The Effects of Gasoline Prices on Food Purchases: Quantity, Quality and Heterogeneity

Ondine Berland[1*] Fabrice Etilé[2†]

August, 2021

[1]Paris-Saclay University, INRAE, AgroParisTech, Economie Publique
[2]Paris School of Economics and UMR 1393 PjSE INRAE

Abstract

Carbon taxes can hinder households' welfare as commuting spending is inelastic. When facing increasing gasoline prices, households react by curbing expenditures on non-gas budget items. In this context, food has been shown to be a key adjustment margin. We use household scanner data to examine the effects of gasoline prices on the food purchases of a representative sample of French households. The estimated elasticity of food spending is approximately -0.2 with most of the effect coming from an adjustment in the unit price of goods. An analysis by food categories reveals that households adjust more on fresh products than on processed ones, which may have consequences for nutritional health. When investigating heterogeneity across households characteristics, we find that the demand response of the poorest income category is stronger than that of the rest of the population. Taken together, our findings suggest that households, especially poor ones, curb food expenditures to preserve gasoline consumption when gasoline prices increase, with ambiguous but potentially detrimental effects on nutritional quality.

Very preliminary results, please do not circulate without permission.

Keywords: France; Food; Gasoline prices; Commuting; Scanner data; Inequality
JEL Classification: D12, I14, L81, Q41

*Corresponding author: Ondine Berland, e-mail address: ondine.berland@gmail.com
†We are grateful to Margaux Jacob for help with data preparation. We thank Claire Chambolle, Basak Bayramoglu, Stéphane De Cara, Caroline Orset, Katheline Schubert and Stéphane Turolla for comments. We gratefully acknowledge research support from AXA Research Fund (AXA Awards 2015, Fabrice Etilé).

1 Introduction

The Yellow Vests movement rose in France from November 2018 until Spring 2019 as a reaction to a planned increase in the carbon tax. These protests stressed the impossibility of disconnecting the design of climate mitigation policies from issues of fairness and redistribution as they opposed the 'end of the world' to the 'end of the month' to emphasize that protecting the environment may have unequally distributed impacts on household welfare, and beyond welfare, on mere survival[1]. In this context, the main purpose of the present study is to investigate the effects of changes in gasoline prices on household food-at-home purchases, a key home budget category corresponding to one of the most vital necessities.

Gasoline prices impact food purchases primarily through an income effect. Gasoline purchases constitute a significant fraction of household expenditures and most empirical estimates show that gasoline demand is price inelastic in the short run (Graham and Glaister, 2002; Hughes, Knittel, and Sperling, 2008; Calvet and Marical, 2011; Berry, 2019). Because commuting is constrained, an increase in gasoline prices constitutes a negative shock on households' disposable income which reduces households' purchasing power (Gicheva, Hastings, and Villas-Boas, 2010). As their disposable income decreases, households are likely to reduce discretionary spending on various goods and services (Ma et al., 2011). While committed expenditures such as housing and commuting cannot be costlessly adjusted in the short term, grocery products could provide substantial margins of adjustment. Among these, food represents the largest budget share and is likely to be significantly impacted by even minor changes in disposable income (Chetty and Szeidl, 2007).

We are interested in the extent to which households may use food as an 'adjustment margin' when gasoline prices increase. We contribute to the literature on how households alter food consumption when facing a negative disposable income shock. Evidence from the USA suggests that when gasoline prices increase households reduce the unit price they pay by purchasing more promotional products (Gicheva, Hastings, and Villas-Boas, 2010), reducing the purchased volumes, shopping frequency and turning towards lower price retailers (Ma et al., 2011). These changes in household consumption may have heterogeneous impacts on their welfare, in the short run (consumer welfare) and in the long run (nutritional health), with consequences for the acceptance of environmental policies and for social welfare that depend on how one frames and weighs the redistributive, health and environmental impacts of food.

[1] See for instance Martin and Islar (2020), and Gollier (2019).

Our empirical analysis exploits nationally representative household home-scan data of the Kantar WorldPanel (KWP) and spans from 2011 to 2013. We match food purchases data with gasoline prices at the municipality-month level to exploit the temporal and spatial variation of gasoline prices. An important identification challenge is that macroeconomic shocks on gasoline prices can impact food prices. In addition, retailers are likely to implement joint price-setting strategies for food and gasoline prices, as they often use gas stations as amenities for attracting and retaining consumers. To limit endogeneity concerns regarding the joint determination of gasoline and food prices at a local level, we implement two strategies. We first estimate OLS models of consumer demand as a function of the national gasoline price, controlling for average local food prices and other determinants to limit endogeneity concerns. We then test the robustness of our findings by estimating models of consumer demand as a function of local gasoline prices, whereby variations in the latter are instrumented with an instrumental variable that proxies the difference in the pass-through rate of shocks on national gasoline prices onto local gasoline prices between localities with different degrees of competition between retailers.

We find that a 10% increase in gasoline prices is associated with a 2% reduction in overall monthly food expenditures. The decrease in food expenditures is almost entirely explained by a decrease in food unit prices, while we observe no reduction in quantity. In line with previous empirical studies from USA and UK that uncovered evidence of significant reduction in food unit prices, in the event of adverse economic shocks (Nevo and Wong, 2019; Griffith, O'Connell, and Smith, 2016), we find that our sample relies on several spending reduction mechanisms such as buying more products from private labels or adjusting more on some product categories with potentially important nutritional consequences. Finally, when investigating households' heterogeneity we find significant income-related heterogeneity in the *relative* consumer response, with the poorest households reacting more than the rest of the sample. This finding, along with back-of-the-envelope calculations based on the baseline amounts spent on food and gasoline per income category, suggests that increasing gasoline prices have potentially regressive effects in terms of food consumption adjustment.

Overall, our results highlight that gasoline prices variation has a non negligible impact on the consumption of non-gasoline items, such as food. The negative within-household effect we find suggests that food represents a substantial adjustment margin. We believe that this study paves the way for a more disaggregated analysis (at the product level) in order to evaluate the nutritional and environmental consequences of the changes in food consumption behaviors we have estimated.

The remainder of this paper is as follows. Section 2 provides a summary of the relevant literature and describes the income effect mechanism. The data used is then outlined in Section 3. Section 4 details the methodology and specification of the analysis, before the results and interpretations are presented in Section 5. In 6 we investigate heterogeneous effects across households, before testing the robustness of our results in Section 7 and concluding in Section 8.

2 Gasoline prices, Income and Food Expenditures

2.1 Gasoline prices and constrained commuting

Carbon emissions contribute to a large extent to climate change and constitute a negative externality. In this context, to durably orient consumer behavior towards low-carbon solutions and achieve a global net emissions reduction, the standard economic framework advocates for a market solution. Numerous economists are in favor of a Pigouvian tax, *i.e* a carbon tax, seen as the most cost-effective lever to reduce carbon emissions by internalizing the social cost of emissions[2]. The French carbon tax was initiated in 2014 at 7€/tCO2 and was planned to gradually increase to reach 86.2€/tCO2 in 2022, and even higher levels in the near future. In November 2018, the combination of an increasing carbon tax rate (from 0.59 cents to 0.65 cents per liter of gasoline[3]) and a context of high oil prices has contributed to the Yellow Vests protests, which resulted in the abandonment of the tax increases initially scheduled. This movement suggests that the carbon tax crucially lacks public support, at least when its revenues are not redistributed. Moreover, it has highlighted that even small increases in gasoline prices can have a strong detrimental effect on household purchasing power.

During the 2000s, the price of a liter of gasoline has been volatile and trending upward (see Appendix Figure A1.1). The French Consumer Expenditure Survey indicates that gasoline expenditures constitute a significant fraction (6% on average) of household yearly spending[4] and these expenses have been showed to be price inelastic (Calvet and Marical, 2011; Berry, 2019). Indeed, mobilities are the result of long run decisions (e.g housing location, job search) that are costly to adjust when small income shocks occur. Moreover, private motorized vehicles remain the core transportation means in both rural areas and large agglomerations (73% of French households use a car for daily commuting).[5] These figures suggest that increasing gasoline prices can negatively affect household welfare. Research in this respect has showed that increasing gasoline prices can have regressive multidimensional effects: across income categories (Bento et al., 2009), vertical, and across locations (Douenne, 2020), horizontal. Nevertheless, this strand of the literature does not tackle the question of the substitution between budget items even though it is crucial to better understand the consequences on households' welfare.

[2]Statement published by *The Wall Street Journal*, Thursday, January 17, 2019. Available at: https://www.clcouncil.org/media/EconomistsStatement.pdf

[3]Source: French Ministry of Environment, url: https://www.ecologie.gouv.fr/fiscalite-des-energies

[4]Source: French Consumer Expenditure Survey (*Budget des Familles*, 2011) - INSEE.

[5]Source: French National Transportation and Travel Survey *Enquête nationale Transports et déplacements*, 2008 - INSEE.

2.2 Income effect

In developed countries, the share of pre-engaged expenses has been increasing, from 12.5% of households' income in 1960 to 30% on average in 2011 in France,[6] with strong variation across income categories. Pre-engaged expenses affect I, the disposable income of households. They occur on a regular basis and cannot be costlessly reduced when facing temporary income shocks. Chetty and Szeidl (2007) highlight the large share of committed expenses in the budget constraint increases the sensibility of households to small income shocks. Thus, when the cost of gasoline increases but income doesn't concomitantly, consumers have less disposable income and try to find ways to reduce spending in other areas (Ma et al., 2011). In a context of decreasing gasoline prices in the US, Gelman et al. (2016) show that the marginal propensity to consume (MPC) out of savings generated by reduced gasoline prices is approximately 1.

Only a few budget items (transport, food, housing, equipment, subscriptions, health insurance and education) account for 70% of households total spending .[7] We can break down the monthly budget constraint of representative household into pre-engaged, commuting expenditures, food expenditures and other expenditures:

$$W = P + d \cdot g_t + A_t + \sum_{k \in K} f_{k,t} \cdot p_{k,t} \tag{2.1}$$

With W representing the total income of the household, P stands for pre-engaged expenditures for which the amount spent is stable over time and known in advance, at least in the short run (e.g housing, insurance, subscriptions and taxes). $d \cdot g_t$ stands for commuting expenditures, d is the commuting distance that is assumed constant in the short run and g_t the price of gasoline that varies monthly. A_t is an aggregate of various budget items that are not committed expenditures (e.g leisure, clothing...).[8] Finally, $\sum_{k \in K} f_{k,t} \cdot p_{k,t}$, is the total food spending where k is a food product category and $p_{k,t}$ is the price of each of these food categories. In this setting, gasoline prices and food expenditures vary monthly.

The disposable income is constant over time and can be expressed as $I = W - P$. Thus, equation 2.1 describes a relation between the disposable income, gasoline spending, food expenditures (which can be aggregated and denoted F_t) and a composite budget item denoted A. When

[6] Source: French Consumer Expenditure Survey (*Budget des Familles*, 2011) - INSEE.

[7] Transport, food, housing, equipment, subscriptions, health insurance and education represent about two thirds of households total expenditures on average. The rest being taxes, clothing and discretionary spending. Source: French Consumer Expenditure Survey (*Budget des Familles*, 2011) - INSEE.

[8] In the remaining of our analysis we consider that the composite budget item A also concerns food-away-from-home and that food refers to food-at-home.

gasoline prices vary and the disposable income does not, households might try to mitigate this increase by either reducing d the demand for gasoline (for example: by relying more on car pooling ; public transportation) or by curbing expenditures on non-gasoline items. However, as discussed above, gasoline demand cannot be adjusted easily in the short run. Therefore, under the hypothesis of two-stages budgeting (households observe how much disposable income they are left with after having paid for gasoline expenditures and decide how to allocate it between leisure and food), a change in gasoline prices translates into an income effect that goes through A_t and F_t (the only remaining adjustment margins).

2.3 Food consumption

Despite the fact that food grocery products individually cost little relative to overall income, after housing and transportation they form a large share of French households' annual expenditures. Additionally, the fact that food expenditures represent an adjustment margin is explained by the very nature of this budget item. Firstly, food shopping is done frequently, generally once a week, so there is substantial opportunity to make adjustments in purchases. Secondly, consumers have access to a wide variety of food products allowing them to reduce their expenses by buying cheaper substitutes. Therefore, food expenditures can be adjusted by changing either the quantity (food volume) or the quality (product price) in the food basket. These adjustments can have significant consequences one households' welfare because what we eat and drink is a key driver of health and economic outcomes. Moreover, socioeconomic inequalities relating to nutritional quality are high (Caillavet et al., 2019).

To our knowledge, two papers have investigated the effect of gasoline prices on grocery expenditures in the US. Gicheva, Hastings, and Villas-Boas (2010) use consumer expenditure survey (CES) as well as sales scanner data and find that gasoline expenditures rise one for one with gasoline prices. They show that households substitute away from food-away-from-home towards groceries and that households turn to promotional groceries to offset the increase in gasoline prices. On average, buying lower cost food and lower priced items within grocery categories allows consumers to decrease the net price paid per grocery item by 5 to 11% for a 100% increase in gasoline prices. In this study, Gicheva, Hastings, and Villas-Boas (2010) focus on a subset of goods (cereal, yogurt, chicken and orange juice) bought in one retail chain, making their results difficult to extrapolate. Ma et al. (2011) use panel data on a sample of 1,000 US representative households and find that an increase in gasoline prices significantly and negatively affects the key outcomes of interest (total number of shopping trips, total purchased volumes and monthly food expenditures). We consider these studies as the closest to our work, nevertheless none of these investigate changes in

consumption across all food products. As discussed before, changing food consumption can have important consequences on households' health if households cut on fresh fruits and vegetables to preserve consumption of less healthy products such as snacks and sodas. Environmental consequences can also arise if households substitute away from locally grown products towards imported products. Moreover, the two aforementioned articles assume that households face a similar price of gasoline across locations. In France it is not the case as the competitive setting and the type of retailer explain geographic variation in gasoline prices (Gautier and Saout, 2015).

3 Data

To study food consumption response to changes in gasoline prices, we use two main databases: the home scanner database from the Kantar World Panel (KWP) for years 2011 to 2013 and gasoline prices data from the French government on the same period. This section describes the data preparation. Table 3.5 presents descriptive statistics for the variables used in the empirical analysis.

3.1 Scanner data

Scanner data is increasingly used in public economics because it is fine grained and allows to study changes in consumer behavior with precision (Chevalier, Kashyap, and Rossi, 2003, Gicheva, Hastings, and Villas-Boas, 2010). The advantage of scanner data over experimental or hypothetical choice approaches is that observations are based on actual purchases in a natural shopping environment. This allows to identify consumer preferences in a realistic setting. Moreover, the granularity of the data enables to track households reactions to small shocks over time. The KWP database has been used to estimate food demand and reactions to health policies (Dubois, Griffith, and Nevo, 2014; Allais, Etilé, and Lecocq, 2015). This database gathers information on food-at-home purchase and socio-demographics for a sample of 20,000 representative households in France.

3.1.1 Food consumption

Kantar provides transaction-level data and the database contains information for every registered food at home purchasing act (date, expenditure, quantity purchased, product type, retailer...)[9]. The next paragraphs briefly describe the data construction.

Kantar provides sample weights per period of four weeks that can easily be converted into monthly data, thus our analysis is at the monthly level. We observe each household for many months (on average 35). Moreover, the time unit corresponds to the frequency at which the disposable income is distributed across the budget items (Morduch and Schneider, 2017).To make the data exploitable, we aggregate transactions per food product categories[10]. To do so we

[9]This database doesn't contain information on food-outside-the-house.

