \beta_{Road} * Road_i + \beta_{Supermarket} * Supermarket_i + \beta_{Independent} * Independent_i + \sum_{j=1}^{J} (\beta_{controls_j} * Controls_{j,i}) + \epsilon_i$,

where the indexes $i = 1{:}4,775,300$ and $j = 1{:}J$, with J the number of control variables (6 in regression (5): competition, border and 4 yearly dummies). $LD0_i$, $LD5_i$, and $LD9_i$ equal 1 if P_i ends with a 0, a 5 or a 9 (LD for Last Digit).

Regression (1) is the most basic regression and only considers three possible last digits (0-, 5- and -9) as explanatory variables. It confirms the descriptive results from Table 2, suggesting that 0-ending prices are more expensive. At this moment, the raw 0-ending price effect reaches 9¢, which any consumer should notice. As such, it is economically significant. A small effect is observed for 9-ending prices (lower than 2¢). No economically significant effect is found for 5-ending prices. Regressions (2) and (3) account for the characteristics of the stations. They reveal that highway stations charge about 10¢ more than non-highway stations. Surprisingly at this stage, they also reveal that supermarket stations are cheaper than an oil company gas stations by only 0.3¢. The competition (number of retailers within a 5 km radius) and the border dummy do not affect the results. The 0-ending price effect remains large (around 8¢) and the R^2 stands weak (around 7%).

The results change with regression (4), which introduces yearly dummies (linked to the price downward trend mentioned in Table 2). The R^2 jumps above 75% and last digit effects are affected, relative to regressions (1) through (3). The 9-ending effect reduces to less than one cent (0.7¢). The 0-ending effect diminishes but remains economically significant at about 3¢. The price spread between oil company and supermarket gas stations now reaches about 4¢, which is in line with the perception of consumers. With regression (5), we test whether this result is robust for all types of retailers. A new dummy is introduced, focusing on oil company gas stations and their specific 0-ending effect. Regression (5) highlights the 0-ending price effect would be specific to oil company gas stations. For the whole population, the 0-ending effect falls below 1¢ whereas it is greater than 4¢ for oil company gas stations. This specific intermediate result remains important in economic terms, suggesting a psychological price (0-ending prices). For a subgroup of stations, it could lead to much higher prices. In alternative regressions, not provided here, we also tested, for all last digits and types of retailers if another similar result could occur. We found no additional result. We also considered additional variables: different measures of competition (10 and 20 km radius), controls tied to population and population density. The results remained the same.

From regressions (1) to (5), the loading factors dealing with 0-ending prices underwent impressive changes (regression (4): introduction of time effects). Such changes question the intermediate results (specific to oil company gas stations). It encourages us to consider alternative econometric specifications. Table 3 offers an additional clue. The proportions of the last digits (whole population) undergo time fluctuations. Some changes could be even more impressive at the individual level, affecting our first results. The potential heterogeneity of gas stations, especially in terms of distribution of last digits, is developed in the next sub-section.

4.2 Heterogeneity of gas stations: fixed-effects regressions

Regression (5) characterizes the stations by several factors, for instance the type of retailers, border effect, and the like. But, the stations' heterogeneity may be imperfectly taken into account.[2] To tackle this issue, we adopt the fixed-effects estimation technique. The results are given by regression (6). For this kind of data, the use of fixed effects represents a crucial point when investigating price-endings. Indeed, all ending price effects are no longer economically significant: they are all at or below 0.5¢. It concerns the 4¢ 0-ending price effect existing in regression (5). If raw data suggest some last digits could lead to higher prices, for specific retailers, there is no last digit/psychological (and economically significant) effect at the price level. To confirm and extend this general result to non 0-, 5- or 9-ending prices, all digits have been tested in detail (unreported regressions). Regression (7) opens the analysis in a minor and new direction. Previous research emphasizes the day of the week effects in pricing (Gibbons and Hess, 1981). In our dataset, all daily estimates are below 0.5¢ and do not affect the last digit conclusions.

