How does fuel demand respond to price changes?

Quasi-experimental evidence based on high-frequency data

Documents de travail

N° 2023-017 - Juillet 2023

Insee

Mesurer pour comprendre

Marine ADAM

Odran BONNET

Etienne FIZE

Tristan LOISEL

Marion RAULT

Lionel WILNER

Institut national de la statistique et des études économiques

2023/17

How does fuel demand respond to price changes? Quasi-experimental evidence based on high-frequency data

MARINE ADAM - ODRAN BONNET - ETIENNE FIZE
TRISTAN LOISEL - MARION RAULT - LIONEL WILNER*

Juillet 2023

Département des Études Économiques – Timbre G201
88, avenue Verdier – CS 70058 – 92541 MONTROUGE CEDEX – France
Tél. : 33 (1) 87 69 59 54 – E-mail : d3e-dg@insee.fr – Site Web Insee : http://www.insee.fr

*Adam, Bonnet: Insee. Fize, Rault: Conseil d'Analyse Économique. Loisel, Wilner: Insee-Crest. Please address correspondence to lionel.wilner@insee.fr. Address: 88 avenue Verdier, 92 120 Montrouge, France. Tel: (+33)187695917.
We thank Ao Wang for his discussion at Insee seminar, Nicolas Carnot, Xavier D'Haultfoeuille, Pauline Givord, Thomas Laurent, Thierry Magnac, Sébastien Roux for useful suggestions, as well as participants at AFSE, JMA and SEHO conferences. We also thank the Groupement des Cartes Bancaires CB (GIE CB), Pierre Leblanc and Corinne Darmaillac at Insee for providing with daily-level transaction data used to adjust for seasonality. We are extremely grateful to Crédit Mutuel-Alliance Fédérale for sharing the data with us, and in particular to key employees for their precious help. All individual data used in this analysis have been anonymized and no single customer can be traced in the data. All data processing has been conducted following the bank's strict data privacy guidelines.

L'ajustement de court terme de la consommation de carburant à des changements de prix
Des estimations menées à partir de données à haute fréquence

Cette étude s'appuie sur des expériences quasi-naturelles (flambée des cours du pétrole en 2022 et remises à la pompe consécutives à la guerre en Ukraine) pour inférer la sensibilité aux prix de la demande de carburant. La granularité des données bancaires, disponibles à une fréquence transactionnelle, permet de bien séparer les effets liés aux anticipations de l'effet-prix. Après avoir contrôlé des anticipations, nous obtenons une élasticité-prix comprise entre -0.4 et -0.21. L'élasticité-prix moyenne varie sensiblement avec la consommation de carburant, mais elle dépend peu du revenu ou du type d'habitat. Des simulations contrefactuelles permettent d'estimer les effets budgétaires, redistributifs et environnementaux des remises à la pompe.

Mots-clés : Demande de carburant ; élasticité-prix ; taxes indirectes ; droits d'accise ; anticipations ; données de transactions.

How does fuel demand respond to price changes?
Quasi-experimental evidence based on high-frequency data

This article exploits quasi-natural experiments provided by both the 2022 crude oil price surge consecutive to the Russo-Ukrainian war and fuel excise tax cuts in France to infer the price sensitivity of fuel demand. The granularity of bank account data available at the transaction level permits to shed new insights on how to properly disentangle anticipation effects from price effects. After controlling for anticipatory behavior, we obtain a price-elasticity comprised between -0.4 and -0.21. The average elasticity exhibits sizeable dispersion with respect to fuel spending, but varies little with income and location. Counterfactual simulations enable us to assess both financial and distributive impacts of the tax policy at stake as well as its effect on CO_2 emissions.

Keywords: Fuel demand; price elasticity; excise tax changes; anticipatory behavior; transaction-level data.

Classification JEL : C18; C51; D12; H23; H31; L71; Q31; Q35; Q41.

1 Introduction

Due to the crude oil price surge consecutive to the Russian attempt of invading Ukraine and the 2022 energy crisis, the budget constraint of many households may have become tighter, and close to binding -especially for those living in rural areas and those who are unable to adjust their fuel consumption due to the absence of any alternate transportation. The short-term price-elasticity is a key parameter of fuel demand that governs how households undergo such a price variation: the policy-maker may therefore be willing to dispose of credible estimates of this sufficient statistics, as well as of its heterogeneity. A huge empirical literature devoted to that issue has already spent time explaining that several requirements must yet be fulfilled in order to provide such estimates. First, the econometrician should rely on exogenous price shocks when inferring the price sensitivity. Second, she must dispose of granular data in order to track consumer response over time. Third, she has to disentangle anticipation effects from price effects, based on the assumption, say, that the former affect the sole timing of purchases, while total consumption depends on the latter only.

In this paper, we rely on a bunch of recent quasi-natural experiments: the oil price surge consecutive to the Russian invasion of Ukraine, and tax policies designed to temper that inflation. Indeed, in several European countries including Germany and France, governments decided to directly subsidize fuel at the pump, which is formally equivalent to excise tax cuts. Those price shocks provide us with an appropriate source of identifying variability, and we exploit those exogenous price variations in order to infer the price sensitivity of fuel demand. Our empirical analysis is based on high-frequency data, namely transaction-level data issued from bank accounts, which includes timestamped operations at the individual level from September 2021 to January 2023. We show that disposing of daily data enables us to finely disentangle anticipation effects from the pure price effect -a long-lasting concern for applied econometricians. Such data enables us to first visualize then neutralize (very) short-run (i.e. daily) anticipation effects, and we thus propose an econometric approach that correctly separates anticipation effects from the sole price effect. Levin et al. (2017) have already pointed out that low-frequency data suffered from such an aggregation bias due to three distinct reasons: (i) a common price coefficient is imposed while price sensitivities might be heterogeneous, say, at some spatial unit (city) level; (ii) less granular datasets do not allow to include appropriate space or time fixed effects viewed as unobserved components which permit to remove any supply-driven variation induced by fluctuations in price over time, for instance; (iii) aggregation might induce some correlation between average prices and the error term, e.g. when correlation between prices and demand shocks on other days, or in other cities, can cause prices and errors in the aggregated panel data to be correlated.

Taking further advantage of our individual data, we then investigate whether the price elasticity displays some heterogeneity across income and location, two possibly relevant dimensions of a compensatory tax-and-transfer scheme. Our findings concur to that average price elasticity, which lies in the [-0.4,-0.21] interval, exhibiting sizeable dispersion with respect to fuel spending, but varying little with income and location. Note yet that responses to a same price change can be quite heterogeneous, in nominal terms, along those dimensions, due to different initial levels of fuel spending. More strikingly, we find sizeable dispersion of the price sensitivity with respect to (past) fuel spending: the elasticity markedly decreases with fuel spending, in absolute. Our results therefore help improve the targeting of compensatory transfer schemes combined with Pigouvian taxes. More broadly, they provide a finer knowledge of fuel spending determinants that is useful to reduce the prediction problem mentioned by Sallee (2019), ideally lowering the number of losers in a Pigouvian-based tax-and-transfer scheme.[1] Last, we perform counterfactual simulations to quantify both financial and distributive impacts of the excise tax policy at stake; our estimates suggest that the average effect per household amounts to saving between €51 and €81 (from 0.15% to 0.24% of income). We find that alleviating the tax burden has relatively less favored low-income individuals, in nominal terms, since high-income individuals benefited most from those excise tax cuts; when expressed as a fraction of income, this gain nevertheless decreases with income, the effective tax rate being diminished by up to 0.26pp at the lower end of that distribution (against 0.09pp only at the top). Finally, the effect of the policy on CO_2 emissions is comprised between +0.24% and +0.46%.