[10]Beforehand we convert each food volumes into grams. In the raw database products are expressed in various volume units: grams, liters or units. Liters have been converted into kilograms using a 1:1 ratio. For unit products, when feasible we have made assumptions about the weight of the product (for instance: a grapefruit weights around 400grams). There are few products that couldn't be converted in grams because they were expressed in units and provided no information about the weight, these products have been dropped from the analysis, they represent less than 1% of yearly purchases.

define 15 food categories based on the *Aliss* food research unit nomenclature (version 12) that focuses on the nutritional content of food products[11]. For instance, carbohydrates and fruits are distinguished as they contain different nutrient types. This categorization is also inspired from the Food Studies literature which suggests that certain food products convey different sociological meaning[12] (Cardon, Depecker, and Plessz, 2019). Table 3.1.1 presents the distribution of monthly food expenditures as well as the average quantity and budget share per food category. [13] Fresh fruits and vegetables, white meat, dairy and snacks represent the main budget shares.

Homescan data are collected with barcode readers. Although they are fine grained and contain detailed longitudinal information on households purchases, one may worry that the reporting effort might vary over time and across households (Etilé, Lecocq, and Boizot-Szantai, 2020). In particular, this might be the case for non barcoded products which have to be registered manually. To ensure longitudinal representativeness of the sample and correct for under-reporting within a month, we use household-purchase sampling weights in all data treatments.

Product category	Spending					Quantity	Budget share
	Mean	St. Dev	p1	p50	p99	Mean	Mean
Carbohydrates	3,98	3,85	0,00	3,07	17,39	1,54	0,01
Fresh fruits and veg.	25,31	22,86	0,00	19,18	106,31	12,25	0,11
Non fresh fruits and veg.	6,23	6,33	0,00	0,00	29,08	2,69	0,03
Red Meat	13,34	16,78	0,00	8,13	75,92	1,09	0,05
White Meat	25,89	23,38	0,00	20,56	104,26	2,75	0,11
Other Meat	12,77	13,15	0,00	9,26	59,92	1,26	0,05
Fish	14,61	18,44	0,00	8,87	87,04	1,35	0,06
Eggs	2,41	2,64	0,00	1,80	11,49	0,28	0,01
Dairy	22,02	14,18	0,00	19,51	68,21	7,76	0,10
Snacks	34,36	22,25	1,51	30,25	106,19	7,21	0,16
Ready meals	15,98	17,14	0,00	11,18	77,78	2,63	0,07
Soft drinks	16,67	12,77	0,00	13,96	59,67	19,15	0,08
Alcoholic beverages	19,71	36,02	0,00	7,16	159,21	4,55	0,07
Seasonings	14,72	9,75	0,00	12,92	45,99	4,09	0,07
Other	1,29	6,62	0,00	0,00	36,06	0,27	0,01
Total	229,29	112,18	47,86	210,69	586,25	7,35	1,00

Notes:

Summary statistics for monthly food expenditures per product category, p1, p50 and p99 refer to percentiles of the distribution. X=0 are months for which the household doesn't consume in the product category, it could be that the household is absent. Spending stands for monthly food expenditures per consumption unit, this variable is deflated by the Consumer Price Index for consumer goods (Base: 2015) and expressed in euros. The last two columns present quantity (monthly volume per consumption unit in kilograms) and budget share per food category. Other meats refers to less common meat such as game meat or mixes of meat. Other as a category refers to baby food, food supplements and food substitutes.

Table 3.1: Summary statistics by food category

[11] These categories are: Carbohydrates (bread, pasta...), Fresh vegetables and fruits, Red meat, White mean, Other meats (game meat, mix meat...), Fish, Eggs, Dairy, Snacks (salty and sugary), Ready made dished (pizza, frozen dishes...), Soft drinks (non alcoholic beverages), Alcoholic drinks, Seasonings (spices, oil...), Canned vegetables or fruits (non fresh vegetables and fruits).

[12] For instance, within the fruit category, we distinguish between fresh and non fresh as richer households tend to buy more fresh fruits whereas poorer ones tend to buy relatively more canned vegetables.

[13] Each variable is expressed in consumption per unit using the OECD modified scale.

3.2 Measuring food consumption

Firstly, we investigate changes in the composition of the food basket in terms of volumes purchased and the price of products[14] to study spending as well as quantity and unit price responses. Our key variable of interest is the food expenditures per consumption unit in euros (monthly) and refers to the total expenditure per household divided by the number of consumption units and measured in constant euros.[15] To measure changes in quantity, we use the total quantity purchased by household in a given time period divided by the number of consumption units. Adjustment in volumes can have important consequences both in terms of health and for the environment (for instance if households increase their consumption of more polluting products). The price reaction is measured by studying changes in the unit price in euros per kilo. This variable is constructed as the expense divided by the quantity expressed in kilograms. Finally, when analyzing household responses across food product categories in section 6, we use a fourth outcome of interest that is the budget share per product category which corresponds to the amount spent on a product category, divided by the total expenditures over a month. We expect these changes in budget shares to be informative of inter-product substitution.

The aforementioned outcomes ought to be informative of changes in households' food consumption behaviors. Nevertheless, as discussed in previous sections, the very nature of food consumption allows households to rely various adjustment margins (cheaper alternatives, switch away from national brands, change of retail chain...). These mechanisms are important to disentangle so to understand on which margins households rely on to decrease food consumption. For this purpose we have defined, in line with the literature, nine variables the statistical distribution of which is described in table 3.2.

Shopping trips and number of visited stores. As a first direct effect, higher gasoline should induce households to try to decrease travel costs by as much as possible. One could therefore expect that they will do so by limiting the number of shopping trips. However, the marketing research shows that, for households with low search costs, shopping more frequently across time (by visiting shops more frequently) and/or space (visiting several different shops) allows to access cheaper food alternatives (see Gauri, Sudhir, and Talukdar, 2008 for a review of the literature). The first variable uses the purchasing date to count the number of trips a households visit monthly. The second one uses the visited store name and combines it with the sales surface to create a unique

[14]The KWP database does not contain detailed information about the nutritional content of products.

[15]Consumption units are defined according to the OECD-modified equivalence scale (OECD, 2013). Inflation series are available one French Statistical Administration's website.

store identifier[16].

Number of purchasing acts In the raw data, purchases are registered at the purchasing act level (ie one product reference, regardless of the number of units purchased). A change in the number of purchasing acts can either suggest that households purchase less varieties during a month or that they shop less frequently (in the sense that they might start buying in bulk, especially if buying in lot tends to be cheaper).

The generated savings from adjusting the number of shopping trips, shop visited and purchasing acts, might be compared with the psychosocial value from shopping and the higher holding inventory costs incurred (Ma et al., 2011). Therefore the effect of higher gasoline prices on the each on household behaviors, as measured with the three aforementioned variables, is hardly predictable.

Supermarkets. If households try to reduce travel costs they might turn to supermarkets[17] was opposed to farmers' market or specialized stores, because supermarkets allow to access a larger set of products. We thus expect a positive effect of gasoline prices on the monthly share of food expenses made in supermarkets.

Hypermarkets. A hypermarket is a supermarket with a sales surface above 2 500 m^2. The intuition goes for large supermarkets that have more varieties than regular supermarkets. Furthermore, in France, hypermarkets commonly sell gasoline which might allow households to increase savings on travel costs. Nevertheless, hypermarkets might be located further away than supermarkets, this might hinder the positive effect of gasoline prices on hypermarket expenses.

Hard discounters. Hard discounters are stores that tend to offer products at more affordable prices to consumers by reducing merchandising and marketing costs (e.g Lidl, Aldi. Therefore, they might allow households to reduce food expenses. However, because they are mainly located in suburbs, shopping there might induce a trade off between higher travel costs and accessing lower food prices.

Internet shopping. Grocery shopping on internet might increase when gasoline prices are higher because it might allow to save on travel costs (if food supplies are delivered at home) as well as to access cheaper food products. However, during our time period of interest, grocery shopping

[16]There is no unique store identifier available in the raw dataset. Combining the two variables that contain information about stores allows to create a unique store identifier. Because we do not have information on stores location, this method has the potential disadvantage of assigning the same identifier to different shops if they belong to the same retail chain and are of same size. However, because the number of stores variable is defined per household, we limit this risk because it is less likely that a households visits to several stores of the same chain and size (except maybe in the largest cities).

[17]This category includes hypermarkets.

online is uncommon: on average only 2 percent of monhtly expenditures are made online. Thus, we do not expect to observe an effect of gasoline prices on shopping online.

Private-label products. The raw food data includes information on whether the purchased product is a private-label or a national brand. Because private-label products tend to be less expensive (the average price per kilo in 2013 is 6.15 €for private labels versus 9.03€for national brand products), when gasoline prices are higher households might increase consumption of private labels.

Organic products. Following the same intuition as the one described before and because organic products tend to be more expensive (the average price per kilo in 2013 is 9.42€versus 7.93 for non organic product). We expect households to decrease organic food purchases when gasoline prices are higher. However, in our sample a very small share of monthly expenditures is devoted to organic products (less than 2% on average) and the share of expenditures for this product category is positively correlated with income[18], this might mitigate the results of our analysis on this product category.

It is worth denoting that the descriptive statistics of table 3.2 are in line with French national statistics[19]. During our time span of interest, food purchases mostly occur in retail stores (a large share of which are large stores such as hypermarkets) and households tend to purchase more national brands and non-organic products.

	Mean	S.D	p1	p50	p99
Number of					
Purchasing Acts	112.75	53.11	23	106	266
Shopping Trips	9.96	5.92	2.00	9.00	30.00
Visited Stores	4.05	2.19	1.00	4.00	10.00
Expenditures Shares					
Supermarkets (%)	89.41	16.85	28.09	100	100
Hypermarkets (%)	41.93	37.62	0.00	37.03	100.00
Hard Discounter (%)	12.41	22.05	0.00	0.00	96.06
Internet Purchases (%)	1.82	7.10	0.00	0.00	33.61
Private-label products(%)	25.99	14.34	2.04	23.77	67.15
Organic products (%)	1.73	4.33	0.00	0.30	21.58

Table 3.2: Summary statistics for monthly variables over the period 2011-2013

[18]In our dataset we observe that the richest households devote to organic products twice the share of expenditures as the poorest households of the sample.

[19]See https://www.insee.fr/fr/statistiques/1283665 for more information on French food consumption patterns

3.3 Household characteristics and selection sample

The KWP database contains yearly information on households' socio-demographics (income class, household size, municipality) and households' equipment, especially the number of cars they own[20].

The KWP follows a nationally representative sample of over twenty thousand French households. Nevertheless not all of them are consuming in a representative manner. Indeed, some households can be very active in a given year and report consuming very little in the next one. To ensure representativeness, Kantar defines yearly weights per household so that a household is considered active (and is assigned a positive weight) if it consumes at least 10 months per year. To ensure consistency over time and because household time-invariant characteristics are likely to be a strong driver of food consumption choices, we define our selection sample as a panel of active households observed from 2011 to 2013. Table 3.3 displays the main observable characteristics of different population samples: the first column is the raw KWP dataset (available for years 2011 to 2014), the second is restricted to the households considered as active by Kantar and spans from year 2011 to 2014, the third one is our selection sample and limits the period of interest to 2011 to 2013. The last column presents statistics for France. The estimation sample gathers 3,547 households who form an unbalanced panel because they are surveyed at least 10 months per year, thus for each household we get 30 to 36 monthly observations. Our selection sample features moderately larger households living in slightly less dense areas relative to the French population average. In comparison to the raw KWP database our sample is composed of older individuals. These characteristics are controled for in the empirical strategy. Regarding the distribution of our sample across space (see Appendix figure A2.2), it appears representative of the geographic distribution of households in Continental France, with high population density in the main agglomerations (Paris, Marseille, Lyon...), the North, near the German border and in coastal areas.[21]

3.4 Gasoline data

To get information about the gasoline price consumers really face we collect gasoline pump prices. Gasoline data for years 2010 to 2013 is extracted from the French government open database[22].

[20] About 90% of our sample own at least one car. It is worth denoting that households who don't use a car might still purchase gasoline if they own a motobike, borrow a car and rely on carpooling to commute, however this information is not available in the KWP.

[21] The analysis is restricted to continental France because French Islands such as Corsica have a different competitive setting (less gasoline stations and limited number of grocery stores).

[22] The data are freely available at https://www.prix-carburants.gouv.fr/rubrique/opendata/ in XML text format

Sample	Full		Active		Estimation		France
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean
Household level statistics:							
Household size	2.58	1.41	2.43	1.35	2.35	1.30	2.2
Living in a rural area (%)	16		20		20		21
Living in Paris' area (%)	21		14		14		19
Car ownership (%)	91		91		91		84
Home ownership (%)	64		68		71		58
At least one member is employed (%)	69		61		55		56
Characteristics of Reference Person:							
Age	49.38	14.96	53.04	14.73	55.56	14.43	-
Observations	20100		10595		3547		

Notes: The household reference person is a senior male member of the household (unless the household is composed of female members only) according to the KWP definition. All figures in the column marked France are for France from the INSEE Census 2013.

Table 3.3: Comparison of sample moments

This dataset contains exhaustive daily information on gasoline prices for all gasoline types in every station in France.

3.4.1 Local gasoline prices

Each yearly dataset contains detailed information on the gasoline station (identification number, GPS coordinates, whether the gasoline station is located on a highway or a national road, price, type of gasoline). There are around 10,000 station in France. Because highroad stations exhibit significantly higher prices than gasoline stations located on national roads, we restrict our analysis to national road gas stations in Continental France, hence 9325 stations.[23] Every station is associated to a zipcode but not to a municipality. This poses a challenge because in France one postal code stands for several municipalities and we aim to match Kantar households with gas station at the finest geographic unit available *i.e* the municipality. Thus we aim to assign every gas station to its closest municipality within a postal code. For this purpose we use the INSEE Geofla database, an administrative database that contains for every municipality the GPS coordinates of its center and its postal code. We then merge this database with every gas station by looping over the total number of stations to match each station with the closest municipality (the computation is done using the *geodist* Stata package, we consider the smallest distance between the center of the municipality and the gas station). With this method, a gasoline station located at the border of two municipalities is paired with the municipality with the closest center even though it might not be the relevant one. This drawback is offset by the

[23]When defining high prices stations as the ones with an average monthly price above 1.10 the monthly price in the living-zone, we find that 47% of the high price stations are located on highways whereas only 5% are located on national roads. Moreover, highways are costly to access (due to tolls). Thus households are not likely to regularly purchase gasoline stations located on highways.

fact that the distributions of gasoline price at the municipality and the living-zone are very similar [24] as showed in Table 3.5. [25]

3.4.2 Measures of gasoline prices

When studying the the distribution of gasoline prices at several geographic levels (municipality, living-zone and national), Table 3.5 statistics indicate that there are relatively few differences across the various prices. Nevertheless, it seems that the larger the geographic unit is, the smaller the average gasoline price will be, which is suggestive of the potential strategic pricing. In the first part of the empirical strategy (the reduced form) we use median monthly national prices as the main explainatory variable. In the second part we instrument national prices using a gasoline price measure referred to as "gasoline sophisticated price" in Table 3.5 that is the median living-zone price if the municipality contains less than 3 gasoline stations and the median price in the municipality is high relative to living-zone prices (higher than 1.10 times the price of the living-zone).[26] Otherwise, it is the median price in the municipality.

3.4.3 Source of variation

In this subsection, we briefly review recent dynamics of oil and gasoline prices and corresponding expectations of future prices. We document that the variation of oil and gasoline prices from 2011 to 2013 was permanent, unanticipated and exogenous to demand conditions in France. These properties of the variation are an important component of our identification strategy.