The question is now to understand the heterogeneity underlined by the fixed-effects. More precisely, what elements explain the difference between the results provided by regressions (5) and (6)? Part of the answer is offered by Tables 2 (average price per year) and 3 (proportions of last digits per year). Table 3 is developed in the Appendix via five sub-tables (Tables 5-9) to consider the different types of retailers and roads. Focusing on 0-ending prices, the spread between regressions (5) and (6) (the 4¢ effect specific to oil company gas stations that vanishes) is explained by two dimensions. At the beginning of the period, the (average) prices were high (in 2012). The same year, the proportion of 0-ending prices was also high for oil companies (about 32%) and then falls regularly during the following years to eventually reach less than 7.9%. This variation is stronger

[2]The authors thank an anonymous reviewer for this suggestion.

for highway stations (from 76.5% to 6.5%) which mainly belong to oil companies. If regression (6) shows ending digits do not affect the price at retail gasoline stations, we may nevertheless say that the prices posted reveal some psychological effects (the distribution of last digits is not random): there are important differences across stations/types of retailers. Table 3 indicates, for the whole population, that the distribution is far from being uniform and is evolving through time. Taken together, Tables 7 and 8 provide additional information. The supermarket gas stations exhibit stable (average) patterns/distributions of ending prices compared to oil company gas stations. Put differently, oil companies have evolving preferences in terms of ending digits.

To better segment and understand the policy of gas stations in terms of last digits, their heterogeneity, we use the k-means clustering method. This unsupervised method is popular to partition observations (here, 11,471 gas stations) into groups. For each gas station, we create a vector of size 10, think of it as the gas station identity card. Each element in the vector is the proportion of a certain ending digit posted by the gas station. All stations considered have at least reported 100 prices. The proportions are thus a good representation of the ending digit strategy for each gas station. The k-means algorithm requires a limited number of choices. The metric we used is the euclidean distance: a common choice in the literature. The number of groups is here an ad-hoc choice. To offer enough variability to the results, we ran the computations with 20 clusters. The clustering algorithm has been applied to four populations: all stations, oil company gas stations, supermarket gas stations, and highway stations. The results are reported in the Appendix in Tables 10 to 13. Each table provides 20 lines: one for each group/cluster. Each cluster is summarized by its centroid (the average pattern of the observations belonging to the partition) and the number of observations in the cluster. Some include more than 10% of the observations whereas others represent less than 0.1% of the data. They are sorted following the number of observations.

Based on these tables, we extract stylized patterns to illustrate the ending digit policies (and the heterogeneity) of gas stations. Starting with Table 10 (all stations), the modal pattern (about 14% of gas stations) is especially relevant after our concern on 0-ending prices and a potential price effect. This centroid aggregates stations that, in a very large proportion (average 97.8%), use 0 as their ending digit. If we decompose the data, a similar pattern represents 20% of oil company gas stations but only 2% of supermarket gas stations. These proportions were probably higher in 2012 than in 2016 (Cf Table 3).

Tables 10-13 underline that the distribution of last digits, at the station level, is highly heterogeneous and often very asymmetric as compared to the means (last line of each table). Proportions above 30% are in bold. 45% of the gas stations belong to a centroid with a modal last digit posted with a proportion greater than 50%. Stations with a uniform distribution represent only 10% (Table 10), centroid

3, all proportions close to 10%).

5 Summary and Conclusion

Our research extends last digit pricing into the context of the French gasoline retail market. The results are based on almost 5 million observations reported by more than 11,000 gasoline retailers over 5 years. Our main results are the following:

- At first glance, oil companies seem to set 0-ending prices at a level of 4¢ higher than all other last-digit prices. Yet, using more appropriate estimation techniques with fixed-effects, 0-ending prices are no longer economically more expensive.

- Controlling for several effects, we verify the idea, popular in media articles, that highways are more expensive than roads (by about 10¢); compared to oil companies, supermarkets charge less (by about 4¢) and independent charge more (by about 2¢).

- Prices ending in 9, 0, and 5 are more popular in the sense that they are more often used than other ending prices. Such results are aligned with Aalto-Setälä and Halonen (2004) who found this pattern for different markets; they are only partly aligned with Lewis (2015), who shows that odd prices ending in 5 and 9 are more popular in US gasoline markets. More precisely, we find evidence that, independently of the kind of road (road or highway) or the kind or retailer (oil company, supermarket, and independent), 9-ending prices are more widely used; 0-ending prices are over-represented, especially in highways and with oil companies and independents; 5-ending prices are more common on roads and by supermarkets.