Literature A vast empirical literature, surveyed for instance in Dahl and Sterner (1991) and Espey (1998), has been devoted to measuring the short-run price elasticity of fuel demand. The latter may differ from the long-run price elasticity since it takes time for

[1] In another but somehow related vein, we wonder whether consumers identically respond to either upward or downward price variations. To that goal, we also infer the price elasticity based on the end of excise tax cuts occurring on January 1st, 2023, and which resulted in a corresponding price increase. We find no evidence of any asymmetry, which is in line with Kilian (2022).

consumers to adjust their response, by shifting to another transportation for instance. Yet those studies have so far relied mostly on disaggregated data, hence facing two fundamental problems.

The first issue is endogeneity arising due to simultaneity: in a demand equation, the price is concomitantly determined by the supply side as a function of the quantity purchased. This simultaneity bias results in OLS suffering from an attenuation bias. The typical solution invoked by the literature consists in finding instruments in order to fix that problem. Such instuments include the West Texas Intermediate (WTI) crude oil spot price, the price of the brent, the average price in the market considered, some tax change -and more generally, any predictor of price like a cost shifter that is as unrelated as possible with demand usage. This solution may nevertheless overestimate the price sensitivity of fuel spending, due to tax aversion for instance.

The second empirical issue that complicates the estimation of demand is anticipatory behavior. When consumers expect price reductions, they may strategically delay their purchases: intertemporal substitution arises possibly through dips (resp. spikes) when future prices are expected to be lower (resp. higher), which invalidates previous approaches. The current quantity then depends not only on current prices, but also on future prices, which violates usual exclusion restrictions at play in both OLS and IV estimation methods: contemporaneous changes in fuel purchases may be larger than expected, and even IV estimates overstate the price sensitivity of demand. A typical solution to deal with this problem consists in introducing leads and lags as in Coglianese et al. (2017), or, more recently, in Kilian (2022); yet this approach relies on parametric assumptions as regards the dependence of expectations with respect to future and past prices. We build upon that literature concerned with anticipations thanks to both high-frequency data and an appropriate econometric methodology.

A few recent studies have resorted to high-frequency data in order to estimate the price sensitivity of fuel spending, hereby trying to quantify the aggregation bias inherent to less granular datasets (as we do), including Levin et al. (2017) and Knittel and Tanaka (2021); the latter disentangle extensive from intensive margins, i.e. driving behavior from travelling distance. We improve upon their methodology by relying on an exogenous source of price variations, namely the 2022 oil crisis partly consecutive to the Russian invasion of Ukraine and corresponding policy responses in France, namely two temporary, successive excise tax cuts starting on April 1st and September 1st, and lasting until the end of 2022. From that viewpoint, the closest paper to ours is Gelman et al. (2022), who also exploit a dataset issued from banking accounts and rely on large unexpected shocks (about -50% in 6 months). They mostly examine cross-price effects with other spending than fuel, though. Another empirical difference lies in their analysis being based on large, but continuous price changes, while we rely on sharp, sudden variations arising at publicly known dates. We therefore view our identification strategy as complementary to theirs; on top of that, we adopt an econometric specification that controls for anticipatory behavior.

The rest of the paper is organized as follows. Section 2 presents our data and the institutional background. To illustrate how anticipation effects can be disentangled from price effects, a toy model is exposed in Section 3. The empirical analysis from Section 4 includes our identification strategy as well as our econometric specification. Section 5 contains our results and an investigation of the heterogeneity of the price elasticity; it also includes counterfactual simulations to quantify both financial and distributive impacts of the tax policy, as well as its effect on CO_2 emissions. Section 6 concludes.

2 Data and context

In this section, we present our de-identified bank account data. Our database is issued from the *Crédit Mutuel Alliance Fédérale*, a French group of banks with about 30 million customers. The construction of key variables follows a recent strand of literature exploiting such data including, e.g., Baker (2018), Ganong and Noel (2019) and Andersen et al. (2023). We dispose of transaction-level data on credit and debit card payments,[2] paper checks, cash withdrawals, cash deposits, bank transfers, and direct debits. We observe the amount of each transaction, in euros; such information is timestamped, hence available at a high frequency. We nevertheless base our analysis on a daily aggregation. On top of that, balance sheets are available each month. The statistical unit of observation is a household; the data contains various socio-demographics on households' members like age, sex, *département*,[3] family status, occupation, and the type of location (in 3 categories:

[2]In France, the use of credit cards is scarce: it accounts for less than 10% of bank cards.

[3]an administrative division like, e.g., the county in the U.S. Mainland France, i.e. France at the exclusion of Corsica and overseas, is divided into 94 *départements*. Metropolitan France includes the two Corsican *départements*.

urban, rural, and semiurban areas).

We define total spending as the sum of outgoing transactions issued by debit card. We measure disposable income as the sum of monthly incoming transfers, up to a €40,000 threshold. Liquid assets are proxied by the sum of balances on different bank accounts (deposit account and savings accounts), and provide us with a measure of liquid wealth. Illiquid assets are equal to the sum of balances on life insurance, stocks, bonds, mutual funds and certificates of deposits. In France, banks are not in charge of retirement savings plans.

Working sample Our estimation period runs from September 2021 to January 2023. Our initial raw data is a sample of about 300,000 households who primarily bank at *Crédit Mutuel-Alliance Fédérale*, this sample being stratified by *départements* of metropolitan France and by 5-year age dummies. To alleviate concerns about representativeness, we proceed to calibration weighting using the method proposed by Deville and Särndal (1992) (see Appendix D for details), and weight our estimating equations using calibration weights. We further restrict our attention to households with the same number of adults (aged at least 18) over the period. We focus on customers who spend at least €150 during three rolling months, either by card or in cash. Moreover, we impose that customers be present and meet previous criteria all over the period, which leaves us with about 182,000 active customers primarily banking at *Crédit Mutuel-Alliance Fédérale*.