Since year 2000, gasoline prices are upward sloping (see Appendix Figure A1.1) and have peaked three times above 1.4€/liter: in 2008 preceding the Great Recession, in 2012 and again in 2018. Our analysis spans from 2011 to 2013.[27] During this period, the gasoline price per liter has risen from 1.28€/liter to 1.48€/liter at its peak, corresponding to a 8% increase in prices. Variation in gasoline prices is well explained by international events (gasoline prices are highly correlated

[24] Living-zones are defined by INSEE as the smallest area in which the inhabitants have access to the most common facilities and services. This geographic unit is especially useful to describe spaces that are not densely populated.

[25] The remaining of our analysis focuses on diesel fuel that is referred to as gasoline in this article. The rationale behind this choice is that diesel fuel is the most popular gasoline type in France during our period of interest (72% of cars in 2012). Moreover, it is worth denoting that diesel fuel and other gasoline types have had fairly similar evolution since 2010 despite a persisting difference in price levels of 0.20cents (unleaded fuel being more expensive than diesel fuel) between 2011 and 2016. Finally, when running the main analysis on non diesel fuel we obtain similar results then the ones with diesel.

[26] This price accounts for higher prices that are explained by low competition in the municipality. The underlying intuition for this measure of gasoline prices is that households living in municipalities with high gasoline prices might commute further away (in the living-zone) in order to find cheaper gasoline. This could be the case for instance in municipalities with low population density.

[27] The carbon tax was introduced in 2014 in France.

with changes in the international prices of refined oil products (Gautier and Le Saout, 2017).[28] These shocks are difficult to predict: Gelman et al. (2016) use one-year-ahead forecast errors and Consumer surveys and show that changes in gasoline prices are anticipated neither by financial markets nor by households.

The price of gasoline can be broken down into three main elements: the purchase price of oil (after refining), which accounts for 75% to 85% of total operating expenses ; distribution costs, which include labor and transportation costs ; and taxes (Gautier and Le Saout, 2017). The last two elements can be assumed relatively stable over time in the sense that they do not change monthly. Therefore the bulk of variation in gasoline prices can be attributed to international and supply side factors (see Appendix **??**), thus national gasoline prices variation can be considered exogenous to French demand conditions.

The pattern of spikes and troughs appears to be specific to gasoline prices and in the short run it is most likely exogenous to other factors that affect household consumption choices (Gicheva, Hastings, and Villas-Boas, 2010). If these variations translate into real changes in the disposable income, we are able to investigate the effect of the induced income fluctuations on consumer expenditures, after controlling for seasonal effects and trends that may affect food spending and grocery purchases. We test whether during our time period of interest gasoline prices follow a random walk using a Dickey-Fuller augmented test and cannot reject that the time series follow a random walk, suggesting that the best prediction of future gasoline prices are today's prices[29] (Anderson, Kellogg, and Sallee, 2013). The results of the Dickey-Fuller augmented test suggest that gasoline prices translate into permanent changes in the income available for non gasoline spending.

3.5 Additional data sources

Indicators of macroeconomic shocks such as the unemployment rate at the employment zone and the evolution of GDP are obtained from the French statistical institute (INSEE).[30]
The Herfindahl Hirshmann index (HHI) that is used for the instrumental variable strategy is computed out of a KWP database which contains monthly information per retailer in every living-zone (number of stores and accumulated store surface in square meters). Market shares per living-zone are computed out of the accumulated sales surface per retail store because it is

[28] In 2011: the increasing gasoline demand of developing countries and the Arab Spring. In 2012, increasing prices are in part caused by international sanctions against Iran and a strike from the Northern Sea suppliers. In 2013 the drop is explained by an increased of the euro's value relative to the dollar.

[29] The reported Dickey-Fuller test statistics was -2.813, and the MacKinnon approximate p-value for the unit root test was 0.19.

[30] The evolution of GDP is defined as the quarterly change in GDP from January 2011 until October 2013.

the best proxy of sales revenues we have.

Table 3.4: Main variables - Descriptive statistics

Variable	Source	Mean	SD	p1	p50	p99	Time unit	Geographic unit
Food spending	KWP 2011-2013	229.36	112.13	47.81	210.67	5585.65	Monthly	Household
Food quantities	KWP 2011-2013	68877	32765	13518	64008	169999	Monthly	Household
Food unit price	KWP 2011-2013	3.52	1.44	1.47	3.33	7.44	Monthly	Household
Laspeyres local index	KWP 2011-2013	1.08	0.18	0.00	1.04	1.72	Monthly	Living-zone
Herfindahl Hirshmann index	KWP 2011-2013	3966.50	2483.98	983.45	3243.26	10000	Monthly	Living-zone
Gasoline municipality price	Datagouv	1.39	0.05	1.29	1.38	1.54	Monthly	Municipality
Gasoline sophisticated price	Datagouv	1.38	0.05	1.29	1.38	1.53	Monthly	Municipality
Gasoline living-zone price	Datagouv	1.38	0.04	1.29	1.37	1.49	Monthly	Living–zone
Gasoline national price	Datagouv	1.37	0.04	1.31	1.37	1.45	Monthly	National
Local unemployment rate	INSEE	9.53	2.11	5.7	9.1	16	Quarterly	Employment zone

Notes:
Unit values are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euro/kilogram. Income per capita is computed as the middle of the income bracket of the household divided by the number of members of the household. Each household monthly variable is weighted by household sample weights. The construction of Laspeyres indices is discussed in Appendix A2.

4 Empirical strategy

4.1 Empirical specification

In the first empirical specification we use the monthly national price as a proxy for gasoline prices faced by consumers.[31]. Since the comovement of gasoline prices is very strong (see Appendix Figure **??**), this approach is likely to be very informative while avoiding issues with a potential endogeneity of local gasoline prices.[32].

If there is an income effect, one would expect to see a change in food expenditures or grocery shopping of household when the price of gasoline changes. To test this assumption we run the following regression:

$$\ln(F_{h,t}) = \alpha_h + \beta \ln(P_t) + \gamma' X_{h,t} + \delta_t + \varepsilon_{h,t} \tag{4.1}$$

Where P_t is the monthly national median gasoline price, α_h are household fixed effects. $\delta_t = \mu_m + \tau_y$, where μ_m stands for the seasonal effects (see Appendix A3.1) and τ_y are yearly fixed effects. $X_{h,t}$ is a vector of household characteristics and local control variables (unemployment rate in the employment zone of household h, local Laspeyres index).[33]

We estimate this regression using the OLS fixed-effects method on the panel of Kantar households where $F_{h,t}$ is a monthly measure of food consumption for household h at time t. Because gasoline and oil prices follow random walks, $\log P_t$ can be treated as permanent, unanticipated and exogenous (Gelman et al., 2016). To the extent that gasoline prices are determined by international supply shocks and the French taxation system rather than by domestic demand - which is our maintained assumption for the sample period - OLS would lead consistent estimates of the cross- elasticity of substitution. In this context the β parameter will be interpreted as the cross-elasticity of food to gasoline prices.

At the aggregate level, one important determinant of food spending is macroeconomic conditions. We account for these by using annual fixed effects and controlling for the quarterly local unemployment rate which can be seen as a measure of local activity. The local Laspeyres index

[31] We use monthly national gasoline price to limit endogeneity concerns. Indeed, when using municipality prices one could fear that these local gasoline prices are jointly determined with the food retail prices in the municipality since large retail stores tend to sell food products as well as gasoline.

[32] It is also worth mentioning that gasoline is a fairly homogeneous good, the quality and composition of which vary little across retailers.

[33] Summary statistics are presented in Table 3.5) The definition of the Laspeyres index and its computation is discussed in Appendix A2.

accounts for changes in local food prices and might capture changes in the living-zone competitive setting between grocery outlets.

The identification also relies on the assumption that national gasoline prices are not directly affected by food prices in the short run. Literature suggests that it is not the case as the bulk of changes in gasoline prices can be attributed to international supply side factors and national taxation policy. Moreover, Bils and Klenow, 2004 show that, when looking at monthly variation, food prices are more sticky then gasoline prices. In France, this is due in part to *menu costs* and to retailer's pricing strategy[34]. Figure **??** in Appendix presents the evolution of national gasoline prices and the national Laspeyres index when controlling for seasonality and time fixed effects: it appears clearly that the gasoline prices variable displays more variation than the Laspeyres moreover the correlation between the two variables is weak (-0.11), suggesting that their variation is not jointly determined. Therefore, if food prices adjust to gasoline prices this adjustment occurs with delay. One could still be concerned about the potential auto-correlation of 'random' variations in the price of oil over time. However, this threat is removed since, as said before, the gasoline price follows a random walk conditional to our controls.

4.2 Instrumental variable strategy

In addition to the reduced form approach that exploits variation in national gasoline prices, we also examine the effect of local gasoline prices, which are closer to the gasoline prices households are exposed to. To overcome the potential endogeneity concerns of gasoline price at the local level, we use an instrument variable strategy that relies on the degree of local competition on the gasoline market.

Our first identification strategy assumes that consumers face a common price across geographic areas which varies monthly. As discussed above, time accounts for the major part of gasoline prices variation. Nevertheless, we observe some cross-sectional variation in gasoline prices across geographic areas, as a variance decomposition exercise suggests that about 10% of the variation in gasoline prices can be explained by geographic factors[35]. We intend to leverage this second source of variation (that is time x spatial) in the following supplementary identification strategy. The strategy that we detail below allows to account for the time-space variation that wasn't accounted for in the main econometric specification that accounts for time (national gasoline prices) and space (household fixed effects) variations separately. Because this additional methodology should

[34]Price changes are made at a centralized level (usually those are retailer's decision made at a regional level) which reduces the frequency of price changes.

[35]See Appendix Table A3.1. These differences in gasoline prices across locations can be due for instance to lags in the transmission of international oil price shocks into gasoline local prices.

capture more variation, as compared to the first one, we expect the effect of national gasoline prices on food consumption to be smaller in magnitude, although close, than the effect of local gasoline prices. Investigate how local gasoline prices affect food consumption should allow to better account for the gasoline price consumers effectively face when purchasing gasoline. To do so, we use, as a local measure of gasoline price, the alternative municipality price described in Section 3.4.2.

The potential joint determination of gasoline prices and food purchases in the municipality poses a challenge: for instance if supermarkets supplying both gasoline and food, maintain low gasoline prices and compensate by having high food prices. To reduce this endogeneity concern, we instrument the local price of gasoline using an IV that accounts for the spatial variation of competition between retail chains. The instrumental variable is the interaction of a measure of local competition (in log) and national gasoline prices (in log). The choice of this IV derives from the fact that market heterogeneity might explain differential exposure to the common shock and has substantial distributional incidence on consumers' welfare as shown in the context of the French soda tax in Etilé, Lecocq, and Boizot-Szantai (2020).

In the context of gasoline prices, the IV strategy should enable us to account for the local competitive setting in the living-zone. Our measure of market heterogeneity is the Herfindahl-Hirschmann index (HHI) for food retail stores because it measures the competitive setting in a living-zone (see 3.5).

The HHI is calculated as follows:

$$\mathcal{HHI} = \sum_{n}^{N} s_n^2$$

Where s_n is the market measured as the cumulative sales surface per food retail chain within a living-zone divided by the total sales surface in the living-zone[36]. The index is computed monthly for each living-zone.

The intuition behind the IV choice is that a more competitive food retail sector is likely to be associated with a more competitive gasoline retail sector. Indeed, the correlation between the number of food supermarkets and the number of gasoline stations within a living-zone is high (0.91). Furthermore the correlation between the number of supermarkets and the HHI is negative (-0.5). Moreover, in France there are three main types of gasoline retail suppliers (Oil corporations, Independents and Supermarkets) of which supermarkets represent the largest share (60% of gasoline stations in continental France belong to supermarkets). It is also worth

[36]Market shares vary between 0 and 100.

mentioning that supermarkets tend to sell gasoline at lower prices relative to the other gasoline sellers (the marginal effect of the gas supplier being a food retail store is minus 7 cents per liter of gasoline on average, see Appendix Table A5.1).[37]

This identification strategy can be considered as an exposure research design, where the HHI measures the differential exogenous exposure to a common shock that is the variation in national gasoline prices. It is worth precising that in this paper we consider that areas with low exposure are areas where the retail competitive setting is low because we expect the transmission of national gasoline shocks into the local prices to be slower. In line with Gautier and Saout (2015) who find that in more competitive settings the frequency of gasoline prices changes is higher. A rationale for this finding is that in less competitive locations, gasoline suppliers have more room to be less stringent in the sense that the degree to which the retailer translates changes in the input price into local gasoline prices could be more arbitrary.

The HHI is set to an initial time period (January 2011), in line with Goldsmith-Pinkham, Sorkin, and Swift (2018).[38] The consistency of the instrumental variable relies on two main assumptions: i) the instrument is not weak and ii) the restriction exclusion holds. The first assumption can be tested by regressing the instrumental variable on local gasoline prices. Results are presented in column (2) of Table 7.1.1. The large F-statistic (23379.84) suggests that the hypothesis of the interaction term (of the HHI with national gasoline prices) being a weak instrument can be rejected. In our setting the exclusion restriction can be expressed as such: the differential effect of higher exposure of one municipality (compared to another) only affects the change in the outcome (food spending) through the endogenous variable of interest, and not through any potential confounding channel. If it is the case that areas with high versus low exposure have other features predicting the change in outcome through channels other than the endogenous variable, the exclusion restriction is threatened. This could happen if for instance, areas with a more competitive setting have lower food prices and lower gasoline prices. Nevertheless, as highlighted by Goldsmith-Pinkham, Sorkin, and Swift (2018): "in cases when the assumption of exogenous shares is not plausible, consistency of the estimator can instead come from many exogenous shocks". This result is proved in Borusyak, Hull, and Jaravel (2018), who show that exogenous independent shocks to many industries lead the IV estimator to be consistent, even when the shares are not exogenous. In our setting, geographic variation comes from use of the

[37] The gasoline dataset we use doesn't contain information about the gasoline retailer. To recover it gasoline stations we use the database that R. Le Saout has kindly agreed to share, this allows us to get information on the type of station for five sixths of our analysis sample. See Appendix .

[38] "We do this for two reasons: first, this choice follows convention. Second, this choice makes the analogy to difference-in-differences clearer: by fixing the shares to an initial time period prior to the shock, there is a single cross-sectional exposure difference that the design is exploiting", Goldsmith-Pinkham, Sorkin, and Swift (2018).

HHI per living-zone. It seems safe to assume that changes in gasoline prices are exogenous to municipalities and more generally to demand conditions, as discussed in the methodology section **??**.

5 Adjustment margins

5.1 Main outcomes

Table 5.1 presents the results of the OLS regression model described in 4.1 for the three main outcomes of interest: (1) monthly food expenditures per consumption unit in euros, (2) monthly food quantities in grams per consumption unit and (3) unit price in euros per kilo.

To measure the intensive margin of consumption, we use a log-log model.[39] The table 5.1 looks at aggregated consumption outcomes (monthly, across all food categories). Because we expect spatial auto-correlation within small geographic units (for instance within a municipality households access the same amenities: roads, stores etc.), we cluster standard errors at the municipality level. For each variable the first column is the regression without controls (columns 1, 3 and 5) and the second one presents results when including control variables (columns 2, 4 and 6)[40]. The estimated national gasoline price coefficient is interpreted as the cross-elasticity of substitution in the sense that it predicts how the outcome interest varies within households when the national price of gasoline varies. As we are using a log-log specification, the change in food consumption resulting from a 1% increase in gasoline prices can be directly interpreted via the coefficient estimated. Our specification are robust to the inclusion of controls.