- The frequency of the last digit changes significantly in the 5 years of observations for oil companies and independent gasoline stations. Supermarket last digit distribution remained stable during the same period. At the gas station/individual level, the distributions of last digits are highly heterogeneous.

To conclude, psychological prices play a role in the sense that 9-, 0-, and 5-last digits are set more often than others. In general, last digits do not exert influence in the sense that they are not more expensive than others, that is retailers do not extract greater rents from consumers by setting higher psychological prices. Such results offer a deeper understanding of the French gasoline market, offering sound evidence for consumers looking for the best opportunities and administrative authorities regulating the retail gasoline market.

In the future, we like to link our results to sales data, something not available in our data at this point. All the results presented only consider price data, and we have no quantifiable way of determining if psychological prices induce consumer purchases. One way to do this is to obtain a volume of gasoline sold as a dependent variable and using price as a control. However, in the future using this data will be of great use to link pricing decisions to revenue and profits using an optimization framework, but for this, we will need sales data.

Acknowledgements

Stanko Dimitrov acknowledges funding support from the Natural Sciences and Engineering Research Council of Canada. The authors thank an anonymous reviewer for his insightful comments.

A Appendix

A.1 Last Digit Proportion per Year by Kind of Road and Retailer

To provide a more comprehensive understanding of the last digit setting, we present here more detailed information corresponding to Table 3.

Digit 4	All years	2012	2013	2014	2015	2016
0	11.5%	16.6%	13.3%	11.6%	10.3%	7.8%
1	3.2%	4.0%	3.2%	3.0%	2.4%	3.3%
2	8.3%	6.4%	6.8%	7.8%	9.7%	9.6%
3	5.4%	4.6%	5.3%	5.4%	5.5%	5.8%
4	8.0%	6.3%	7.7%	8.1%	8.3%	9.1%
5	10.9%	9.8%	11.0%	11.4%	11.3%	11.1%
6	5.3%	4.7%	5.5%	5.5%	5.3%	5.3%
7	6.7%	5.2%	5.8%	6.0%	7.3%	8.2%
8	5.9%	5.9%	6.4%	6.3%	5.5%	5.5%
9	35.0%	36.6%	35.1%	34.9%	34.6%	34.2%

Table 5: Last Digit Proportions per Year: Road

Digit 4	All years	2012	2013	2014	2015	2016
0	24.7%	76.5%	39.4%	18.4%	8.4%	6.5%
1	0.3%	0.2%	0.2%	0.6%	0.3%	0.4%
2	1.5%	0.3%	0.7%	1.2%	2.1%	2.1%
3	1.1%	0.3%	0.7%	1.3%	1.4%	1.3%
4	34.3%	1.7%	24.1%	32.1%	35.6%	56.6%
5	1.3%	0.3%	0.6%	1.3%	1.7%	1.8%
6	0.9%	0.3%	0.6%	0.9%	1.2%	1.2%
7	1.0%	0.3%	0.5%	0.8%	1.6%	1.4%
8	1.6%	0.3%	0.8%	1.0%	1.3%	3.2%
9	33.2%	19.9%	32.6%	42.4%	46.4%	25.6%

Table 6: Last digit proportions per year; Highway

Digit 4	All years	2012	2013	2014	2015	2016
0	16.4%	34.2%	23.1%	17.6%	12.3%	7.9%
1	1.6%	2.2%	1.5%	0.9%	0.8%	2.4%
2	9.6%	4.4%	7.2%	9.6%	11.7%	11.5%
3	5.3%	3.0%	5.1%	5.4%	5.8%	6.1%
4	12.5%	5.7%	10.8%	12.4%	12.9%	16.1%
5	7.4%	4.6%	6.8%	7.5%	8.2%	8.2%
6	4.9%	3.3%	5.2%	5.2%	5.2%	5.2%
7	7.3%	3.5%	5.4%	5.9%	8.4%	9.5%
8	4.2%	3.4%	5.2%	4.8%	3.8%	4.3%
9	30.8%	35.7%	29.7%	30.9%	30.9%	28.8%