Fuel spending Our bank account data provide the Merchant Category Code (MCC) classification. Based on that taxonomy, we consider that spending categorized with codes 5541 and 5542 corresponds to fuel spending as Andersen et al. (2023) and Gelman et al. (2022) do. Figure 1 displays the distribution of the amount of a transaction, in euros, which is a mixture of a continuous distribution, the mode of which lies nearly 55 euros, and of a discrete distribution over round numbers, typically 30, 20, 50 or 40 euros, as well as other multiples of 5 euros. Figure 2 shows further that the typical interpurchase duration, i.e. the time interval between two visits at the pump, is 7 days. We then adjust fuel spending for seasonal variations based on card transaction data provided at the daily level by the *Groupement des Cartes Bancaires CB* (GIE CB), the leading domestic card and mobile payment system in France, that brings together around 130 bankings or similar institutions offering payment services in France.[4] To that aim, we divide observed fuel spending by the 2019 ratio of daily fuel spending over average fuel spending, based on that external database.[5] Last, we obtain fuel quantity, in liters, as the ratio of that adjusted fuel spending over the fuel price index; we now explain how we compute the latter.[6]

Prices Timestamped and geolocated fuel prices are disclosed at the gas station level by a French governmental website.[7] Such data has already been used by researchers: see, e.g., Montag et al. (2021) or Gautier et al. (2022). It contains information on each and any price change for different kinds of fuel (diesel and different types of gasoline: super unleaded petrol (SP95), super unleaded petrol (SP95-E10), super unleaded petrol (SP98), etc.). In the subsequent analysis, we focus on two types of fuel: diesel and standard gasoline, which we confound with SP95-E10, given that the latter exhibits similar variations over time as both SP95 and SP98. On top of that, the data provides with an identifier and the location of each retailer.

As detailed in Appendix A of Gautier et al. (2022), the first step consists in mapping raw data to a daily panel dataset at the (retailer, type of gasoline) level. Since different price changes may occur within the same day, we consider the price that prevails at 5pm as Montag et al. (2021) do. In a second step, we remove inactive stations, which we define as stations that have not experienced any price change since at least 30 days, following Gautier et al. (2022). We then trim outliers by deleting top and bottom 1% of price observations for each (*département*, type of fuel, day). Admittedly, transaction prices are measured with error: we ignore the exact location of purchase, hence we approximate them with their daily average in the *département*.

As another limitation of our data, we lack information about the type of fuel actually purchased, diesel or gasoline, which is yet unimportant provided that those prices similarly covary. Empirically, those prices are very correlated: the corresponding Pearson coefficient

[4] In the DinD exposed in section 4.1, such an adjustment is not necessary. See also section D.1.

[5] We also exclude October 2022, due to strikes in refineries, which were responsible for rationing in many localities.

[6] Cross-border purchases, which result from trade-offs that involve, in particular, the distance to the frontier and the ratio of foreign over domestic prices, are excluded from the current analysis. More precisely, we exclude individuals living next to a border, which we identify in the data as soon as they purchase some fuel abroad -holidays aside. Foreign transactions occurring during holidays are also removed from the subsequent analysis.

[7] https://www.prix-carburants.gouv.fr/rubrique/opendata/.

is 0.9 over the whole period of observation, even though diesel and gasoline prices sometimes experience different short-run variations due to specific conditions affecting the oil market, for instance. We therefore build a fuel price index that weighs diesel and gasoline prices differently within a *département* according to strata based on observed households' characteristics. According to the French survey *Enquête Mobilité*,[8] these characteristics (income, in four groups, the type of location (urban, rural, semiurban), age group (less than 30, 30-60, more than 60), and 2019 fuel spending, in four groups) are good predictors of the type of fuel purchased. From this survey, we impute the corresponding weight of diesel in the fuel mix in each stratum defined by the Cartesian product of those characteristics.

Context: War in Ukraine, energy crisis, and policy responses (temporary excise tax cuts) Fuel prices have experienced substantial variations from 2019 to 2023, especially in 2022, for instance due to an oil price surge consecutive to the Russian invasion of Ukraine starting on 02-24-2022. The world then faced a pervasive oil crisis: for the first time since the Great Recession, the price of a barrel exceeded the symbolic $120 threshold, in nominal terms. In France, the government decided to intervene by directly subsidizing prices at the pump. On 03-12-2022, Prime Minister Castex made an official announcement to explain that the before-tax gasoline price would be diminished by 0.15€ per liter from April 1st onwards (about 0.18€ per liter including VAT, with some minor geographic variations due to *département*-specific VAT rates), see Figure 3. While this first public intervention was bound to last until the end of Summer 2022, the Parliament decided to extend it to the beginning of October, consecutive to the energy crisis. As announced by Prime Minister Borne at the end of July 2022, a 0.3€ discount per liter has then been effective on the after-tax price from 09-01-2022 onwards, i.e. an extra 0.12€ subsidy for each liter purchased. This second price reduction has prevailed until mid-November 2022 when that discount has been reduced to 0.1€ per liter, before its complete removal on January 1st, 2023. Meanwhile, the leading French oil company, TotalEnergies, proposed an extra 0.20€ promotion for each liter purchased in its gas stations, effectively lowering transaction prices by 0.50€ per liter from 09-01-2022 to mid-November (and still offering an extra 0.1€ discount per liter from that time onwards). All those reductions disappeared at the end of 2022. Note also that before the implementation of those substantial price cuts, which

[8]Detailed results of this survey are available online at https://www.statistiques.developpementdurable.gouv.fr/resultats-detailles-de-lenquete-mobilite-despersonnes-de-2019.

all aimed at mitigating the rise in crude oil prices, prices were already increasing at a high pace, even before the Russian invasion of Ukraine.

In what follows, we focus on the time period ranging from September 2021 to January 2023, and we rely on policy-driven fuel price reductions as the primary source of identifying variability in order to causally infer price effects. We view the two public interventions described above as quasi-natural experiments, which provide us with exogenous price changes. In France, per unit excise taxes represent about 60% of fuel prices. When announcing a direct discount at the pump, the French government in fact and equivalently proposed to offer a discount on those taxes. These public policies were publicly disclosed, hence salient to consumers. Figure 3 suggests that the evolution of fuel demand at the time of announcement is consistent with anticipatory behavior by forward-looking consumers: people strategically refrain from buying and wait for lower future prices once they are aware of lower prices in the future. Figure 25 in Online Appendix further confirms the salience of that intervention, and indicates that consumers mostly adapted to the policy by buying less before price reductions (hence adjusting at the intensive margin), rather than by visiting gas stations less often (the number of transactions being a proxy for the extensive margin). This anticipatory behavior however renders the identification more subtle, and requires to properly disentangle short-term intertemporal substitution from the true price effect.

3 Theoretical framework

To illustrate how the price effect can be disentangled from anticipation effects in a dynamic setting, we resort to a simple conceptual framework, namely a stylized inventory model of fuel stockpiling behavior. We then explain how this setting can be meaningful for empirical analysis, especially as regards identification.