Gasoline prices have a negative effect of food consumption: when the national price varies by 1%, food expenditure decreases by 0.2%. For a typical household who spends 200€ in food per person per month and 100€ in gasoline[41]: a 3% increase in gasoline[42] leads to a 3€ increase in gasoline expenditures and a 1.2€ decrease in food expenditures per person and per month, assuming that the demand for gasoline is inelastic.[43]

This decrease in expenditures can be decomposed into two parts. Firstly, a quantity effect: the volume of food purchases in grams (per consumption unit) decreases when gasoline prices increase

[39] Our model treats null consumption as a missing value. We observe very few households who spend zero € monthly in food: we loose 10 observations over the entire period of interest. This point is further discussed when presenting regressions results per food category in the next section 5.2.

[40] Age is not included as a control in these regressions because for over one third of the households in the selection sample age information is not available. For regressions in which the age of the household head is controlled for see Appendix Table **??**. In these regressions, the age coefficient is weakly or non significant and the difference between the two main coefficients of interest (national gasoline price) is non significant.

[41] These statistics are extracted from the 2011 Budget des Familles and an Ipsos technical report "*Enquête sur les mobilités du quotidien dans les régions françaises*" (2019).

[42] The usual monthly variation in gasoline prices is around 2 to 3 percent on average. It is worth denoting that the lower volatility of gasoline prices relative to oil is due to the high taxes on gasoline in the French context (about 60% of the price).

[43] With a 3% increase in gasoline prices, the typical French household now spends 103€ in gasoline. This translates into a 3x0.2 unit decrease in food consumption, as food expenditures are twice as big as gasoline expenditures, the household decreases food expenditures by 3x0.2x2=1.2€.

suggesting that households might try to save money by slightly cutting the food basket volume. Secondly, a unit price reaction: by buying less costly products (for instance by substituting within product categories), household can reduce their food spending. The coefficient of gasoline prices is statistically significant and negative for unit prices and not significantly different from zero for the volumes consumed. These results indicate that households would rather buy cheaper products than diminish their food intake. This finding is in line with the literature: when facing a small income shock, households would rather purchase cheaper substitutes than reduce the volumes they are used to consume (Gicheva, Hastings, and Villas-Boas, 2010).

Regarding the controls variables: in line with intuition, income has a positive effect on food spending and the unit price. Households who own the house they live in tend to spend more in food, we consider that this variable stands for a proxy of capital wealth. Household size has a significant and negative effect on food expenditures per consumption unit, mostly through its impact on quantities per consumption units: a rationale for this is that when there could be a scaling effect in the sense that when the number of household members increases there might be less waste (relative to smaller households that buy similar volumes because of the product packaging), moreover this effect might also be explained by the fact that quantities are expressed in consumption units it could be that a new member in the household leads to less than a proportional increase in quantities per consumption unit, translating into a negative coefficient. The local Laspeyres index which measures the variation of prices within the living-zone has significant and negative coefficients for spending and unit prices. The local employment rate can be interpreted as a indicator of economic activity: when it increases food at home spending increase, suggesting that when unemployment decreases, consumption shifts somewhere outside what the data captures[44]. This finding is in line with the food studies literature that highlights that richer and employed households spend more in food outside the house than poorer ones (Recours and Hébel, 2006, Caillavet, Lecogne, and Nichèle, 2009).

[44]It is worth reminding that the KWP database is exclusively information of food at home consumption and does not capture food consumption outside the house.

	(1) Spending	(2) Spending	(3) Spending	(4) Quantities	(5) Quantities	(6) Quantities	(7) Unit price (€/ kg)	(8) Unit price	(9) Unit price
National Gasoline Price	-0.215***	-0.210***	-0.201***	0.052	0.057	0.068	-0.267***	-0.268***	-0.270***
	(0.071)	(0.071)	(0.071)	(0.080)	(0.080)	(0.080)	(0.044)	(0.044)	(0.043)
Income		0.049*	0.050*		0.020	0.022		0.028**	0.027**
		(0.027)	(0.026)		(0.030)	(0.030)		(0.014)	(0.014)
Household size		-0.148***	-0.148***		-0.125***	-0.125***		-0.023***	-0.022***
		(0.014)	(0.014)		(0.015)	(0.015)		(0.006)	(0.006)
Local Laspeyres			0.075***			-0.069***			0.144***
			(0.012)			(0.013)			(0.008)
Unemployment rate (municipality)			0.017***			0.011***			0.005***
			(0.003)			(0.004)			(0.002)
Additional controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.481	0.485	0.485	0.432	0.433	0.434	0.635	0.635	0.637
Households	3548	3546	3546	3548	3546	3546	3548	3546	3546
Observations	123079	122816	122814	123078	122815	122813	123078	122815	122813

Note:

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Spending stands for food expenditures per consumption unit. Spending, unit prices and gasoline prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per kilogram and resp. euros per liter). Quantities are expressed in grams per consumption unit. Additional controls are: Age of the household head, an dummy variable for whether at least one member of the household has a job and a dummy variable for whether the household the house/flat it lives in.

Table 5.1: OLS regressions, pooled

5.2 Heterogeneity across food categories

To better understand how food consumption adjusts to variation in national gasoline prices, we investigate the impact of this change for the different food product categories described in the data section. Table 5.2 presents these product category when monthly food spending is the outcome of interest[45]. The next paragraph describes the results of this table and three tables with different outcomes of interest that are presented in the Appendix[46].

Similarly to the previous section, we use a log-log model to measure changes in the intensive margin. Because we work with highly aggregated food product categories, the vast majority of households consumes a non-zero quantity of each product category (for instance in carbohydrates, vegetables/fruits, dairy, seasonings)[47]. In future works, it would be interesting to define more disaggregated product categories and to study changes for the extensive margin, because when facing a positive disposable income shock households might turn to more expensive product categories (e.g fresh fish).

In Table 5.2, we observe for half of the product categories a less than proportional and significant coefficient of national gasoline prices, suggesting a negative relation between the price of gasoline and food spending for those categories. Fresh vegetables and fruits, red meat, fish and alcoholic beverages are the categories that display the largest cross-elasticities of substitution in absolute terms, above 0.5. These goods can be considered as superior goods in the sense the baseline budget shares devoted to these goods is larger for rich households than for poorer ones (Andrieu et al., 2005). These product categories constitute the largest adjustment margins and, as discussed before, the adjustment is likely to occur via two channels. It seems that for fresh vegetables/fruits, alcohol and fish (although to a smaller extent) and snacks households reduce the unit price of the product whereas the volumes purchased varies relatively less. This suggests that when facing a disposable income shock households try to maintain their consumption in these food categories and instead buy cheaper options. On the other hand, for red meat and white meat households adjust by decreasing the quantities rather than the unit price. Therefore, it seems that for meat products cheaper options could be perceived as worse. A potential rationale for this result is that in the case of fresh fruits and vegetables switching to less expensive products (e.g replacing

[45]The regressions results for the "Else" category (that regroups food substitutes and baby food) are not presented in the Tables because this product category is very diversified (baby food, food supplements...) and is not considered as a key outcome of interest for this study.

[46]See Tables A4.1, A4.2, A4.3.

[47]As we measure intensive margins: the number of households present in the sample across specifications varies. For example, the number of households for the egg category (column 7) is lower compared to other categories. This discrepancy is explained by the fact that some households own hens and therefore never purchase eggs. Regarding alcohol, meat, dairy it could be that some households follow dietary restrictions (no alcohol, vegetarian, vegan).

Table 5.2: OLS regressions on spending per food category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Spending	Carbs	Fresh greens.	Red m.	White m.	Other m.	Fish	Eggs	Dairy	Snacks	Ready Made	Soft drinks	Alcohol	Seasonings	Canned
National Gasoline Price	-0.296*	-0.576***	-0.503***	-0.281**	-0.248	-0.587***	-0.217*	0.010	-0.129	-0.356**	0.342***	-0.515**	-0.103	-0.214
	(0.152)	(0.114)	(0.163)	(0.143)	(0.160)	(0.163)	(0.124)	(0.102)	(0.105)	(0.160)	(0.132)	(0.204)	(0.116)	(0.151)
Income	0.061	-0.068	0.110**	0.016	0.133***	0.085*	-0.052	0.084**	0.084**	0.120**	0.092**	0.053	0.021	0.057
	(0.043)	(0.049)	(0.049)	(0.041)	(0.048)	(0.048)	(0.039)	(0.042)	(0.039)	(0.059)	(0.042)	(0.071)	(0.032)	(0.049)
Household size	-0.169***	-0.168***	-0.172***	-0.150***	-0.176***	-0.203***	-0.168***	-0.155***	-0.132***	-0.158***	-0.136***	-0.167***	-0.164***	-0.163***
	(0.024)	(0.019)	(0.023)	(0.022)	(0.021)	(0.019)	(0.015)	(0.020)	(0.018)	(0.023)	(0.018)	(0.022)	(0.015)	(0.019)
Local Laspeyres	0.071***	0.044**	0.095***	0.060***	0.056**	0.079***	0.047**	0.058***	0.037**	0.087***	0.059***	0.306***	0.043**	-0.009
(per product category)	(0.023)	(0.019)	(0.028)	(0.022)	(0.024)	(0.027)	(0.020)	(0.018)	(0.018)	(0.025)	(0.021)	(0.036)	(0.019)	(0.024)
Unemployment rate	0.015**	0.033***	0.018***	0.014**	0.022***	0.015**	0.017***	0.017***	0.015***	0.013**	0.013**	0.004	0.009**	0.008
(municipality)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(0.008)	(0.004)	(0.007)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes						
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.339	0.637	0.413	0.451	0.398	0.464	0.446	0.463	0.471	0.457	0.422	0.511	0.416	0.332
Households	3542	3542	3502	3539	3539	3534	3480	3546	3546	3539	3546	3490	3546	3535
Observations	105020	119969	94242	118198	112180	105414	89612	121291	121946	109607	118908	85482	121087	105947

Note:
Carbs refers to carbohydrates; fresh greens: fresh vegetables and fruits; Red m. (resp. White m. and Other m.) to red meat (resp. White meat and Other meat) ; Soft: non alcoholic beverages ; Canned: non fresh fruits and vegetables.
Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Spending stands for food expenditures per consumption unit. Spending and unit prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per liter). Additional controls are: Age of the household head, an dummy variable for whether at least one member of the household has a job and a dummy variable for whether the household the house/flat it lives in.

local apples, supposed to be more costly, with imported apples) is perceived less like a quality sacrifice than in the case of meat.

Households seem to adjust less on average on more staple products: carbs, dairy, eggs, seasonings and canned vegetables/fruits. We interpret these tendencies as suggestive that households might want to maintain sufficient calorie intake, in line with the literature (Caillavet et al., 2005).

Non alcoholic beverages is the only category for which expenditures increase. This result ought to be investigated further and could suggest that soft drinks are an imperfect substitute for some other product categories (e.g fruit juices instead of fresh fruits, coke instead of alcohol) .

Taking the average monthly food expenditure and the baseline budget shares per food category, one can compute the expected change in expenditures (in the sense of what would happen if there was a one to one transmission from fuel expenditures to food expenditures at constant budget shares) and compare it with the estimated change in expenditures for every category.[48] This can be used to better apprehend the reactions of households and which product categories are privileged adjust margins when households face a disposable income shock. Figure 5.2 offers a visualization of these differences (colored in grey) [49] between the actual (estimated) change in orange and the expected change in blue. A positive expenditures change (resp. negative) suggests that for a specific product category households adjust less (resp. more) than expected. It appears that households adjust by more than expected in terms of fresh fruits and vegetables, red meat, fish and snacks. Whereas the adjust less mostly in soft drinks (this is due to a quasi absence of reaction in soft drink expenditures). It is worth denoting that soft drinks are the only product category with non significant estimated coefficients, thus one can consider a zero change in this category after the change in gasoline price.

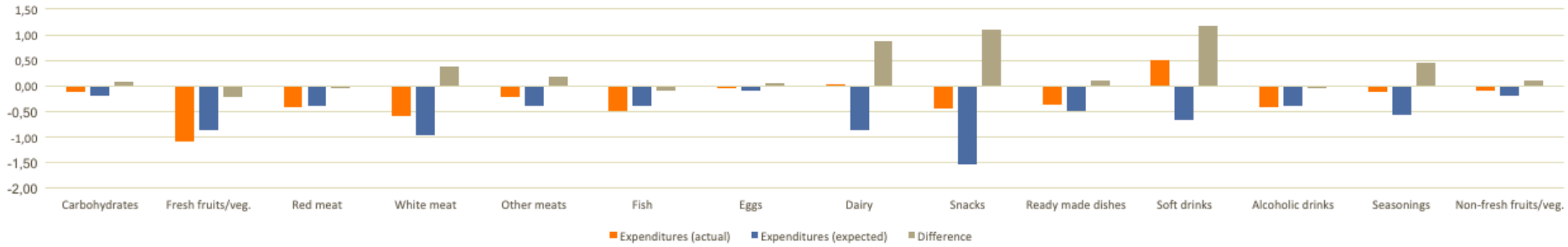
Finally, for most products the bulk of the response seems to be explained by drop in the unit price. Overall, the results of the analysis on product categories suggests that household could adjust as follows: realizing that their gasoline expenditures are increasing over the month, households try to cut in their food expenditures by cheaper products in order to reduce the overall cost of the food basket.[50]

[48] In this computation we assume a baseline monthly gasoline expenditure of 100€, a baseline level of 1.3€/liter and a 0.03% in gasoline prices.

[49] Starting from the left: the first bars are the actual change in expenditures, the second bars: the expected change in expenditures, the last bars: the difference.

[50] Family size has a consistent and negative effect on food spending across product categories this is suggestive of a scaling effect. Having disposable income spread across more members might increases sensitivity to gas prices.

Figure 5.1: Expenditure change (euros) at set change in gasoline price



Notes:

Differences between the estimated change in euros and the expected change in euros per product category when gasoline prices vary by 3% and when assuming a 1:1 transmission of the change in gas expenditures to food expenditures. This figure represents the extent to which the average household react to a change in gasoline prices in every product category.

Graph suggested interpretation:

When gasoline prices increase by 0.03 cents per liter, this translates in a 2.31% increase in gasoline price. For a household who spends 104€per month in gasoline, this is equivalent to a 2.4€increase in his budget. Assuming that a household has a one to one elasticity (in the sense that she would decrease food expenditures by the same amount ie 2.4€): this household who spends 0.01% of its budget in carbohydrates at baseline, should reduce carbohydrates expenditures (per consumption unit) by 0.19€and we observe that this household reduces carbohydrates by 0.12€. Therefore the average household adjusts slightly less on carbohydrates than expected, suggesting that when gasoline prices increase households do not over-reduce their consumption of carbohydrates: this product category seems to be an inferior good in line with the literature on *Giffen* goods. Conversely, the average household over reduces her consumption of fish when facing an income shock (the expected change was -0.39€and the estimated change is -0.49 leading to an over adjustment of -0.1).

5.3 Mechanisms

As discussed above, when gasoline prices increase households reduce food expenditures and the unit price effect dominates the quantity effect. The related literature highlights that in order to decrease the unit price households can rely on different mechanisms (such as buying more products in sale, Gicheva, Hastings, and Villas-Boas, 2010, or buying more private labels and in bulk, Griffith, O'Connell, and Smith, 2016). Using a similar specification than the one used in the previous subsections we investigate several outcomes that can be informative of the mechanisms at play (the selection of which are discussed in the data section 3.2). Results are displayed in Tables 5.3 and 5.3.