Table 7: Last Digit Proportions per Year; Oil Company

Digit 4	All years	2012	2013	2014	2015	2016
0	7.8%	9.2%	8.1%	7.9%	7.2%	6.8%
1	4.2%	4.9%	4.2%	4.0%	3.8%	4.1%
2	6.7%	7.4%	6.2%	6.5%	6.9%	6.5%
3	5.1%	5.2%	5.2%	5.3%	4.9%	5.0%
4	6.7%	6.4%	6.9%	6.9%	6.5%	6.6%
5	13.1%	12.3%	13.0%	13.2%	13.5%	13.6%
6	5.2%	5.3%	5.3%	5.5%	4.9%	5.0%
7	5.8%	5.9%	5.7%	5.9%	5.6%	5.8%
8	6.8%	7.0%	6.8%	6.9%	6.8%	6.6%
9	38.5%	36.4%	38.5%	37.9%	39.8%	39.9%

Table 8: Last Digit Proportions per Year: Supermarket

Digit 4	All years	2012	2013	2014	2015	2016
0	34.0%	51.1%	37.4%	30.0%	27.0%	24.7%
1	1.5%	1.5%	1.5%	1.4%	1.4%	1.5%
2	3.0%	2.5%	2.7%	3.3%	2.7%	3.6%
3	2.6%	2.6%	2.9%	2.6%	2.3%	2.6%
4	9.7%	2.7%	9.9%	13.1%	11.0%	12.4%
5	6.5%	5.4%	6.7%	6.1%	6.7%	7.6%
6	2.9%	2.5%	3.0%	3.2%	2.9%	3.2%
7	4.3%	3.7%	4.0%	5.0%	4.4%	4.6%
8	5.6%	4.1%	4.4%	5.4%	5.6%	8.0%
9	29.9%	23.9%	27.6%	29.8%	36.0%	32.0%

Table 9: Last Digit Proportions per Year: Independent

A.2 Stations, last digits and clustering via the kmeans algorithm

Table 10: Clustering stations via their proportions of ending digits: all gas stations

Last Digit	0	1	2	3	4	5	6	7	8	9	Nb of stations	Prop of stations
Centroid 1	**97.8%**	0.1%	0.2%	0.1%	0.3%	0.3%	0.1%	0.2%	0.2%	0.8%	1,589	13.85%
Centroid 2	7.1%	5.6%	8.3%	7.5%	8.4%	12.7%	7.0%	8.5%	8.1%	27.0%	1,226	10.69%
Centroid 3	11.0%	7.7%	9.9%	8.7%	9.3%	10.9%	8.8%	9.5%	9.8%	14.5%	1,147	10.00%
Centroid 4	1.4%	1.5%	17.3%	8.7%	10.8%	10.5%	8.7%	10.3%	7.6%	23.3%	1,128	9.83%
Centroid 5	4.6%	3.7%	6.6%	5.2%	7.0%	14.8%	5.4%	6.2%	6.7%	**39.8%**	1,109	9.67%
Centroid 6	2.7%	0.9%	1.7%	1.8%	3.1%	8.8%	1.9%	1.9%	2.6%	**74.6%**	828	7.22%
Centroid 7	0.8%	0.8%	15.2%	6.0%	12.9%	10.0%	6.3%	9.9%	4.0%	**34.2%**	816	7.11%
Centroid 8	3.4%	2.3%	4.5%	3.5%	5.7%	11.8%	3.7%	4.4%	5.1%	**55.7%**	782	6.82%
Centroid 9	0.8%	0.3%	0.4%	0.3%	1.3%	2.1%	0.4%	0.4%	0.6%	**93.4%**	730	6.36%
Centroid 10	**58.1%**	0.9%	4.5%	3.0%	5.3%	5.5%	2.9%	3.5%	3.1%	13.2%	462	4.03%
Centroid 11	3.8%	1.4%	2.6%	1.9%	2.4%	29.3%	1.9%	2.0%	2.6%	**52.2%**	394	3.43%
Centroid 12	0.6%	0.1%	0.3%	0.2%	29.2%	0.7%	0.2%	0.2%	0.7%	**67.7%**	384	3.35%
Centroid 13	**39.0%**	0.4%	1.5%	1.0%	9.3%	2.4%	1.0%	1.2%	2.3%	**42.0%**	266	2.32%
Centroid 14	18.2%	2.6%	4.7%	3.4%	4.5%	**31.4%**	4.4%	3.9%	6.3%	20.6%	169	1.47%
Centroid 15	3.9%	4.0%	5.9%	5.8%	9.8%	10.0%	7.6%	8.3%	27.6%	17.2%	134	1.17%
Centroid 16	**35.4%**	0.5%	0.6%	0.5%	**44.0%**	1.0%	0.6%	0.6%	0.9%	15.9%	108	0.94%
Centroid 17	1.8%	0.0%	0.0%	0.0%	**90.7%**	0.1%	0.1%	0.0%	0.1%	7.2%	79	0.69%
Centroid 18	2.0%	0.8%	1.5%	1.9%	8.1%	5.0%	2.0%	3.5%	29.4%	**45.9%**	69	0.60%
Centroid 19	2.2%	0.3%	0.4%	0.4%	4.6%	0.9%	0.7%	1.0%	**79.3%**	10.2%	46	0.40%
Centroid 20	0.3%	0.0%	0.9%	0.0%	0.0%	7.0%	**82.5%**	0.2%	0.8%	8.3%	5	0.04%
Mean	12.2%	3.0%	7.9%	5.2%	9.3%	10.5%	5.0%	6.4%	5.6%	34.9%	11,471	