3.1 A stylized inventory model of fuel stockpiling behavior

Let a representative agent maximize her intertemporal utility with respect to her fuel consumption c, subject to intertemporal budget constraint and to the law of motion of fuel inventory i.[9] Given that the period considered in our empirical application below is typi-

[9] The model is a simplified version of typical inventory models used, e.g., by Hendel and Nevo (2006).

cally a day or a week, it is reasonable to assume no depreciation of fuel (when stockpiled), a discount factor equal to one, and a zero interest rate. Denoting the instantaneous utility derived from consumption by $u(.)$, fuel purchases by q, fuel prices by p, permanent income by Y, and storage costs by $C(.)$,[10] the agent solves:

$$\max_{(c,i)} \sum_{t=0}^{T} [u(c_t) - C(i_t)] \quad \text{s.t.} \quad \sum_{t=0}^{T} p_t q_t \leq Y \tag{1}$$

$$i_t \leq i_{t-1} + q_t - c_t \tag{2}$$

Under the assumption of no fuel waste, the law of motion of fuel inventory binds at all periods:

$$\max_{(c,i)} \sum_{t=0}^{T} [u(c_t) - C(i_t)] \quad \text{s.t.} \quad \sum_{t=0}^{T} [p_t c_t + p_t(i_t - i_{t-1})] \leq Y \tag{3}$$

In the optimum, the intertemporal budget constraint binds, the Euler equation holds, and fuel inventory is ruled by:

$$C'(i_t) = \lambda(p_{t+1} - p_t) \tag{4}$$

The latter equation makes it clear that stockpiling behavior is governed by the expected change in prices. Parametrizing $C(i_t) = \theta i_t^2$ with $\theta > 0$ leads to:

$$i_t = \lambda \frac{p_{t+1} - p_t}{2\theta}, \tag{5}$$

and considering further a quadratic utility function of the form $u(c_t) = c_t - \alpha c_t^2$, with $\alpha > 0$, yields a linear demand:[11]

$$c_t = \frac{1 - \lambda p_t}{2\alpha}. \tag{6}$$

The model therefore predicts that observed purchases are given by:

$$q_t = c_t + \lambda \frac{p_{t+1} + p_{t-1} - 2p_t}{2\theta} = \frac{1}{2\alpha} - \lambda \left(\frac{1}{2\alpha} + \frac{1}{\theta} \right) p_t + \frac{\lambda}{2\theta} p_{t-1} + \frac{\lambda}{2\theta} p_{t+1}, \tag{7}$$

[10] Taking the tank's capacity into account in the model is then possible, for instance by considering the limit case when those costs become infinite (see also the discussion below).

[11] Marshall's second law of demand is verified: the price-elasticity decreases with consumption, in absolute: $-\frac{\partial \log(c_t)}{\partial \log(p_t)} = \frac{\lambda p_t}{1 - \lambda p_t} = \frac{1}{2\alpha c_t} - 1$.

hence a specification such that:

$$q_t = q_0 + \beta p_t + \gamma_t \max(\mathbb{1}_{p_{t-1} \neq p_t}, \mathbb{1}_{p_{t+1} \neq p_t}) \tag{8}$$

where $\beta = -\frac{\lambda}{2\alpha}$. On top of the price effect, anticipation effects $\gamma_t = \lambda \frac{(p_{t+1}-p_t)-(p_t-p_{t-1})}{2\theta}$, which are non-zero as soon as prices fluctuate, alter current consumption. This specification provides a micro-foundation for the toy econometric model exposed below in section 3.2 as well as for our estimating equation (10). Note that anticipation effects increase with storability: they vanish (resp. are exacerbated) when θ tends to $+\infty$ (resp. 0), that is, when storage is impossible (resp. not costly) -when the good is perishable or when the tank is full, for instance.[12]

That observed purchases depend on lags and leads of prices on top of current prices, as in the right-hand side of (7), is reminiscent of Coglianese et al. (2017). Though stylized, this conceptual framework thus rationalizes any reduced-form approach like theirs that involves a regression of purchases on past, current, and future prices when aiming to recover the price-elasticity.[13] It is also immediate to check that the price effect $\beta = -\frac{\lambda}{2\alpha} = -\lambda\left(\frac{1}{2\alpha} + \frac{1}{\theta}\right) + \frac{\lambda}{2\theta} + \frac{\lambda}{2\theta}$ can be retrieved from the sum of coefficients related to current, past, and future prices, which helps explain why Coglianese et al. (2017) intuitively proceed as such.

3.2 Implications for identification

Previous insights shed light on the identification of both price and anticipation effects. To illustrate, we now present a toy econometric model derived from previous specification, which empirically permits to disentangle anticipatory behavior from price-sensitivity. Empirically, the model relates to a single, expected price reduction as the one experienced around September 1st, 2022. In the same vein, Appendix C.2 provides with another model that is more relevant in the case of an expected[14] price surge followed by some anticipated price reduction of the same magnitude, as was the case in March-April 2022.

[12] Note also that those anticipation effects γ_t are shaped here by parametric assumptions made in the inventory model, contrary to what prevails in our agnostic approach below where these coefficients are not subject to such restrictions.

[13] It is straightforward to see from equation (5) that inventory behavior acts as the theoretical driver of such an empirical approach.

[14] In the very short-run, at least.

A simplified version of the second excise tax cut, i.e. the policy-driven price change of September 1st, 2022, is described by Figure 4a. We consider a 4-period model whereby periods are indexed by $k = 1, \dots, 4$. In the first two periods, prices are assumed to be constant, and equal to their regular level: $p_k = p$, $\forall k = 1, 2$. Consecutive to governmental intervention, prices fall to $p_k = p - \Delta p$, $\forall k = 3, 4$, where $\Delta p > 0$ is the amount of the excise tax cut. By definition, periods 1 and 4 are immune of any anticipation effect, such that consumption is driven by pure price motives during those periods. In contrast, anticipation effects are at stake in periods 2 and 3 (the *anticipation window* hereafter): consumers strategically refrain from buying in period 2, but eventually buy in period 3 what they did not buy in period 2. Put differently, part of consumption is postponed from period 2 to period 3 in order to enjoy the discount -but not to period 4, by assumption: anticipation effects affect the timing of purchase only, while prices determine the amount of fuel purchased over the whole episode. We also emphasize that consumers cannot postpone *sine die* due, e.g., to tank capacity: in practice, periods 2 and 3 may last one or two weeks (see the discussion on the empirical duration of the anticipation window in section 4.2).

To ease exposure, we assume further that the researcher observes prices and purchases at the aggregate level here, but the reasoning is similar when based on micro data. Due to previous considerations, she seeks to estimate the following linear model:

$$q_t = q_0 + \beta p_t + \gamma_2 \mathbb{1}_{t=2} + \gamma_3 \mathbb{1}_{t=3} + u_t, \tag{9}$$

based on four moment conditions: $\mathbb{E}(u) = 0$, $\mathbb{E}(pu) = 0$ on top of $u_2 = u_3 = 0$. To make an explicit link with previous subsection, the inventory model would impose supplementary constraints: $\gamma_2 = -\lambda \frac{\Delta p}{2\theta} < 0$ and $\gamma_3 = \lambda \frac{\Delta p}{2\theta} > 0$, and would then predict that $i_1 = i_3 = i_4 = 0, i_2 = -\lambda \frac{\Delta p}{2\theta}$, hence that $q_2 = c_1 - \lambda \frac{\Delta p}{2\theta} < q_1 = c_1 < q_4 = c_4 < q_3 = c_4 + \lambda \frac{\Delta p}{2\theta}$. Consistently with the econometric model at stake, $\gamma_2 = q_2 - c_2 = -\lambda \frac{\Delta p}{2\theta} = q_2 - q_1, \gamma_3 = q_3 - c_3 = \lambda \frac{\Delta p}{2\theta} = q_3 - q_4$, thus $\gamma_2 + \gamma_3 = 0$ (cf. constrained estimator below).