We find that when gasoline prices are higher households tend to increase expenses at the supermarket relatively to other food suppliers. More specifically, a 10% increase in gasoline prices triggers a 0.7% rise in the share of food expenditures made at the supermarket (the coefficient is significant at the 5% threshold). The average proportion of supermarket expenses is high (89%) suggesting that there is little adjustment margin for households. Nevertheless, for some households turning to supermarkets must represent an adjustment margin most likely because it allows to reduce the commuting costs (since supermarkets allow to access a large product variety simultaneously). The demand response for hypermarkets is less clear (positive and non-significant coefficient). It is most likely due to the fact that two competing mechanisms might occur: on the one hand, going in a hypermarket allows to purchase gasoline and food all in once. On the other hand, hypermarkets tend to be further away than other shops, therefore traveling longer distances to access food might be discouraged by higher gasoline prices. Similarly, we observe weakly and non significant coefficients for columns (3), (4) and (6). These results are most likely explained by the fact that the majority of households does not relies on hard discounter, online purchasing nor spends a large fraction of their food budget on organic products. Nevertheless, and in line with intuition, we estimate a positive coefficient for purchasing both at hard discount stores and online, and a negative estimate for the share of organic products (which tend to be have a higher unit price on average). The most interesting result of this table perhaps, along with the result on supermarkets, is the large increase (and strong statistical significance) of the share of private-label products. Firstly because most households have access to these products, and also because they tend to be way cheaper on average than national brand products (as described in the data section). Thus, this 3.6 increase in the share of food expenses devoted to private label products is suggestive of households changing consumption behavior in order to

access cheaper food when gasoline prices are higher[51].

When looking at the number of purchasing acts households carry out monthly[52] we observe that this number decreases significantly with gasoline prices. This might suggests either that households purchase less varieties during a month or that they shop less frequently. A strand of the Food studies literature suggests that income is correlated with more variety in the products a household consumes (see Thiele and Weiss, 2003 for a review of the literature) and our results are in line with it, they are also supported by the fact that we find that when gasoline prices are higher households visit less shops on average during a month. As for the second mechanism that suggests that households would increase buying in bulk it is supported by the fact that we do not observe a quantity effect (as described in the first part of this section) while we find a price effect suggesting that households might buy larger packs per shopping trips but similar quantities over the month through reducing the number of shopping trips because the unit price per kilo of lots is lower relative to smaller packs.

The number of shopping trips as well as the number of visited stores per month decreases with gasoline prices[53]. These results suggest that higher gasoline induce households to try to decrease travel costs by as much as possible. One could have expected to observe the opposite effect, in line with the marketing literature suggesting that poorer households tend to have lower search costs and access cheaper food alternatives by shopping more frequently across time and/or space. Because our analysis studies short term effects through temporary and small income effects, we believe that search costs are fairly stable in our context and that this is a rationale for why the most direct effect (the commuting cost channel) dominates.

The key findings of this section can be summarized as follows. First, households tend to decrease food consumption as a reaction to changes in national gasoline prices, which is suggestive of the existence of an income effect. Second, when decomposing the change into a quantity and a unit

[51]The impacts on the nutritional quality are rather ambiguous as one requires a highly disaggregated analysis (at the product level) to conclude: indeed there are several food products for which private labels are clearly worse in France (e.g deli meats) whereas for others (e.g floor, sugar etc) the qualities are very similar, or even higher nutritional qualities for few snacking products. For more details see the reports of the French Consumer Association *60 Millions de Consommateurs*: https://www.60millions-mag.com/2017/09/21/que-valent-vraiment-les-marques-de-distributeurs-11375.

[52]Purchasing during one shopping session two of the same pasta boxes counts as one purchasing act. Thus, this outcome doesn't distinguish for the volumes purchased.

[53]Because the number of shopping trips and the number of visited stores are count variables taking a limited number of values, the use of count data models is appropriate. In Appendix A4.2 we compare the results yield by the OLS method with those from Poisson Pseudo-Maximum Likelihood. They are very similar for both variables in terms of magnitude. However, the count data model seems to provide more precise estimates.

	(1) Supermarkets	(2) Hypermarkets	(3) Hard Discounters	(4) Internet	(5) Private-label	(6) Organic
National Gasoline Price	0.069**	0.021	0.426*	0.160	0.364***	-0.043
	(0.028)	(0.138)	(0.226)	(0.345)	(0.077)	(0.210)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes		
Adj. R^2	0.708	0.717	0.700	0.550	0.676	0.601
Observations	122692	89589	52597	14031	122367	64707

Notes:

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels.

Table 5.3: OLS regressions on different mechanisms, pooled

	(1) Purchased products	(2) Shopping trips	(3) Visited stores
National Gasoline Price	-0.230***	-0.339***	-0.180**
	(0.068)	(0.069)	(0.072)
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes
Adj. R^2	0.554	0.666	0.626
Observations	122806	122806	122806

Notes:

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels.

Table 5.4: OLS regressions on different mechanisms, pooled (continuation)

price effect, it seems that the unit price adjustment dominates. Third, by looking at different product categories, we find that households adjust less in more staple goods than in goods that can be seen as superior. Finally, it seems that households rely on different adjustment margins to reduce their food expenditures.

6 Heterogeneity across households

As highlighted in Douenne (2020) and Berry (2019), who measure the monetary incidence of the carbon tax across income groups, changes in gasoline prices are likely to affect individuals heterogeneously based on their income and geographic characteristics. Therefore, after having measured the average effect of gasoline prices on food consumption, it is of interest to investigate whether households might react heterogeneously to this shock based on their characteristics. In the following subsections, we discuss heterogeneity across various dimensions.

6.1 Vertical differences

Because poorer households devote a larger budget share to gasoline [54], we expect that different income categories might react heterogeneously to a uniform increase in gasoline prices.

In the KWP database the economic class is an indicator variable that takes values between 1 and 4, this variable is a function of the income level of the household, the size of the household and the age of the household members (that is used to compute consumption units)[55]. To investigate heterogeneity, we first distinguish households by their income class.

Table 6.1 presents the results of the estimation of equation 4.1 on different income samples.

When comparing the columns 1 to 4 estimates of the cross-elasticities of demand, we observe that the poorest income category is the only one with a statistically significant estimate and also the one with the larger effect size. Even though intuition suggests that the poorest households should react more on average to an increase in gasoline prices, the non significant coefficients found for the remaining income categories might seem surprising and are likely explained by unobserved heterogeneity in terms of other determinants (in particular car dependency) as suggested in Douenne (2020). Moreover, for richer households (here the two top income categories), the amount spent on gasoline is substantially larger than for their poorer counterparts (on average 1600 per year for the rich against 900 for the poor)[56], so the actual expenditure change faced is substantially larger for the rich meanwhile food consumption (per consumption unit) is relatively similar across income categories.[57] Therefore, a 10% increase in national gasoline price corresponds to a 7.5€[58] increase in monthly gasoline expenditure for poor people but a full 13€ increase in monthly

[54] The respective budget shares spent on gasoline items of the poor is 0.07 against 0.05 for the rich. According to the French Consumer Expenditure Survey (*Budget des Familles*, 2011) - INSEE.

[55] In our selected sample: 432 have a modest income, 1493 are lower middle, 1084 are upper middle and 538 are well-off. It is worth denoting that the poor and non poor samples are mutually exclusive and jointly exhaustive.

[56] Source: French Consumer Expenditure Survey (*Budget des Familles*, 2011) - INSEE.

[57] 239€per month for the rich vs 203€ per month for the poor. Source: KWP panel.

[58] Computation: 900/12 * 0.1% = 7.5

gasoline expenditure for the rich. If the effect on total monthly food expenditures is, on average, about -4€ [59] for both categories, given the baseline amounts spent by each income category on gasoline and food, it seems that poor people reduce food consumption in a similar proportion than the increase in gasoline expenditures, seen in level euros, while richer households reduce food consumption by a lot less then the associated change in gasoline expenditure additional gasoline expenditure.

	Poor	Medium Poor	Medium Rich	Rich
National Gasoline Price	-0.484**	-0.113	-0.183	-0.283
	(0.205)	(0.116)	(0.126)	(0.227)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.490	0.471	0.469	0.495
Observations	14476	51822	38934	17582

The income class (poor, non poor) is defined by KWP as the income bracket when accounting for household size and consumption units. Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Spending stands for food expenditures per consumption unit. Spending and gasoline prices and are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per liter).

Table 6.1: Income categories subsamples

6.2 Horizontal differences

Spatial characteristics such as the size of the employment zone (in terms of jobs) or the municipality type (for instance: whether it is urban, peri-urban rural or isolated) are likely to determine the extent to which households are gasoline dependent. It is indeed clear that workers who live and work in large cities with a dense public transportation network are likely to be less car-dependent as compared to workers living in rural locations. However, apart for the top largest cities and their outskirts, most French households use a car for their daily commutes (see Appendix Figure A2.1) and the traveled distances are fairly similar regardless of the type of municipality[60]. Therefore, spatial differences, that are often referred to as horizontal differences, might be a relevant heterogeneity dimension in the context of our study.

Because rural and urban are two large categories with lots of within heterogeneity, we define, in line with the grey literature[61], categories of municipalities along which car use is likely to

[59] Computation: 203 * -0.02 = -4.06.

[60] On average the distance from one's house to one's job is 13km for urban locations, 17km for the peri-urban, 19km for multipolar municipalities and 16km for rural municipalities.

[61] We mostly rely on the 2008 transportation survey of the French Institute of Statistics see https://www.insee.fr/fr/metadonnees/source/serie/s1277.

differ. We first investigate if living in a municipality that is part of an employment zone that gathers less than ten thousands jobs implies a larger reaction to higher gasoline prices. We expect that households working in the largest employment zones to have better access to public transportation and thus to be less car dependent and thus should adjust food consumption less when gasoline prices increase. We then investigate if households living in a rural or a small (less than two thousands inhabitants) municipality react more strongly to higher gasoline prices. The rationale behind this second variable is that 49% of the Yellow Vests where living in these rural and small locations and we expect them to be the most car dependent.

Table 6.2 presents the results of this analysis. In both columns, the interaction coefficient is not statistically significant. This result suggests that there are statistical differences between geographic location types. These findings are likely explained by the heterogeneity that persists within municipalities and the size of our sample (2381 municipalities when France has 36000). Moreover, Douenne (2020) suggests that the majority of households heterogeneity remains unexplained when using consumption data.

	(1) Spending	(2) Spending
National Gasoline Price	-0.244***	-0.165 **
	(0.093)	(0.080)
Large employment zone	-0.083**	
	(0.035)	
Large employment x Gas	0.076	
	(0.102)	
Small Municipality		0.076**
		(0.037)
Small x Gas		-0.097
		(0.109)
Size of the HH	-0.027***	-0.025***
	(0.007)	(0.007)
Employed	-0.056***	-0.057***
	(0.020)	(0.020)
House Owner	0.017	0.021
	(0.015)	(0.015)
Age	0.008***	0.008***
	(0.001)	(0.001)
Local Laspeyres	0.084***	0.064***
	(0.023)	(0.018)
Local unemployment rate	0.006	0.034***
	(0.005)	(0.007)
Income	0.222***	0.215***
	(0.013)	(0.014)
Department FE	Yes	Yes
Year FE	Yes	Yes
Seasonal Effects	Yes	Yes
Controls	Yes	Yes
Ajd. R^2	0.139	0.153
Observations	123046	123046

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Spending stands for food expenditures per consumption unit. Spending and gasoline prices and are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per liter).

Table 6.2: Spatial differences

7 Robustness

7.1 Local gasoline prices

7.1.1 2SLS

A second estimation strategy allows to account for the effect of local gasoline prices. It is worth mentioning that again we run log-log regressions. Column (1) of Table 7.1.1 presents the results of the "naive" OLS regression where local gasoline prices is the key explanatory variable. The next two columns are related to the IV strategy: column (2) presents the first stage results and column (3) the second stage results. The comparison of column (1) and (3) shows that both coefficients are statistically significant at the 1% threshold and that the naive OLS estimate is smaller in absolute terms than the 2SLS estimate (0.149 against 0.195). The fact that the reduced form coefficients and the IV coefficients are very similar suggests that the time-space variation is small relative to the variation from national gasoline prices. The fact that municipalities with a low food competitive setting are the ones for which we measure a higher cross-elasticity of demand is likely due to the fact that places could be more rural, hence locations where households car commuting is more constrained[62].

Overall, in this second specification, the use of the IV allows to account for the time-space variation that wasn't accounted for in the econometric specification of the previous subsection in which we accounted for the time variation (using national gasoline prices) and the spatial variation (with the household fixed effects). Nevertheless the difference between the "naive" estimate and the 2SLS estimate suggests that using local gasoline prices to explain food consumption changes would likely lead to bias estimates. Thus, it seems that this identification strategy that uses an IV could substantiate results from the main section by using additional variation in gasoline prices that is due to local determinants.

[62] One could have been interested in studying the asymmetry in pass-through in the sense that it could be that national upward variations in gasoline prices have less effect on local gasoline prices where there is more competition between distributors, and downward variations have more effect. Nevertheless, this pricing strategy should only be transitory otherwise it would lead gasoline suppliers to loose money in the long run and Gautier and Saout (2015) do not find evidence of asymmetry in pass-through.

	OLS	First Stage	IV
	(1)	(2)	(3)
	Spending	Local Gas. Price	Spending
Local Gasoline Price	-0.149***		-0.195***
	(0.055)		(0.065)
HHI x National gas.		0.132***	
		(0.001)	
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. R^2	0.470	0.895	0.006
F-stat	144.338	5017.853	144.749
Observations	122333	122333	122333

Notes:

Robust standard errors, adjusted for clustering at the living-zone level, are presented in parentheses. ***, **, *, indicate significance at the 1%, 5% and 10% levels. By clustering at the living-zone level, we account for spatial spillovers.
Spending stands for median of monthly food expenditures per consumption unit. Spending and gasoline prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per liter). Local gasoline price is the alternative municipality gasoline price described in the Data section 3.4.2. HHI stands for the Herfindahl-Hirschmann index per living-zone in January 2011. In column (3) local gasoline prices are instrumented with the interaction of the logarithm of HHI and the logarithm of national gasoline prices. The controls vector includes the log of the HHI in January 2011, the log of the household income, the household size, an activity dummy, a house ownership dummy, the age of the household head, the local Laspeyres index and the unemployment status of the household head

Table 7.1: OLS and 2SLS, food spending per household

7.2 Car Owners Sample

Our main analysis, does not account for car ownership for two main reasons: firstly, the vast majority (91%) of our sample of interest declares having at least one car. Secondly, some of those who declare not owning one might still buy gasoline either because they are renting or borrowing a car or because they could use another type of motorized vehicle such as a motocycle. Nevertheless, we expect the subsample of car owners to be more affected by variation in gasoline prices relative to the non car owner sample. To test for this assumption we restrict our analysis to the subsample of car owners in our main analysis, the results are presented in table 7.2. In line with intuition, we find that the magnitude of the effect of gasoline on food consumption is slightly larger (-0.211 versus -0.201) when restriction to households who declare owning at least one car. Similarly to the analysis on the full sample, the decrease of monthly food expenditures goes through a drop in the unit price.