Table 11: Clustering stations via their proportions of ending digits: oil company gas stations

Last Digit	0	1	2	3	4	5	6	7	8	9	Nb of stations	Prop of stations
Centroid 1	**99.4%**	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.1%	0.2%	1,087	19.73%
Centroid 2	0.9%	1.1%	17.5%	8.5%	11.0%	10.6%	8.6%	10.3%	7.5%	24.1%	1,020	18.52%
Centroid 3	0.3%	0.4%	16.6%	5.7%	11.9%	10.8%	6.2%	9.5%	3.3%	**35.2%**	607	11.02%
Centroid 4	6.1%	6.0%	10.6%	9.7%	10.3%	10.4%	9.0%	11.0%	8.8%	18.1%	457	8.30%
Centroid 5	4.1%	3.5%	7.6%	7.9%	11.1%	9.5%	6.2%	9.5%	6.6%	**34.1%**	412	7.48%
Centroid 6	0.5%	0.1%	0.2%	0.1%	29.1%	0.6%	0.1%	0.1%	0.3%	**69.1%**	333	6.04%
Centroid 7	1.7%	0.1%	0.3%	1.5%	4.0%	1.8%	1.3%	0.3%	0.7%	**88.4%**	325	5.90%
Centroid 8	3.1%	0.9%	3.2%	2.5%	9.2%	7.3%	3.0%	4.0%	9.0%	**57.8%**	190	3.45%
Centroid 9	24.7%	1.7%	10.6%	6.0%	8.1%	9.9%	6.1%	7.2%	6.0%	19.8%	153	2.78%
Centroid 10	**46.2%**	0.7%	6.9%	4.4%	7.3%	5.8%	4.2%	5.3%	3.6%	15.8%	147	2.67%
Centroid 11	**87.3%**	0.2%	1.5%	0.9%	2.1%	1.3%	0.9%	1.1%	0.8%	4.2%	124	2.25%
Centroid 12	**45.3%**	0.1%	0.4%	0.3%	11.3%	0.7%	0.4%	0.2%	2.1%	**39.3%**	117	2.12%
Centroid 13	**74.7%**	0.1%	2.3%	1.3%	3.3%	2.0%	1.3%	1.7%	1.2%	12.2%	112	2.03%
Centroid 14	**61.1%**	0.6%	4.5%	2.6%	6.7%	4.8%	2.9%	3.3%	3.2%	10.4%	111	2.01%
Centroid 15	0.9%	0.0%	0.0%	0.0%	**91.3%**	0.1%	0.1%	0.0%	0.1%	7.5%	75	1.36%
Centroid 16	26.2%	1.0%	1.2%	0.9%	**34.0%**	1.7%	1.0%	1.1%	1.6%	**31.3%**	68	1.23%
Centroid 17	**42.1%**	0.1%	0.0%	0.0%	**52.1%**	0.1%	0.1%	0.1%	0.1%	5.3%	52	0.94%
Centroid 18	**33.7%**	0.1%	0.4%	0.3%	6.7%	0.5%	0.4%	0.2%	0.9%	**56.8%**	51	0.93%
Centroid 19	1.6%	0.2%	0.2%	0.1%	10.5%	0.6%	1.0%	0.3%	**68.7%**	16.9%	35	0.64%
Centroid 20	2.7%	1.0%	2.2%	1.3%	2.1%	**36.1%**	1.6%	1.5%	4.3%	**47.1%**	33	0.60%
Mean	16.4%	1.6%	9.6%	5.3%	12.5%	7.4%	4.9%	7.3%	4.2%	30.8%	5,509	