Among the four parameters $(q_0, \beta, \gamma_2, \gamma_3)$, she is primarily interested in the marginal effect of prices. Consistently with observation, she expects that $q_2 < q_1 < q_4 < q_3$: it must be that $q_1 < q_4$ as a result of lower prices, i.e. $p - \Delta p = p_4 < p_1 = p$. One should have $q_2 < q_1$ due to strategic delay of purchases on period 2, i.e. before the price reduction; it then follows that $q_3 > q_4$ since people who refrained from buying at higher prices should now buy at lower prices.

A naive approach issued from an OLS estimation that would omit to nonparametrically control for anticipation effects in periods 2 and 3, *de facto* imposing that $\gamma_2 = \gamma_3 = 0$, would yield: $\hat{\beta}^n = \frac{(q_1+q_2)/2-(q_3+q_4)/2}{\Delta p}$ (see Appendix C.1.3 for further details). By definition, that estimator does not permit to separate anticipation effects[15] from the pure price effect, which results in spuriously relying on $(q_2,\ q_3)$ to infer the marginal effect of price. Controlling now for what happens during the *anticipation window*, which is centered around the moment when prices fall, yields the unconstrained estimator: $\hat{\beta}^u = \frac{q_1-q_4}{p_1-p_4} = \frac{q_1-q_4}{\Delta p}$ (cf. Appendix C.1.1), which recovers the desired price effect net of any strategic effect. Anticipation effects are $\hat{\gamma}_2^u = q_2 - q_1 < 0$ and $\hat{\gamma}_3^u = q_3 - q_4 > 0$. By construction, this procedure dismisses any contribution from periods 2 and 3, which entails a loss of information. Our proposed estimation procedure consists rather in imposing the constraint that $\gamma_2 + \gamma_3 = 0$, i.e. in assuming that anticipation effects sum up to zero all over the anticipation window.[16] Put differently, our identifying assumption posits that individuals may refrain from buying fuel in period 2 for pure intertemporal substitution motives, because they wait for lower prices, but that they will eventually buy an excess quantity in period 3 that exactly corresponds to default quantity from period 2. Though equal to the unconstrained estimator (cf. Appendix C.1.2), the constrained estimator $\hat{\beta}^c$ being independent from $(q_2,\ q_3)$ results from both the specific price process considered here and the symmetry of the episode with respect to the moment when prices fall. By contrast, the unconstrained estimator $\hat{\beta}^u$ is generally independent from (q_2, q_3). Empirically, small price variations during that anticipation window may be exploited for inference -contrary to what would happen without imposing that constraint.

Though simplified, this conceptual framework closely resembles the situation that prevails as regards the second excise tax cut implemented on September 1st. Equipped with the above toy model, observed prices and purchases, and adjusting 2022 data for seasonality based on 2021 observations as in the DinD strategy from section 4.1 below (see Appendix C.3), we obtain an elasticity of -0.38 in the absence of any constraint on γ_2 and γ_3, therefore relying on the unconstrained estimator. The constrained estimator amounts to -0.4 under the constraint that anticipation effects exactly compensate over the antic-

[15]Those effects are negative when $k = 2$ and positive when $k = 3$.

[16]Hence the empirical test of $H_0 : q_1 + q_4 = q_2 + q_3$, given the above price process. Under that assumption, $\hat{\gamma}_2^c = \frac{(q_2-q_1)+(q_4-q_3)}{2} < 0$.

ipation window, $\gamma_2 + \gamma_3 = 0$. The naive estimator is -0.73 when $\gamma_k = 0$, $\forall k = 2, 3$, i.e. when anticipations act as a confounder. Those figures turn out to be close to econometric point estimates (see below), and already give a flavor of the magnitude of the anticipation bias, namely $(-0.73) - (-0.4) \approx -0.33$. Any difference with the actual econometric estimation lies in that the model (i) does not account for covariations of prices and quantities within each period, and (ii) slightly departs from observation since, empirically, prices do not behave exactly as in the theoretical setting considered here.

To sum up, the main insights of the toy model are the following: (i) anticipations bias the naive estimator downwards; (ii) the constrained estimator should not differ much from the unconstrained estimator, when the latter is feasible; (iii) the former is more precise, which especially matters when the latter is empirically uninformative.

4 Empirical analysis

In that section, we explain how observed variations in prices over time within our observation period can be exploited to infer the price sensitivity of fuel demand. In particular, we rely on substantial price changes, including various price increases,[17] combined with two downwards, policy-driven price changes: the 0.18€ per liter excise tax cut from April 1st, 2022, and the extra 0.12€ per liter reduction on after-tax prices from September 1st, 2022. We show that these sharp price variations provide us with valuable information, which enables us to recover the shape of the demand function based on our high-frequency dataset. The identifiying variability stems from sharp price changes viewed as quasi-natural experiments. Our empirical methodology consists in disentangling anticipation effects from the aversion to prices.

4.1 Identification strategy

Our approach is inspired by the event study literature and exploits the second public intervention, the extra €0.12 per liter excise tax cut, from September 1st, 2022 as a quasi-natural experiment. A simple comparison of fuel purchases before and after the tax cut would yet be misleading due to seasonality of fuel spending; however, under the assumption

[17] about +50% from September 2021 to the end of February 2022, +30% during the two weeks following the declaration of Ukrainian war, +20% in May-June 2022, +€0.2 per liter from mid-November 2022, and +€0.1 per liter from January 1st, 2023 onwards.

that the pattern of fuel purchases would have been the same in August-September 2022 as in August-September 2021, it is then legitimate to proceed to such a comparison. Formally, this seasonal adjustment is analogous to a DinD design, whereby the "treatment group" would be any household in 2022 (the treatment being the exogenous tax cut) and the "control group" the same household observed exactly one year before. Figure 5 makes it clear that our empirical setting looks close to previous theoretical model. Identification mostly rests on prices falling sharply on September 1st, 2022 but also, to a minor extent, on their pattern not being as flat as in 2021. The reason why we cannot resort to a similar identification strategy as regards the first public intervention in April 2022 is that we lack a credible comparison year, due to partial lockdown occurring in April 2021.[18]

To address potential concerns about measurement error and simultaneity bias, we also resort to an IV strategy based on a post-9/1 dummy (indicating whether the discount at the pump is effective or not) as an instrument for prices. This approach further enables us to compare what one would obtain when relying on sharp tax-based price changes as the sole source of variability, as opposed to other smaller price fluctuations, on top of tempering any endogeneity concern.