	(1) Spending	(2) Spending	(3) Spending	(4) Quantities	(5) Quantities	(6) Quantities	(7) Unit price (€/ kg)	(8) Unit price	(9) Unit price
National Gasoline Price	-0.223***	-0.219***	-0.211***	0.045	0.050	0.061	-0.270***	-0.270***	-0.272***
	(0.075)	(0.075)	(0.075)	(0.080)	(0.080)	(0.080)	(0.042)	(0.042)	(0.042)
Income		0.053**	0.054**		0.030	0.031		0.023	0.022
		(0.027)	(0.027)		(0.029)	(0.029)		(0.014)	(0.014)
Household size		-0.145***	-0.145***		-0.125***	-0.125***		-0.021***	-0.020***
		(0.014)	(0.014)		(0.015)	(0.015)		(0.006)	(0.006)
Employed		0.034*	0.033		0.005	0.005		0.029***	0.028***
		(0.021)	(0.020)		(0.019)	(0.019)		(0.009)	(0.010)
House Owner		0.085***	0.090***		0.088***	0.089***		-0.002	0.002
		(0.032)	(0.032)		(0.034)	(0.034)		(0.019)	(0.019)
Age		0.000	0.001		-0.003	-0.003		0.003**	0.004**
		(0.007)	(0.007)		(0.005)	(0.005)		(0.002)	(0.002)
Local Laspeyres			0.072***			-0.073***			0.145***
			(0.013)			(0.013)			(0.008)
Unemployment rate (municipality)			0.017***			0.012***			0.005***
			(0.003)			(0.004)			(0.002)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.480	0.483	0.483	0.419	0.421	0.421	0.627	0.628	0.630
Observations	111941	111678	111676	111940	111677	111675	111940	111677	111675

Note:

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Spending stands for food expenditures per consumption unit. Spending, unit prices and gasoline prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros (resp. euros per kilogram and resp. euros per liter). Quantities are expressed in grams per consumption unit. Additional controls stands for Age of the household head, an dummy variable for whether at least one member of the household has a job and a dummy variable for whether the household the house/flat it lives in.

Table 7.2: OLS regressions (households with at least one car)

8 Conclusion

Our use of scanner data to assess the impact of changes in gasoline prices on household food purchases has important policy implications. First, increasing gasoline prices through a carbon tax may have a non negligible negative short-term impacts on consumer welfare by constraining households to curb their food expenditures to preserve their commuting habits. Second, we find that most of the adjustment in overall expenditures is channeled through a drop in the unit price. Third, households tend to substitute away from more expensive product categories, such as fresh fruits and vegetables, fish or red meat, with likely nutritional and environmental impacts. This shows that it is crucial to account for such substitutions when evaluating the costs and benefits of small policy-induced income variations. Fourth, the income effect produced by an increase in gasoline price has a stronger absolute consequences for the less well-off households. We see these findings as evidence that there might be a stark contrast between the certain short-term welfare costs of increased gasoline taxation and its uncertain consequences over the long-term, especially for low-income households. Yet, while this shows why a carbon tax may be seen as unfair and trigger social unrest, the way households would adapt their food consumption over the long-term remains to be studied.

Our study is not without limits (especially this preliminary version). It covers a short-period, 2011 to 2013,[63] and it would be worth analyzing more directly the effects of an increase in the carbon tax. We have here estimated the elasticity of food consumption to the gasoline price in a period where the carbon tax rate was kept constant.[64] This price elasticity might differ from the tax elasticity for two reasons. First, the pass-through of the carbon tax onto gasoline prices is unlikely to be 100%. It will vary over time and across space, depending on the characteristics of local gasoline markets. Second, an increase in the carbon tax may have a behavioral effect in addition to a standard income effect, especially if it is widely discussed and advertised, as it renders more salient the budget constraint, but also signals the importance of environmental issues. Having said that, our estimates of cross-price elasticities are of interest in an ex-ante perspective for the design of environmental policies, and they are robust as they exploit substantial variations in gasoline prices.

[63] The magnitude of the spikes observed during our analysis are comparable to the ones observed in 2018 that have lead to the rise of the Yellow Vest movement. Nevertheless the 2012 price increase is mostly explained by changes in oil prices. The later price increase observed over 2014-2018 is due to both oil prices and increasing tax rates.

[64] This is currently the case since the evolution of the carbon tax has been frozen since December 2018.

References

Allais, O., F. Etilé, and S. Lecocq. 2015. 'Mandatory labels, taxes and market forces: An empirical evaluation of fat policies.' Journal of health economics 43: 27–44.

Anderson, S. T., R. Kellogg, and J. M. Sallee. 2013. 'What Do Consumers Believe About Future Gasoline Prices?' Journal of Environmental Economics and Management 66 (3): 383–403.

Andrieu, É., F. Caillavet, A. Lhuissier, M. Momic, and F. Régnier. 2005. 'L'alimentation comme dimension spécifique de la pauvreté. Approches croisées de la consommation alimentaire des populations défavorisées.' Les Travaux de l'observatoire national de la pauvreté et de l'exclusion sociale 2006: 247–277.

Bento, A. M., L. H. Goulder, M. R. Jacobsen, and R. H. Von Haefen. 2009. 'Distributional and efficiency impacts of increased US gasoline taxes.' American Economic Review 99 (3): 667–99.

Berry, A. 2019. 'The Distributional Effects of a Carbon Tax and its Impact on Fuel Poverty: A Microsimulation Study in the French Context.' Energy Policy 124: 81–94.

Bils, M. and P. J. Klenow. 2004. 'Some Evidence on the Importance of Sticky Prices.' Journal of political economy 112 (5): 947–985.

Borusyak, K., P. Hull, and X. Jaravel. 2018. 'Quasi-experimental shift-share research designs.' Tech. rep., National Bureau of Economic Research.

Caillavet, F., N. Darmon, F. Létoile, and V. Nichèle. 2019. 'Four decades of household food purchases: changes in inequalities of nutritional quality in France, 1971-2010.' Economie et Statistique 513 (1): 69–89.

Caillavet, F., N. Darmon, A. Lhuissier, F. Régnier et al. 2005. 'L'alimentation des Populations Défavorisées en France: Synthèse des Travaux dans les Domaines Économique, Sociologique et Nutritionnel.' Les travaux de l'Observatoire national de la pauvreté et de l'exclusion sociale 2006: 279–322.

Caillavet, F., C. Lecogne, and V. Nichèle. 2009. 'La consommation alimentaire: des inégalités persistantes mais qui se réduisent.' Cinquante ans de consommation en France : 49–62.

Calvet, L. and F. Marical. 2011. 'Consommation de carburant: effets des prix à court et à long terme par type de population.' Economie et statistique 446 (1): 25–44.

Cardon, P., T. Depecker, and M. Plessz. 2019. Sociologie de l'Alimentation. Armand Colin.

Chetty, R. and A. Szeidl. 2007. 'Consumption commitments and risk preferences.' The Quarterly Journal of Economics 122 (2): 831–877.

Chevalier, J. A., A. K. Kashyap, and P. E. Rossi. 2003. 'Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data.' American Economic Review 93 (1): 15–37.

Douenne, T. 2020. 'The vertical and horizontal distributive effects of energy taxes: A case study of a french policy.' The Energy Journal 41 (3).

Dubois, P., R. Griffith, and A. Nevo. 2014. 'Do prices and attributes explain international differences in food purchases?' American Economic Review 104 (3): 832–67.

Etilé, F., S. Lecocq, and C. Boizot-Szantai. 2020. 'Market Heterogeneity and the Distributional Incidence of Soft-drink Taxes: Evidence from France.' .

Gauri, D. K., K. Sudhir, and D. Talukdar. 2008. 'The temporal and spatial dimensions of price

search: Insights from matching household survey and purchase data.' Journal of Marketing Research 45 (2): 226–240.

Gautier, E. and R. Le Saout. 2017. 'L'ajustement microéconomique des prix des carburants en France.' Economie prevision (1): 1–24.

Gautier, E. and R. L. Saout. 2015. 'The Dynamics of Gasoline Prices: Evidence from Daily French Micro Data.' Journal of Money, Credit and Banking 47 (6): 1063–1089.

Gelman, M., Y. Gorodnichenko, S. Kariv, D. Koustas, M. D. Shapiro, D. Silverman, and S. Tadelis. 2016. 'The Response of Consumer Spending to Changes in Gasoline Prices.' Tech. rep., National Bureau of Economic Research.

Gicheva, D., J. Hastings, and S. Villas-Boas. 2010. 'Investigating Income Effects in Scanner Data: Do Gasoline Prices Affect Grocery Purchases?' American Economic Review 100 (2): 480–84.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2018. 'Bartik instruments: What, when, why, and how.' Tech. rep., National Bureau of Economic Research.

Gollier, C. 2019. Le climat après la fin du mois. Presses Universitaires de France.

Graham, D. J. and S. Glaister. 2002. 'The demand for automobile fuel: a survey of elasticities.' Journal of Transport Economics and policy : 1–25.

Griffith, R., M. O'Connell, and K. Smith. 2016. 'Shopping around: how households adjusted food spending over the great recession.' Economica 83 (330): 247–280.

Hughes, J., C. R. Knittel, and D. Sperling. 2008. 'Evidence of a shift in the short-run price elasticity of gasoline demand.' The Energy Journal 29 (1).

Ma, Y., K. L. Ailawadi, D. K. Gauri, and D. Grewal. 2011. 'An empirical investigation of the impact of gasoline prices on grocery shopping behavior.' Journal of Marketing 75 (2): 18–35.

Martin, M. and M. Islar. 2020. 'The 'end of the world'vs. the 'end of the month': understanding social resistance to sustainability transition agendas, a lesson from the Yellow Vests in France.' Sustainability Science : 1–14.

Morduch, J. and R. Schneider. 2017. The Financial Diaries: How American Families Cope in a World of Uncertainty. Princeton University Press.

Nevo, A. and A. Wong. 2019. 'The elasticity of substitution between time and market goods: Evidence from the Great Recession.' International Economic Review 60 (1): 25–51.

OECD. 2013. OECD framework for statistics on the distribution of household income, consumption and wealth. OECD Publishing.

Office, I. L. and R. Turvey. 2004. Consumer Price Index Manual: Theory and Practice. International Monetary Fund.

Recours, F. and P. Hébel. 2006. 'Les Populations Modestes Ont-Elles Une Alimentation Déséquilibrée.' Paris: Credoc (Cahiers de Recherche) .

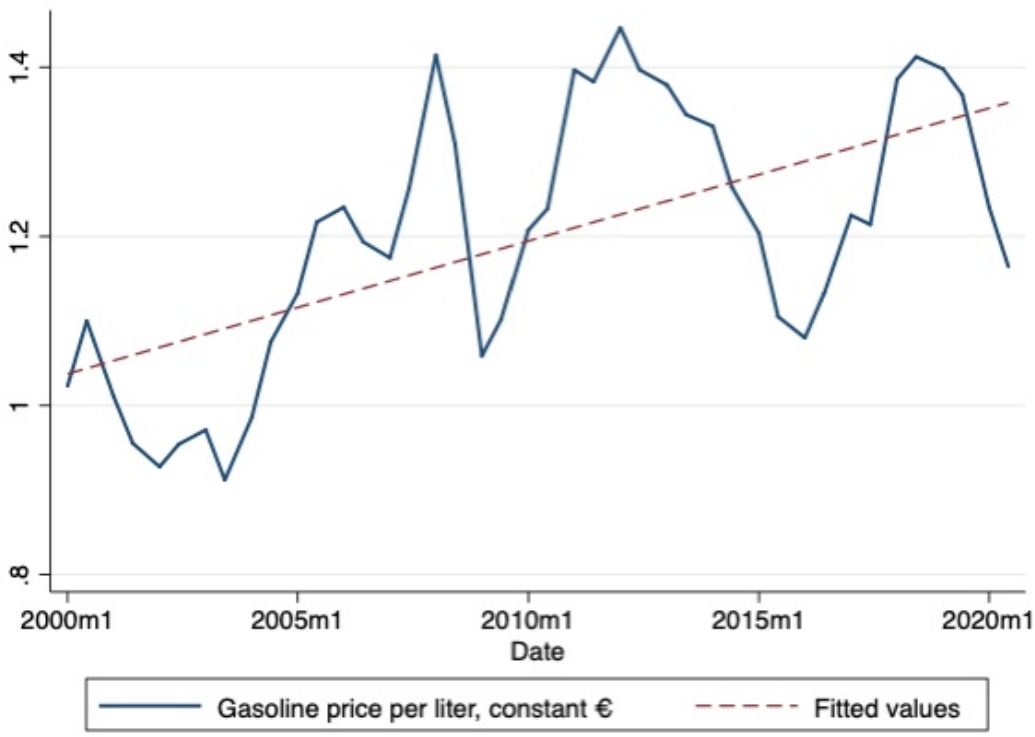
Thiele, S. and C. Weiss. 2003. 'Consumer demand for food diversity: evidence for Germany.' Food Policy 28 (2): 99–115.

Appendix

9 Appendix

A1 Additional information about the context

Figure A1.1: Recent evolution of gasoline prices



Source: National Road Committee data, €/liter current value (CPI=100 in 2015)

Figure A1.1 plots the time series of gasoline prices in France from January 2000 to July 2020. Gasoline prices display an increasing trend over this period. The highest values are attained in 2008, 2012 and 2018. The latest drop (early 2020) marks the beginning of the COVID-19 pandemic.

A2 Additional information about the data

A2.1 Construction of the price indices

Laspeyres indices are price index formula that can be used to investigate prices changes. In the present study we compute monthly indices for food at two levels: a local level, per living-zone, and the national level. These indices are used as control variables in our analysis, they aim to

account for food prices changes over time since food prices changes are a strong determinant of food consumption variation. Laspeyres indices are build on households active between 2011 and 2013.

The Laspeyres formula at time t for a food product i is: $\mathcal{L}_{it} = \frac{p_{kt}p_{i0}}{q_{i0}p_{i0}}$

Where p_0 is the price at baseline (year 2011 in this analysis).

In our analysis we aggregate product by food categories and we distinguish 15 food categories. Let's denote k the product category with $k \in (1; 15)$. The KWP dataset doesn't contain information about the price of product instead it provides the spending and the quantity per purchase. The unit price is computed out of these two variables. For every product i in the product category k the unit price of category k is computed as[65]:

$$p_k = \frac{\sum_i s_i}{\sum_i q_i}$$

The local Laspeyres for living-zone c is computed as follows:

$$\mathcal{L}_{c,t} = \frac{\sum_k p_{kct} q_{k0}}{\sum_k p_{kc0} q_{kc0}}$$

When the living-zone contains less than 5 Kantar households, we replace the living-zone Laspeyres by an employment zone Laspeyres to reduce endogeneity concerns.

The National Laspeyres is computed as follows:

$$\mathcal{L}_t = \frac{\sum_k p_{kt} q_{k0}}{\sum_k p_{k0} q_{k0}}$$

It is worth denoting that conversly to the INSEE food prices indices, the Laspeyres indices we construct are not composed of a stable sample over time but rather of every consumed product that we aggregate in fifteen categories[66]. Therefore the Laspeyres indices might capture a change in product preferences over time. Nevertheless since our analysis encompasses a relatively small time interval 3 years and as food preferences evolve relatively slowly over time, one can assume that food preferences are relatively stable on average during our time period. Despite these differences, the INSEE and the national Laspeyres have relatively similar distributions[67]. When

[65]Spending and quantities are weighted by Kantar purchase weights. Spending are deflated by the consumer index price.

[66]The product classification is stable over time

[67]INSEE mean= 98.27877, INSEE SD=1.91 ; Laspeyres mean= 102.4634, SD=5.77)

using the INSEE food price index[68] as a control instead of the national Laspeyres in the main specification of interest 4.1, the coefficients are fairly similar (same sign, close magnitude)[69].

[68]INSEE food prices are available at the following url: https://www.insee.fr/fr/statistiques/serie/001764287.

[69]the log of the INSEE food price index coefficient is statistically significant and equal to 1.51 ; the coefficient of national gasoline prices is statistically significant as well and becomes -0.72 and its SD is 0.09.