Table 12: Clustering stations via their proportions of ending digits: supermarket gas stations

Last Digit	0	1	2	3	4	5	6	7	8	9	Nb of stations	Prop of stations
Centroid 1	6.8%	6.5%	9.4%	7.7%	8.9%	12.1%	8.0%	8.4%	9.6%	22.9%	649	12.12%
Centroid 2	10.0%	8.9%	9.6%	9.0%	9.3%	10.9%	9.5%	9.4%	10.5%	12.7%	602	11.24%
Centroid 3	5.8%	4.9%	8.3%	6.1%	7.4%	16.0%	6.1%	6.9%	6.8%	**31.8%**	595	11.11%
Centroid 4	4.8%	3.9%	6.7%	5.1%	6.9%	13.4%	5.4%	6.0%	6.1%	**41.8%**	562	10.49%
Centroid 5	3.6%	2.8%	5.0%	3.9%	5.8%	12.0%	4.2%	5.0%	5.9%	**51.9%**	447	8.35%
Centroid 6	3.6%	1.8%	3.4%	2.7%	4.0%	9.8%	2.7%	3.2%	4.7%	**64.1%**	331	6.18%
Centroid 7	0.5%	0.3%	0.4%	0.3%	0.5%	1.9%	0.3%	0.3%	0.4%	**95.2%**	320	5.97%
Centroid 8	1.8%	1.0%	2.0%	1.3%	2.4%	12.3%	1.5%	1.7%	1.9%	**74.1%**	302	5.64%
Centroid 9	1.9%	0.8%	1.3%	1.0%	1.7%	5.7%	1.1%	1.3%	1.7%	**83.4%**	297	5.55%
Centroid 10	3.3%	1.3%	2.3%	1.8%	2.3%	24.3%	1.8%	1.9%	2.4%	**58.6%**	294	5.49%
Centroid 11	5.1%	2.0%	3.9%	2.8%	3.5%	**32.4%**	2.7%	3.0%	3.9%	**40.7%**	227	4.24%
Centroid 12	18.3%	3.9%	6.4%	5.4%	5.8%	21.5%	5.4%	5.4%	7.3%	20.7%	192	3.58%
Centroid 13	3.6%	3.1%	5.3%	5.0%	8.1%	12.3%	5.6%	7.0%	16.3%	**33.8%**	130	2.43%
Centroid 14	**96.9%**	0.1%	0.2%	0.2%	0.2%	0.5%	0.3%	0.2%	0.5%	1.0%	128	2.39%
Centroid 15	**39.6%**	2.1%	3.1%	2.7%	4.8%	7.9%	2.5%	3.1%	4.0%	**30.4%**	79	1.47%
Centroid 16	**65.6%**	1.8%	1.9%	2.8%	2.5%	7.4%	1.7%	2.1%	2.5%	11.7%	67	1.25%
Centroid 17	4.7%	4.0%	4.7%	5.5%	9.0%	10.0%	5.6%	7.5%	**31.7%**	17.3%	66	1.23%
Centroid 18	4.1%	1.4%	1.3%	1.4%	**37.3%**	3.3%	2.1%	1.4%	2.8%	**45.0%**	35	0.65%
Centroid 19	3.3%	0.8%	1.1%	0.9%	1.4%	2.4%	1.8%	2.6%	**77.1%**	8.7%	17	0.32%
Centroid 20	4.7%	11.4%	**31.3%**	3.5%	5.8%	6.7%	7.7%	8.2%	7.6%	13.0%	16	0.30%
Mean	7.8%	4.2%	6.7%	5.1%	6.7%	13.1%	5.2%	5.8%	6.8%	38.5%	5,356	