We control for anticipation effects as well as for their consequences once the event, i.e. the price reduction, has realized. Former empirical studies on fuel demand have proposed parametric solutions to deal with anticipation effects: see, e.g., Coglianese et al. (2017) who resort to price lags and leads based on monthly-level data. We resort here to a nonparametric approach, which makes full use of our high-frequency dataset. We hence rely on the covariation of prices and purchases, net of anticipation effects: intertemporal substitution effects act as a nuisance factor in the estimation of the price sensitivity of demand. As a result, we control for daily effects during the anticipation window which is centered around the event. Consistently with theoretical arguments exposed previously, we impose that those effects sum to zero: our identifying assumption is that very short-term (i.e. daily) variations in fuel purchases around the event correspond to pure intertemporal substitution, but do not impact the total quantity purchased within that time window.[19]

[18] April 2020 is not possible either due to strict lockdown. April 2019 could have been a relevant comparison year; unfortunately, the information about the MCC has been available in the data since September 2019 only.

[19] In a wording borrowed from the bunching literature, there is no excess mass after event, once pre-event default mass has been netted out.

Equipped with those zero-sum, daily dummies designed to neutralize anticipatory behavior, it is then possible to recover the sole price effect, which we are primarily interested in.

Our identification relies on the assumption that, in the absence of the tax cut, fuel purchases would have exhibited similar patterns over time in 2021 and in 2022. Figure 7 depicts the corresponding difference, and suggests that this hypothesis has some empirical relevance: previous assumption cannot be rejected on the basis of the data looking at what happens before September 1st. When testing for the existence of any significant difference in the pattern of fuel purchases over time, short-run anticipations should be left aside: as already explained, it is largely expected that a policy-induced dip be observed within a one- or two-week anticipation window, followed by a spike at the beginning of the post-event era. As a robustness check, we resort to the year 2019 as an alternate comparison year.[20] Replicating the same exercise with that other control year yields to similar conclusions.

4.2 Econometric specification

We first aggregate our data into 10,777 cells of individuals in the same *département*, income group (in four intervals), age group (less than 30, 30-60, more than 60), type of location (rural, urban, or semiurban), and 2019 fuel spending category (in four intervals). Our estimations are then weighted according to the sampling importance of those cells. Though this mild choice substantially reduces the computational burden inherent to dealing with high-frequency individual data, it does not reduce our identifying power, since diesel and gasoline prices are measured at *département* $\times$ day level. It is yet worth noting that our fuel price index does vary within a *département* due to the cell-specific fuel mix. Besides, our estimations include cell-specific fixed effects in order to take the heterogeneity of fuel spending across cells into account.

We then distinguish calendar time t, measured at the daily level, from year $y = 2021, 2022$. We restrict our sample to observations ranging from mid-July to the beginning of October, both in 2021 and 2022. Our dependent variable, q_{cty}, is the fuel quantity, in liters, purchased by individuals belonging to cell c on day t of year y, adjusted for seasonal

[20] We omit to consider year 2020 as a valid control year: fuel spending was severely impacted by the Covid-19 pandemic and consecutive policy restrictions.

variations.

$$q_{cty} = \beta p_{cty} + \sum_{h=t_2-\Delta}^{t_2+\Delta} \gamma_{hy} \mathbb{1}_{h=t} \mathbb{1}_{y=2022} + \alpha_{cy} + \mu_t + \eta_{cty}, \tag{10}$$

where p_{ct} are prices, α_{cy} is a cell-year fixed effect, μ_t is a day-of-the-year fixed-effect (after adjusting for seasonality, i.e. after adjusting 2021 calendar days so that they be comparable with those of 2022). t_2 corresponds to the beginning of the second excise tax cut, namely September 1st. The time interval $[t_2 - \Delta, t_2 + \Delta]$ therefore designates the anticipation window around that event, and Δ is a bandwidth parameter set by the researcher (see below). To control for anticipation effects, equation (10) is estimated under the constraint that

$$\sum_{h=t_2-\Delta}^{t_2+\Delta} \gamma_{h,2022} = 0, \tag{11}$$

as explained before. The identification of the price effect β[21] hence proceeds from the ratio of the difference in fuel purchases that are adjacent to the anticipation window over the difference in corresponding prices, remember the $\frac{q_1-q_4}{\Delta p}$ estimator from section 3. The DinD basically adjusts the numerator for seasonality by considering 2022 purchases net of 2021 purchases, and given the absence of any (substantial) variation in prices around September 2021 (i.e. in the denominator). Standard errors are computed with two-way clustering by cell and by year-day.

In practice, the choice of the anticipation bandwidth Δ may be guided either from a statistical criterion, or from economical considerations. A reasonable value should be close to the typical interpurchase duration, about 7 days (remember Figure 2): everything happens as if people made a regular visit to the gas station the same day of each and every week. Though consumers are able to manipulate the timing of their visit to the gas station, especially when they foresee price changes, they are constrained by their tank capacity. Alternatively, the researcher may resort to the most parsimonious model that fits the data, and try to minimize the BIC with respect to the parameter Δ. Including pre- and post-event daily dummies substantially improves the fit of the model, due to strategic delay of purchases; hence the benefit of further controlling for those variables exceeds, by far, the cost from the mere viewpoint of parsimony. To circumvent that issue, we exclude days

[21] The price elasticity ε is computed at the means from the price coefficient β using that $\frac{\partial \log(q)}{\partial \log(p)} = \frac{\partial q/\partial p}{q/p} \equiv \beta \frac{p}{q}$. In practice, we report $\hat{\beta}\frac{\overline{p}}{\overline{q}}$, denoting by $\overline{X}$ the average of X.

within the anticipation window when computing the BIC. Figure 26 in Online Appendix shows that the BIC reaches its minimum when $\Delta = 13$. On top of that, Figure 8 displays how the estimated price elasticities vary with Δ. For small values of Δ, the estimation does not properly control for anticipations, mechanically overestimating the reaction to price changes by incorrectly attributing short-run intertemporal substitution motives to price sensitivity: this downwards bias results in a -0.46 point estimate. When Δ increases, our estimation method better controls for anticipation effects, and sounds fruitful in disentangling strategic delaying of purchase from contemporaneous response to price change. When $\Delta = 7$, our favorite estimate for the price elasticity becomes -0.24. Reassuringly, estimates obtained with higher values for Δ remain stable, and not significantly different from -0.24: when $\Delta = 15$, the price elasticity hardly reaches -0.23, for instance.

Moreover, we verify that our inference primarily stems from the tax cut as the main identifying variation. To do so, we perform an OLS estimation in the absence of that source of variability: we further include as a covariate the post-9/1 dummy, which effectively removes the shock.