Figure A2.1: Distribution of car reliance across municipalities

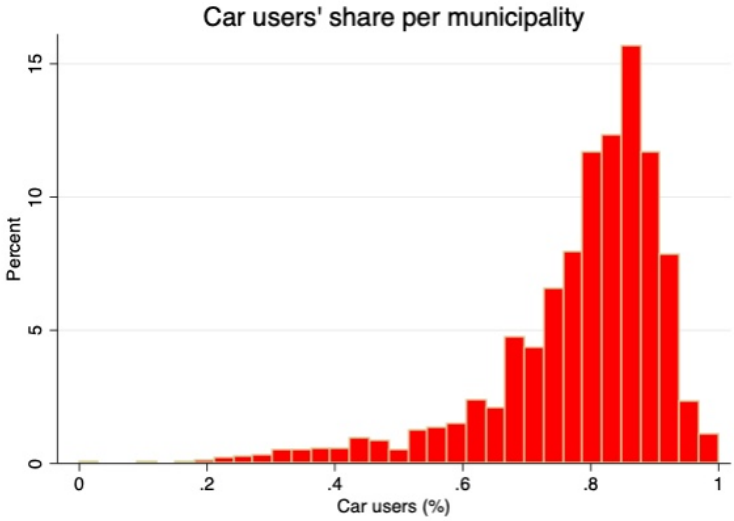


Figure Notes: The car users' share corresponds to the number of workers using car as a main transportation mode commuting divided by the population in the municipality

A2.2 Additional descriptive statistics

Figure A2.1 is based on the 2015 Population Census produced by INSEE[70]. It suggests that in the vast majority of municipalities car is the main transportation mean. In the Parisian living-zone, the share of households who mainly rely on car to commute daily is 0.41.

[70]We use the 2015 Population Census wave for availability reasons. Because there is a strong hysteresis across time, we expect the 2011, 2012, 2013 modal transportation shares to have similar values on average.

A2.3 Geographic distribution of the selection sample

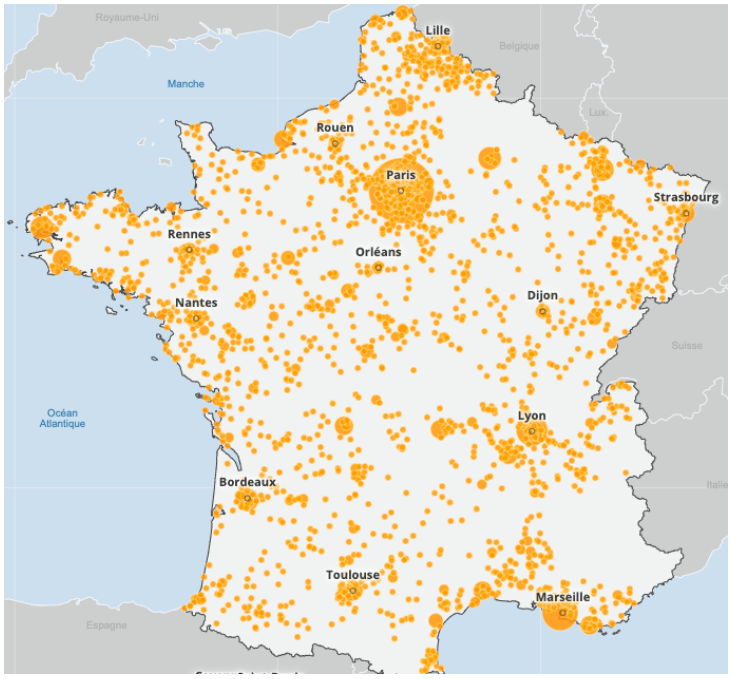


Figure A2.2: Mapping of the selection sample

Source: Own representation of the households mapped at the municipality level, displayed using INSEE's map production online tool.

A3 Additional information on the methodology

A3.1 Seasonal effect coding

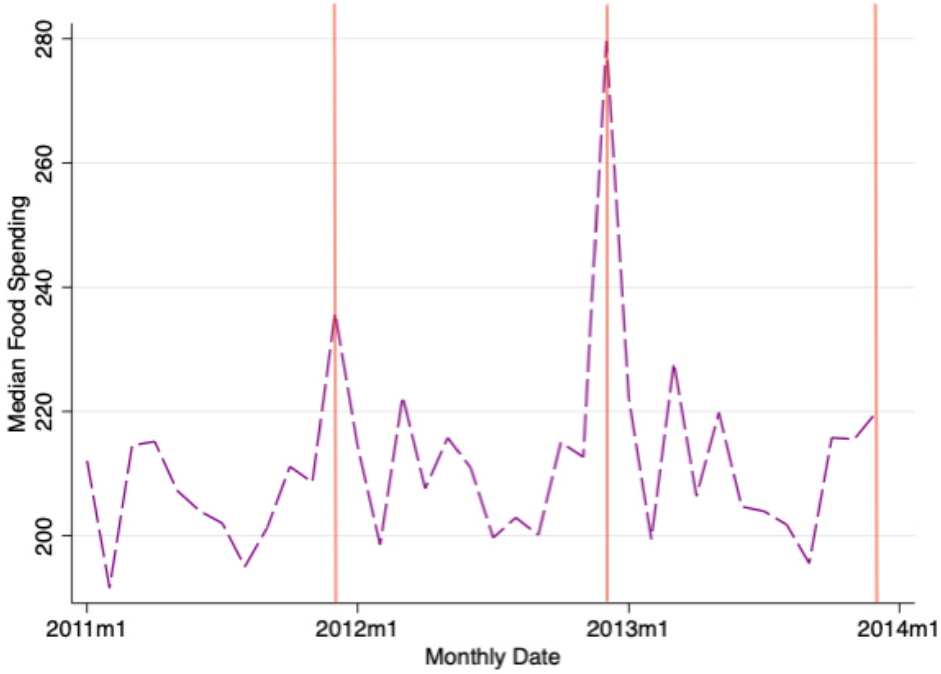
There are regular fluctuations in prices or quantities that are synchronized with the season or the time of the year. Those pikes have two main explanations: climate and custom (Office and Turvey, 2004). The first concern is limited as we are working with highly aggregated product categories. The second one is strong as we expect active retail buying before Christmas which translates in the data in high observed spikes in the spending distribution in December explain by Christmas[71] as highlighted with red bars in **Figure A3.1**[72]. It is crucial to account for seasonality as it affects purchase decisions. The consumption model can be described as such: Y, the consumption variable over the year is defined as the sum of monthly effects and a constant (that is the yearly mean) and an error term. To account for seasonal deviations around the mean we use seasonal effects that are coded as follows:

- the reference month r (in our case January, hence $r = 1$) is coded as -1 if month = r, 0 otherwise.
- for $m \in \{2, 12\}$ =1
  - $\mu_m = 1$ if $month = i$
  - $\mu_m = 0$ if $month \neq i$
  - $\mu_m = 0$ if $month = 1$

[71] When looking at monthly consumer spending in the US, Ma et al., 2011 observe that the higher spending peaks happen around the Thanksgiving date.

[72] One can observe other seasonal patterns such as drops in food at-home expenses during summer months (July and August)

Figure A3.1: Evolution of monthly food budget



A3.2 Source of variation

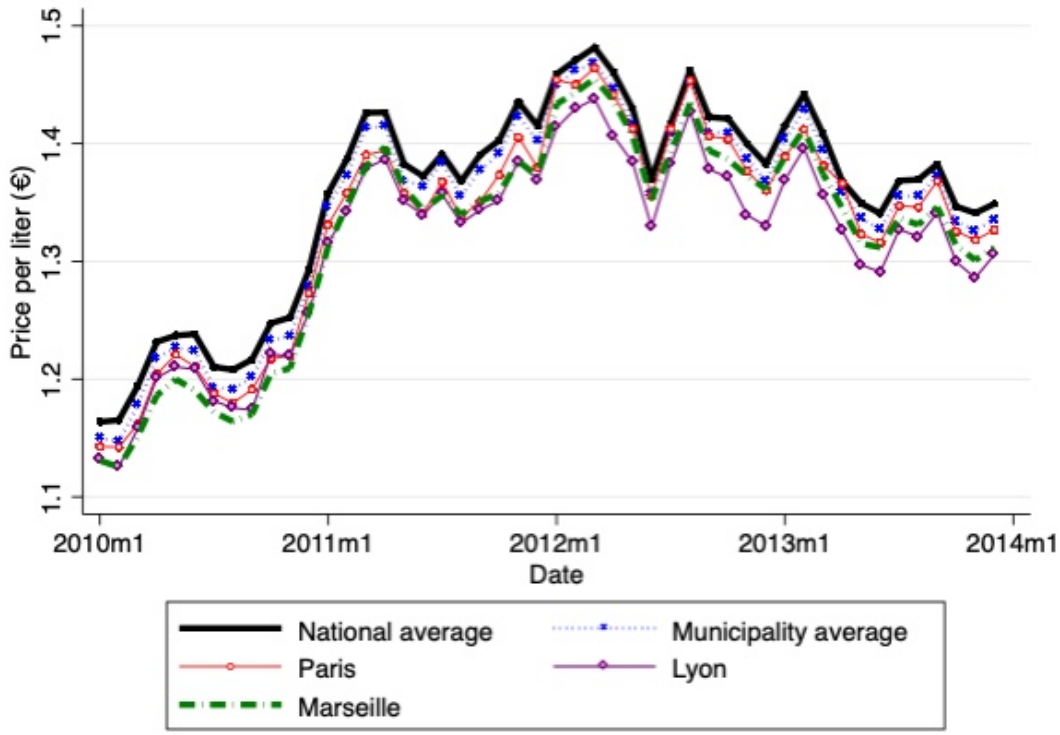
	Daily gasoline prices (2011-2013)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FE time	0.64	.	0.64	.	.	0.64	.
FE municipality	.	0.32	0.51	.	.	.	.
FE time*municipality	.	.	.	0.83	.	.	.
FE living-zone	.	.	.	.	0.32	0.20	.
FE time*living-zone	.	.	.	.	.	.	0.73
Nb. Obs	2,133,743	2,133,738	2,133,738	2,122,747	2,133,743	2,133,743	2,132,180
Ajd. R^2	0.41	0.27	0.66	0.68	0.11	0.51	0.52

Notes:
This table presents the correlations between fixed effects and daily prices. The adjusted R^2 is obtained from the regression of daily gasoline prices on fixed effects. Time stands for month*year. The constant for every model is 1.38. Fixed effects are centered around zero.

Table A3.1: Decomposition of gasoline prices variation

To investigate the drivers of gasoline prices variation, we run various regressions with fixed effects to compare their explanatory power. For this purpose we compare the adjusted R^2 values between the different specifications. Table **Table A3.1** presents those specifications and stands for a variance decomposition along temporal and spatial components of gasoline prices. It can be used to better understand what are the key dimensions that explain variation in gasoline prices. The main takeaway of is that the time dimension (monthly) explains over 40% of the price variation, municipality accounts for 27% and catchment area only 11%. This suggests that the level that describes best prices is the month and the finest geographic level (in our case the

Figure A3.2: Dynamics of gasoline prices across main metropolitan areas



municipality).

Figure ?? presents the evolution of oil and gasoline prices and encompasses years 2011 to 2013[73]. Gasoline prices are measured as the national median of prices over the sample of selected pumps, the shaded area around the curve represents the 25th and 75th percentiles of the distribution of the gasoline prices variables. Oil prices variation is larger than for gasoline prices in terms of magnitude, nevertheless it seems that the two curves move jointly and in a similar direction. The high correlation between the growth rates of oil prices and gasoline prices (0.68) is suggestive of oil prices variation explaining an large part of gasoline prices variation.

Figure ?? presents the prices evolution of national gasoline and the Laspeyres index obtained after controlling for seasonal variation and yearly fixed effects, hence the presented time series are the residuals of the following OLS regression:

$$\ln(Y_{m(y)}) = \sum_{m=2}^{12} \mu_m + \delta_y + \varepsilon_{m(y)}$$

[73]Each variable is deflated by the Consumer Price Index for consumer goods (Base: 2015) and is expressed in euros per liter. The European brent spot price per barrel in dollars is obtained on the US Energy Information Administration's website https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=M. The price per barrel is converted in euros using the exchange rates series provided by the US Federal Reserve. Finally, the oil price per liter is obtained by dividing the price per barrel per 159.

Figure A3.3: Dynamics of oil and gasoline prices

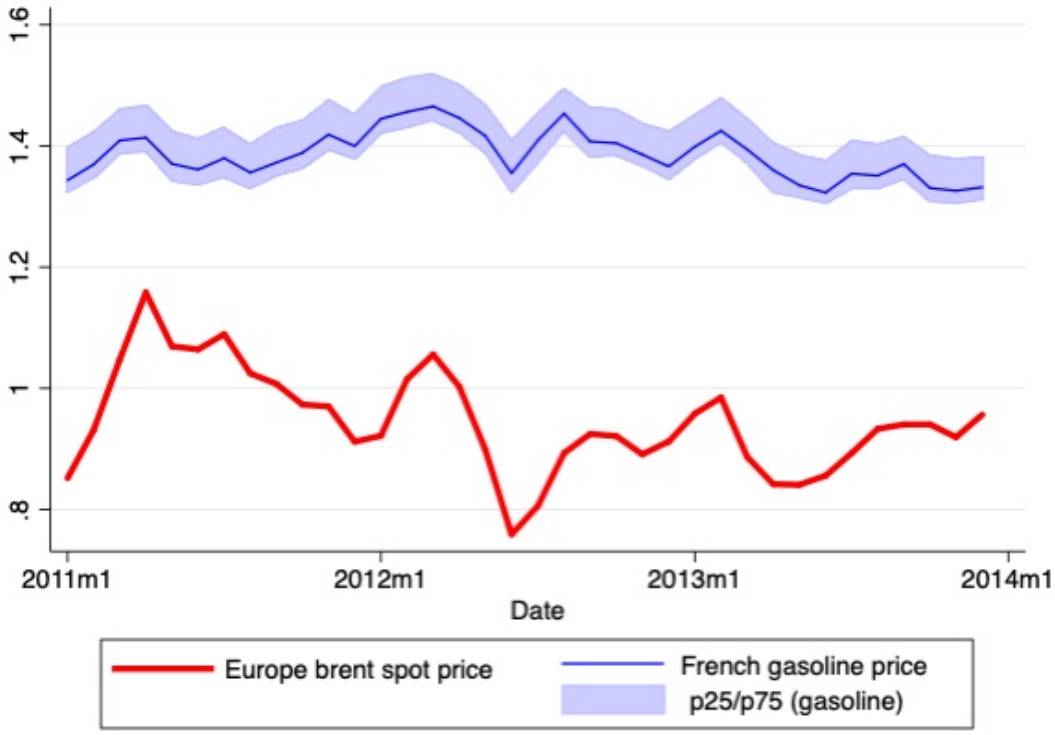
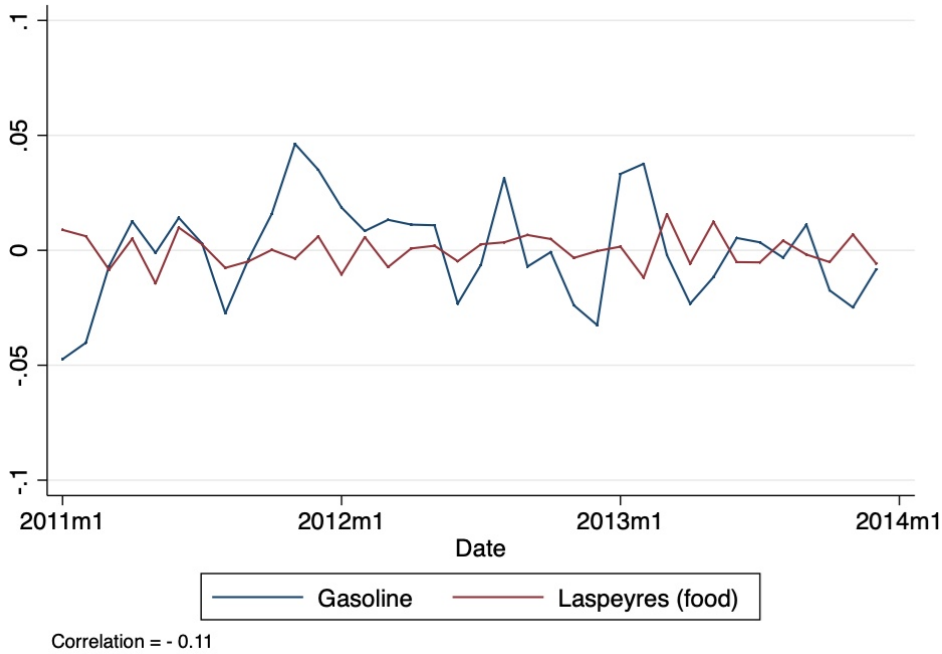


Figure A3.4: Evolution of national gasoline prices and national Laspeyres index



Where $Y_m(y)$ is alternatively the gasoline price per liter and the Laspeyres index in month m of year y. μ_m stands for seasonal effects with January as the reference month and δ_y yearly are fixed effects.