Table 13: Clustering stations via their proportions of ending digits: highway gas stations

Last Digit	0	1	2	3	4	5	6	7	8	9	Nb of stations	Prop of stations
Centroid 1	**98.7%**	0.0%	0.0%	0.0%	0.5%	0.0%	0.0%	0.0%	0.0%	0.7%	75	12.21%
Centroid 2	**45.4%**	0.0%	0.1%	0.1%	12.7%	0.1%	0.1%	0.1%	0.8%	**40.8%**	73	11.89%
Centroid 3	0.4%	0.0%	0.0%	0.0%	**98.1%**	0.1%	0.1%	0.1%	0.1%	1.2%	53	8.63%
Centroid 4	1.2%	0.0%	0.0%	0.0%	29.2%	0.2%	0.1%	0.1%	0.3%	**68.9%**	50	8.14%
Centroid 5	**43.9%**	0.1%	0.0%	0.0%	**50.2%**	0.1%	0.3%	0.1%	0.4%	4.9%	47	7.65%
Centroid 6	2.0%	0.1%	0.4%	0.3%	15.0%	0.6%	0.3%	0.3%	0.2%	**80.7%**	35	5.70%
Centroid 7	29.4%	1.3%	1.5%	1.4%	26.3%	1.7%	1.1%	1.5%	2.9%	**33.1%**	35	5.70%
Centroid 8	**31.9%**	0.1%	0.1%	0.0%	13.1%	0.1%	0.0%	0.1%	3.0%	**51.7%**	34	5.54%
Centroid 9	27.6%	0.6%	0.5%	0.5%	**41.8%**	0.5%	0.7%	0.5%	0.8%	26.6%	24	3.91%
Centroid 10	3.1%	0.7%	1.9%	1.8%	**41.9%**	1.1%	0.7%	1.9%	2.2%	**44.7%**	23	3.75%
Centroid 11	0.5%	0.5%	17.3%	7.7%	11.3%	12.3%	8.2%	10.0%	6.7%	25.6%	23	3.75%
Centroid 12	**41.2%**	0.6%	0.7%	0.4%	26.2%	5.3%	0.6%	0.6%	0.8%	23.5%	20	3.26%
Centroid 13	0.1%	0.0%	0.0%	0.0%	**74.4%**	0.1%	0.3%	0.0%	0.1%	25.1%	19	3.09%
Centroid 14	**70.9%**	0.1%	0.1%	0.0%	16.9%	0.2%	0.2%	0.1%	0.2%	11.5%	19	3.09%
Centroid 15	**47.0%**	0.9%	4.4%	4.2%	9.1%	4.5%	3.6%	3.4%	6.1%	17.0%	18	2.93%
Centroid 16	6.2%	1.1%	2.1%	4.9%	15.6%	2.5%	2.3%	1.7%	14.9%	**48.9%**	15	2.44%
Centroid 17	1.1%	0.0%	0.0%	0.0%	2.3%	0.3%	0.0%	0.1%	0.0%	**96.1%**	15	2.44%
Centroid 18	22.5%	0.0%	0.1%	0.0%	**73.2%**	0.0%	0.2%	0.0%	0.2%	3.9%	13	2.12%
Centroid 19	0.1%	0.0%	0.0%	0.0%	10.6%	0.0%	0.0%	0.0%	**71.1%**	18.2%	12	1.95%
Centroid 20	6.4%	8.9%	9.0%	12.4%	9.2%	9.0%	9.9%	9.4%	9.0%	16.8%	11	1.79%
Mean	24.7%	0.3%	1.5%	1.1%	34.3%	1.3%	0.9%	1.0%	1.6%	33.2%	614	

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