4.3 External validity

To mitigate further any concern about identification being too local, we complement previous approach with a similar econometric estimation based on the whole period of observation. For the March-April period corresponding to an oil price surge followed by a compensatory tax cut, we refer the toy model exposed in Appendix C.2. Doing so allows us to rely on other sources of identifying variability, including the beginning of the Russian invasion of Ukraine on 02-24-2022 (denoted by t_0), the first public intervention on 04-01-2022 (denoted by t_1), the reduction of the temporary tax cut in mid-November 2022 (denoted by t_3), and the end of that temporary tax cut at the beginning of 2023 (denoted by t_4). However, we cannot control for seasonality as above, due to the pandemics acting as a confounding factor. Namely, we specify:

$$q_{ct} = \beta p_{ct} + \sum_{h=t_0}^{t_1+\Delta} \gamma_h^1 \mathbb{1}_{h=t} + \sum_{k=2}^{4} \sum_{h=t_k-\Delta}^{t_k+\Delta} \gamma_h^k \mathbb{1}_{h=t} + \alpha_c + \mu_t + \eta_{ct}, \tag{12}$$

with $\mu_t \equiv X_t'\beta + \delta t$, where δ captures any linear trend in fuel purchases and X_t account for temporal controls including day-of-the-week fixed effects[22] and holidays.[23] To control for anticipation effects, equation (12) is again estimated under the constraint

$$\sum_{h=t_0}^{t_1+\Delta} \gamma_h^1 = 0, \forall k = 2,3,4, \quad \sum_{h=t_k-\Delta}^{t_k+\Delta} \gamma_h^k = 0. \tag{13}$$

To assess the plausibility of our estimation method, we allow for anticipation effects around a fake event that would have occurred in June and July 2022. We therefore estimate a less parsimonious model which controls for 61 supplementary daily dummies from 06-01-2022 to 07-31-2022.

5 Results

5.1 Main estimates

Based on equation (10) and the DinD strategy implemented around the second excise tax cut (September 1st), our preferred estimates of the price elasticity belong to the range [-0.4,-0.21]. Indeed, Table 1 converts the estimated coefficient $\hat{\beta}$ into a -0.21 (0.07) price elasticity, obtained with the constrained OLS estimator (Column II). When instrumenting by the introduction of the tax cut, we obtain a higher estimator (Column V), in absolute: -0.4 (0.08), as would be the case with an attenuation bias due to simultaneity or to measurement error, for instance. Yet it is not much more imprecise, though the difference between IV and OLS is statistically significant at 5%.

On top of this admittedly local, but causal empirical evidence, we confront our estimates to those obtained when relying on the whole period ranging from September 2021 to January 2023, based on equation (12). The main lesson from Table 4 is that we find elasticities which belong to the [-0.38,-0.26] interval, still included in previous range. This exercise is reassuring from an empirical viewpoint since it somehow assesses the external validity of our previous approach. Moreover, using dummies for sharp price changes (the

[22]Daily-level data reveal that fuel purchases exhibit strong within-week variations: tanks are much more often refilled on Fridays and Saturdays. By definition, such a seasonality cannot be observed based on low-frequency data.

[23]interacted with the day-of-the-week.

war, the beginning and the end of tax cuts) as instruments yields very similar results (Table 5, Raw 2): this empirical finding suggests that those shocks provide the main effective source of identifying variation over the whole period.

Estimations based on the sole March-April 2022 period, i.e. the war and the first excise tax cut, are also in line with previous findings (Table 3). The constrained OLS estimator, -0.18 (0.06), is not significantly different at 5% from previous constrained OLS estimator, -0.21 (0.07). However, it is worth mentioning that the period considered here has a short duration, and mechanically mixes different anticipation effects on top of the price effect. For this reason, the estimation may look more fragile than the one based on a single price change, which sounds more immune to such confounders.

Previous estimates fall in the range of existing results in the literature, i.e. from -0.46 to -0.1 according to Davis and Kilian (2011), depending on the identification strategy chosen. Instrumental variables implemented on micro data tend to yield a higher sensitivity, while macro-based time series approaches often point out to a smaller elasticity. On the 1989-2008 period, in the U.S., Coglianese et al. (2017) obtain a -0.37 point estimate, as Knittel and Tanaka (2021) do in Japan. Still in the U.S., and according to Levin et al. (2017), that price elasticity would be comprised between -0.35 and -0.27; Gelman et al. (2022)'s preferred estimate is -0.2. Based on monthly data at the state level, Kilian (2022) has recently found a -0.31 price elasticity, up to 2014, and -0.2 since then. To directly compare our results with those of Davis and Kilian (2011) for whom a \$0.1 per gallon tax (i.e. a 3.12% price increase) would induce gasoline demand to fall by 1.43%, we estimate that a similar price increase (€0.058 per liter) would depress demand by between 0.66% and 1.25%.

The naive approach, which would omit to take anticipations into account by imposing $\gamma_{h,2022} = 0, \quad \forall h = t_2 - \Delta, \ldots, t_2 + \Delta$, is displayed in Columns I and IV of Table 1: the OLS estimate of the price elasticity, -0.44 (0.07), would then suffer from an expected downward bias (-0.23), and the same prevails with IV (-0.36). When restricted to the sole March-April months, the naive estimator amounts to -0.72 (0.16), still suffers from an anticipation bias, the magnitude of which tends to be higher than before, consistently with insights from section 3.2 and Appendix C.2. On the whole, our results concur to an anticipation bias that points downwards and that is comprised between -0.4 and -0.2.

When excluding the anticipation window from our estimation sample, indirectly relaxing our identifying assumption that anticipation effects compensate over that time period,[24] the unconstrained OLS estimator amounts to -0.29 (0.06), see Column III of Table 1, and the unconstrained IV estimator is -0.37 (0.07), both differences with corresponding constrained estimators being not significant at 5% (remember that constrained and unconstrained estimators should be close). More strikingly, the unconstrained OLS estimator based on the sole March-April period amounts to -0.31 (0.24), hence it is very imprecise for the reason evoked in section 3.2. Its theoretical uninformativeness stems from the fact that prices experienced a surge and nearly came back to their initial level after the anticipation window (remember Figure 6). Excluding that anticipation window should thus lead to an infeasible estimator: in practice, the standard error dramatically increases.

Note also that the point estimates of naive, constrained and unconstrained estimators (resp. -0.76, -0.4, and -0.37) in the DinD setting turn out to be close to the ones derived in the toy model (-0.73, -0.4, and -0.38, see Appendix C.3), given observed prices and purchases during corresponding periods acting here as sufficient statistics for the inference of the price elasticity.

To assess the validity of our identification strategy, we include the post-September 1st dummy as a covariate, i.e. we remove the tax-based price shock as our main source of identifying variability. Relying on small, short-term covariations of prices and purchases only, we logically obtain an unplausible estimate of +0.96 (0.38) along with a large standard error, see Column IV of Table 2. We proceed to a similar test when relying on the whole period, controlling for as many dummies as sharp price variations at stake (the war, the beginning and the end of temporary excise tax cuts), hence neutralizing those price shocks. This exercise makes it clear that much identifying power is lost since the estimation becomes more imprecise (Table 5, Raw 4).

The importance of anticipation effects can be assessed by looking at Figure 9 which depicts the $\hat{\gamma}$ coefficients recovered over the whole period. It is confirmed that ignoring such effects in a demand estimation is highly misleading since those short-run intertemporal substitution effects substantially shape the pattern of demand, on top of the price effect.