Figure **??** suggests that when accounting for time variation the correlation between gasoline prices and Laspeyres indices is low. It is also clear that the on average the magnitude of monthly gasoline prices changes is larger than for the Laspeyres.

A4 Additional results

A4.1 Analysis by food product category

Description of the food product categories

KWP assigns to each purchasing act the variable "Subgroup" that corresponds to 207 narrowly defined product groups. We define our fifteen categories as follows:

1. *Carbohydrates*: Pasta, Bread, Semolina, Cook-Type Cereals
2. *Fresh Vegetables and Fruits*: Fresh Vegetable, Fresh Fruit
3. *Red Meat*: Beef, Mutton, Lamb, Horse
4. *White Meat*: Chicken, Turkey, Veal, Rabbit, Pork, Poultry, Ham
5. *Other Meat*: Game Meat, Cold Cuts, Frogs, Kangaroo, Mix of Meat
6. *Fish*: Fish, Seafood, Fish eggs, Surimi, Cephalopods, Mix of Fish
7. *Eggs*: Hen Eggs, Quail Eggs
8. *Dairy*: Goat Cheese, Cow Cheese, Sheep Cheese, Melted Cheese, Milk
9. *Snacks*: Sugary Biscuits, Jam, Honey, Chocolate Spread, Cereal/Granola Bars, Chocolate, Pastries, Breakfast Drink Preparation, Breakfast Cereals, Ice Cream, Deserts, Dry Fruits and Seeds, Salty Biscuits, Olives, Crisps
10. *Ready Meals*: Prepared Dishes, Frozen Dishes, Canned Dishes
11. *Soft Drinks*: Sodas, Coffee, Tea, Infusions, Water, Chicory, Syrups, Juices
12. *Alcoholic Drinks*: Cocktail, Rum, Vodka, Cider, Champaign, Punch, Wine Aperetif, Liquor, Other Alcohol, Wine, Wisky-Bourbon, Bubbly Wine
13. *Seasonings*: Spices, Oil, Vinegar, Butter, Croutons, Breadcrumbs, Raw Pastry, Confectionary Flavorings, Flour, Cornflour, Prepared Crust, Coconut Milk, Cream, Lemon Juice, Fresh Herbs, Dry Herbs, Garlic, Onion.
14. *Canned Vegetables and Fruits*: Canned Fruits, Canned Vegetables, Frozen Fruits, Frozen Vegetables, Lyophilized Vegetables, Beans, Dried Vegetables, Packaged Vegetables
15. *Other*: Baby Food, Chewing Gum, Food Supplements

Quantities	(1) Carbs	(2) Fresh greens.	(3) Red m.	(4) White m.	(5) Other m.	(6) Fish	(7) Eggs	(8) Diary	(9) Snacks	(10) Ready Made	(11) Soft drinks	(12) Alcohol	(13) Seasonings	(14) Canned
National Gasoline Price	-0.477***	0.018	-0.414***	-0.209	-0.130	-0.405**	-0.020	0.009	-0.396***	-0.181	0.594***	-0.246	-0.230*	-0.329**
	(0.146)	(0.125)	(0.159)	(0.159)	(0.144)	(0.164)	(0.324)	(0.135)	(0.097)	(0.168)	(0.207)	(0.184)	(0.129)	(0.147)
Income	0.039	-0.096*	0.068	0.021	0.060	0.058	-0.105	0.070	0.017	0.066	0.101*	0.039	-0.038	0.051
	(0.040)	(0.053)	(0.047)	(0.046)	(0.046)	(0.047)	(0.164)	(0.053)	(0.045)	(0.062)	(0.058)	(0.058)	(0.034)	(0.050)
Household size	-0.163***	-0.155***	-0.168***	-0.142***	-0.158***	-0.203***	-0.144***	-0.129***	-0.114***	-0.139***	-0.055**	-0.165***	-0.146***	-0.146***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.021)	(0.019)	(0.055)	(0.024)	(0.021)	(0.024)	(0.024)	(0.021)	(0.016)	(0.019)
Local Laspeyres	0.011	0.006	-0.037	-0.010	-0.024	-0.048*	-0.007	-0.087***	-0.028	-0.027	-0.212***	-0.244***	0.011	-0.088***
	(0.023)	(0.020)	(0.027)	(0.024)	(0.022)	(0.027)	(0.032)	(0.024)	(0.018)	(0.025)	(0.032)	(0.033)	(0.020)	(0.023)
Unemployment rate	0.018***	0.020***	0.017***	0.015**	0.022***	0.017**	-0.008	0.015**	0.018***	0.012*	-0.000	0.010	0.006	0.007
(municipality)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.014)	(0.007)	(0.006)	(0.007)	(0.009)	(0.008)	(0.005)	(0.007)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ajd. R^2	0.337	0.592	0.353	0.438	0.404	0.413	0.438	0.493	0.528	0.445	0.502	0.564	0.400	0.353
Households	3542	3542	3502	3539	3539	3534	3312	3546	3546	3539	3546	3490	3546	3535
Observations	105020	119925	94242	118198	112180	105414	36154	121291	121946	109607	118908	85482	121087	105947

Notes:
Carbs refers to carbohydrates; fresh greens: fresh vegetables and fruits; Red m. (resp. White m. and Other m.) to red meat (resp. White meat and Other meat) ; Soft: non alcoholic beverages ; Canned: non fresh fruits and vegetables.
Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Quantities are expressed in grams per consumption unit.

Table A4.1: OLS regressions on quantities per food category

Table A4.2: OLS regressions on budget shares per food category

Budget shares	(1) Carbs	(2) Fresh greens.	(3) Red m.	(4) White m.	(5) Other m.	(6) Fish	(7) Eggs	(8) Diary	(9) Snacks	(10) Ready Made	(11) Soft drinks	(12) Alcohol	(13) Seasonings	(14) Canned
National Gasoline Price	0.000	-0.032***	-0.024***	-0.003	-0.008	-0.010	0.000	0.014*	0.044***	-0.009	0.038***	-0.017	0.006	-0.001
	(0.003)	(0.009)	(0.009)	(0.011)	(0.007)	(0.009)	(0.002)	(0.007)	(0.011)	(0.010)	(0.007)	(0.014)	(0.006)	(0.004)
Income	-0.001	-0.007*	0.005**	-0.005*	0.002	0.002	-0.002**	0.003	0.002	0.003	0.002	0.002	-0.004*	-0.001
	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.002)	(0.002)
Household size	0.000	-0.002	-0.001	-0.000	-0.001	-0.003***	0.000	0.000	-0.001	-0.001	-0.000	0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Local Laspeyres	0.000	-0.003**	0.002	-0.001	-0.000	0.000	-0.000	-0.003**	-0.005***	0.001	-0.002	0.016***	-0.003***	-0.003***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Unemployment rate (municipality)	-0.000	0.001***	0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.001**	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.386	0.641	0.364	0.392	0.357	0.435	0.371	0.507	0.598	0.573	0.439	0.573	0.407	0.346
Households	3546	3546	3546	3546	3546	3546	3546	3546	3546	3546	3546	3546	3546	3546
Observations	122814	122814	122814	122814	122814	122814	122814	122814	122814	122814	122814	122814	122814	122814

Notes:
Carbs refers to carbohydrates; fresh greens: fresh vegetables and fruits; Red m. (resp. White m. and Other m.) to red meat (resp. White meat and Other meat) ; Soft: non alcoholic beverages ; Canned: non fresh fruits and vegetables.
Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Budget shares are computed as the monthly food expenditures per category over the total monthly food expenditures.

Table A4.3: OLS regressions on unit prices per food category

Unit prices	(1) Carbs	(2) Fresh greens.	(3) Red m.	(4) White m.	(5) Other m.	(6) Fish	(7) Eggs	(8) Diary	(9) Snacks	(10) Ready Made	(11) Soft drinks	(12) Alcohol	(13) Seasonings	(14) Canned
National Gasoline Price	0.181**	-0.601***	-0.089	-0.071	-0.119	-0.182**	-0.245	0.001	0.267***	-0.176**	-0.252	-0.270**	0.128**	0.115
	(0.082)	(0.059)	(0.076)	(0.064)	(0.074)	(0.086)	(0.255)	(0.093)	(0.056)	(0.088)	(0.156)	(0.133)	(0.064)	(0.090)
Income	0.022	0.028	0.043	-0.005	0.073***	0.027	0.147	0.014	0.067***	0.053**	-0.009	0.014	0.059***	0.005
	(0.027)	(0.020)	(0.026)	(0.016)	(0.024)	(0.023)	(0.121)	(0.035)	(0.022)	(0.025)	(0.045)	(0.047)	(0.016)	(0.026)
Household size	-0.006	-0.013**	-0.005	-0.007	-0.017**	0.001	-0.056	-0.026*	-0.019**	-0.019**	-0.081***	-0.003	-0.018***	-0.017**
	(0.012)	(0.006)	(0.007)	(0.006)	(0.007)	(0.009)	(0.043)	(0.014)	(0.009)	(0.008)	(0.017)	(0.018)	(0.006)	(0.007)
Local Laspeyres	0.061***	0.037***	0.132***	0.070***	0.080***	0.128***	0.054***	0.146***	0.065***	0.115***	0.270***	0.550***	0.032***	0.080***
	(0.013)	(0.008)	(0.012)	(0.008)	(0.010)	(0.014)	(0.019)	(0.015)	(0.010)	(0.013)	(0.026)	(0.027)	(0.011)	(0.012)
Unemployment rate (municipality)	-0.003	0.013***	0.001	-0.002	0.000	-0.001	0.024**	0.002	-0.003	0.001	0.013**	-0.006	0.003	0.000
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.010)	(0.005)	(0.003)	(0.004)	(0.007)	(0.006)	(0.003)	(0.004)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.455	0.511	0.547	0.545	0.457	0.419	0.616	0.554	0.565	0.379	0.481	0.414	0.419	0.429
Households	3542	3542	3502	3539	3539	3534	3312	3546	3546	3539	3546	3490	3546	3535
Observations	105020	119925	94242	118198	112180	105414	36154	121291	121946	109607	118908	85482	121087	105947

Notes:
Carbs refers to carbohydrates; fresh greens: fresh vegetables and fruits; Red m. (resp. White m. and Other m.) to red meat (resp. White meat and Other meat) ; Soft: non alcoholic beverages ; Canned: non fresh fruits and vegetables.
Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses ; ***, **, *, indicate significance at the 1%, 5% and 10% levels. Unit prices and gasoline prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros per kilogram (resp. euro per liter).

A4.2 Regression models for the study of margins

In our main analysis we use OLS models. Because in subsection 5.3 we study count variables such as the number of shopping trips and the number of visited stores per month we here compares the results from OLS models with the ones from count data models. In particular, table A4.4 presents the results obtained from both methods (OLS and Poisson Pseudo-Maximum Likelihood) for each count variable[74]. The obtained results are very similar in terms of magnitude. However, we obtain more precise results when using a count data model.

	OLS		PPML	
	(1)	(2)	(3)	(4)
	Shopping trips	Shopping trips	Visited stores	Visited stores
National Gasoline Price	-0.339***	-0.180**	-0.355***	-0.168***
	(0.069)	(0.072)	(0.050)	(0.055)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.666	0.626		
Observations	122806	122806	122806	122806

Robust standard errors, adjusted for clustering at the municipality level, are presented in parentheses. ***, **, *, indicate significance at the 1%, 5% and 10% levels. The PPML model only provides Pseudo-R^2 that are worth 0.176 and 0.327 respectively.

Table A4.4: Margins: OLS and Count Data models

[74]For the count data model we use the *Stata* command **ppmlhdfe**. It is worth noting that both regression techniques are used on log-log models since in the OLS method the explained variable and national gasoline price is log-transformed when in the Count Model only the explanatory variable (in our case the national gasoline price is log-transformed).

A5 Discussion

A5.1 Local gasoline prices

Heterogeneity of gasoline prices per station type

The literature on gasoline prices (Gautier and Saout, 2015) highlights that in France, gasoline stations price differently by supplier type: it seems that supermarkets (and in particular hypermarkets) offer lower prices than oil corporations and independent stations. The dataset we use to get gasoline prices doesn't provide information about the type of station. To recover the type of gasoline stations we use the database that R. Le Saout has kindly agreed to share[75]. This database contains a station typology and has been created in 2009 thanks to online data scrapping[76]. This typology has been updated in 2011 and 2013 but not for all stations. The data contain exhaustive information for 2009, this allows to use the typology on five sixths of our sample (we loose 1320 over a total of over 9000 stations). The dependent variable is daily gasoline prices (accounting for inflation). As a reminder, the selection sample is all metropolitan French gasoline stations selling diesel, excluding highways.

Having this database allows us to test the assumption that gasoline prices are lower in supermarkets. It is worth denoting that most stations are supermarket stations (60%), the rest is 35.44% of oil corporations and independents (around 6%). Table A5.1 present the results of an OLS regression where the dependent variable is gasoline daily price at the pump and the explanatory variable is an indicator of the type of buyer. In this specification we use time and municipality fixed effects to account for time variation at the finest geographic level, that is the municipality in our case. The results suggest the marginal effect of the seller of gasoline being a supermarket is minus 0.07/euro per liter *ceteris paribus*. This is indicative of supermarkets pricing lower other suppliers (Oil corporations and Independents).

[75]Ronan Le Saout is an economic researcher and the Deputy Director of the French *Ecole nationale de la statistique et de l'analyse de l'information* (ENSAI).

[76]This database is used in Gautier and Saout (2015) and in Gautier and Le Saout (2017).

	(1) Gasoline Price	(2) Gasoline Price	(3) Gasoline Price
Supermarket (0/1)	-0.072***		
	(0.002)		
Oil corporation (0/1)		0.068***	
		(0.002)	
Independent (0/1)			0.039***
			(0.003)
Constant	1.442***	1.376***	1.398***
	(0.001)	(0.001)	(0.000)
Municipality FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R^2	0.843	0.823	0.723
Observations	262451	262451	262451

Notes:

Robust standard errors, adjusted for clustering at the living-zone level, are presented in parentheses. ***, **, *, indicate significance at the 1%, 5% and 10% levels.
The table encompasses years 2011 to 2013 and is restricted to our selection sample of gasoline stations. Gasoline price is the daily price per gasoline station. Time stands for date. Prices are deflated by the Consumer Price Index for consumer goods (Base: 2015) and are expressed in euros per liter of gasoline.

Table A5.1: Correlates of gasoline prices with station type