To evaluate whether our model is able to accurately predict fuel purchases, Figure 10

[24] This is equivalent to nonparametrically control for daily dummies during the anticipation window; it is almost as if we dismissed the whole information provided by that time interval when inferring the price effect.

provides a comparison of predicted with actual demand. The fit of the model estimated on the whole period looks quite satisfying in this regard.[25]

5.2 Robustness checks

In that subsection, we proceed to various sensitivity analyses in order to check the robustness of previous evidence with respect to methodological choices: (i) we change the comparison year in the DinD, (ii) we estimate an alternative parametric model, (iii) we consider different subperiods, and (iv) we address a possible concern related to the measurement of prices.

First, the DinD estimation procedure looks rather robust with respect to the choice of the comparison year. When considering 2019 instead of 2021, we obtain a -0.13 (0.14) point estimate for the price elasticity, and -0.58 (0.17) in the naive approach. These estimates are noisier due to a different seasonality of fuel spending in 2019.

Second, we document the sensitivity of our results with respect to the functional form chosen, namely a quasi-Poisson regression. This parametric assumption is motivated by our dependent variable taking either null or positive values, on the one hand, and by the simple interpretation of the price coefficient as the price elasticity, on the other hand.[26] In the analogue of the DinD strategy, we consider a model where $q_{cty} \sim \mathcal{P}(\lambda_{cty})$ and specify:

$$\log(\lambda_{cty}) = \varepsilon \log(p_{cty}) + \sum_{h=t_2-\Delta}^{t_2+\Delta} \gamma_{hy} \mathbb{1}_{h=t} \mathbb{1}_{y=2022} + \alpha_{cy} + \mu_t. \tag{14}$$

The estimation proceeds from maximum likelihood, and it is again subject to the constraint (11). When we consider the whole period instead, we assume that $q_{ct} \sim \mathcal{P}(\lambda_{ct})$ with

$$\log(\lambda_{ct}) = \varepsilon \log(p_{ct}) + \sum_{h=t_0}^{t_1+\Delta} \gamma_h^1 \mathbb{1}_{h=t} + \sum_{k=2}^{4} \sum_{h=t_k-\Delta}^{t_k+\Delta} \gamma_h^k \mathbb{1}_{h=t} + \alpha_c + \mu_t. \tag{15}$$

The estimation also proceeds from maximum likelihood, and it is now subject to the set of

[25] Putting aside what happens on January 2023 when there were substantial threats of fuel rationing: France then experienced many refineries blockades that were related to the social movement caused by the 2023 retirement reform.

[26] In that quasi-Poisson regression, one has $\frac{\partial \log(\mathbb{E}q)}{\partial \log(p)} = \frac{\partial \log(\lambda)}{\partial \log(p)} \equiv \varepsilon$, which refers to the price-elasticity of the average demand.

constraints (13). In both cases, standard errors are computed with two-way clustering by cell and by day.

Empirically, the choice of the functional form sounds rather innocuous: when opting for the quasi-Poisson regression instead of a linear model, we obtain estimates in Columns I to III of Table 2 that compare well to the ones in the very same columns of Table 1. Raw 3 of Table 5 provides with the results based on the whole period, which do not differ much from the baseline (Raw 1). Moreover, the quality of the prediction does not depend much on the parametric specification adopted: it is rather high regardless of the functional form chosen, linear or quasi-Poisson (see Figure 27 in Online Appendix).

Third, we estimate our model on different subperiods (Raws 5 to 7 of Table 5): (i) from January to September 2022, (ii) we remove June and July 2022, two months during which fuel prices unexpectedly rose at a peaceful rate consecutive to the energy crisis, and (iii) we combine experiments (i) and (ii), i.e. we rely on January-May as well as on August-September subperiods only. In the latter case, we have effectively removed much identifying variation to infer the price sensitivity of demand: standard errors increase dramatically. If anything, our estimated elasticity tends to be lower, in absolute, when prices change consecutive to some public intervention. This empirical result does not support behavioral explanations based on salience effects, for instance.

Fourth, to alleviate any concern about endogeneity of our fuel price index, we replace the latter with the price of the diesel. Our results do not vary by much (Raw 8 of Table 5).

We also investigate possible asymmetry in the response of fuel consumption to fuel price changes, we find like Kilian and Vigfusson (2011) and Kilian (2022) that there is none (see Appendix Table 12), which contrasts with Levin et al. (2022) who estimate that gasoline demand is three times as elastic when prices rise above their average as when prices fall below this average.

5.3 Heterogeneity of the price elasticity

In that subsection, we wonder whether the price elasticity of fuel demand is homogeneous amongst groups of consumers with similar observed characteristics, or not. We first investigate whether the average price elasticity varies with income (Figure 11a) or location (Figure 11b), which turns out not to be the case. Remembering nevertheless that the price elasticity measures a relative reaction, and that fuel consumption is higher for wealthier individuals as well as for those living in rural areas. As a result, the latter respond more to fuel price changes, on average, in nominal terms. By contrast, a dimension along which that average price elasticity exhibits sizable dispersion is (past) fuel consumption (Figure 11c): "dependent households" who rely much on the car as their primary transportation are less elastic, as the intuition suggests. For example, individuals in the bottom quartile of (past) fuel spending have an average elasticity comprised between -1.06 (0.24) and -0.62 (0.22), while those in the top quartile have an average elasticity of -0.32 (0.07) to -0.19 (0.06). Figure 11d shows further that this is especially the case for liquidity-constrained households, which leads us to conclude that dependent and liquidity-constrained individuals are most likely to undergo any rise in fuel prices. We believe that this empirical evidence is of practical relevance and has important implications in terms of public policy: when designing transfer schemes to compensate the losers of, say, fuel inflation, the decision-maker may want to finely target such households, remember Sallee (2019). It requires however for her to dispose of corresponding information about consumption and liquidity.

We next perform a more systematic search of the relevant dimensions of heterogeneity, and allow for the coefficient β to directly depend on observed characteristics (based on the IV estimation of the DinD specification in Section 4.1). To that purpose, we resort to the method of causal forests pioneered by Athey et al. (2019). Based on that approach, Figure 12 displays sorted group average treatment effects issued from a segmentation of our sample into five groups. We are then able to perform a Chernozhukov et al. (2018)'s test, according to which homogeneity is rejected: the 20% most price-sensitive individuals have an elasticity of about $-0.8(0.09)$ while the 20% most inelastic have a null price elasticity, the difference being statistically significant at 5%. This empirical evidence is thus consistent with fuel being a necessity good for almost every car driver.

Our estimated price elasticities differ quite substantially across individuals (Table 6), and it is possible to determine who are the most price-sensitive individuals in terms of both socioeconomic characteristics and geographic location (Table 7). It turns out that individuals with a lower fuel spending, who are older and poorer (in terms of both income and liquidity) are more elastic.

Those results are close to the ones obtained by Kilian (2022): according to them, states with lower income, higher unemployment rates, and lower urban shares respond more to price variations. Yet an important difference is that they derive from individual data.

These results may be viewed as a contribution to the optimal market design of second-best policies, namely externality-correcting tax-and-transfer schemes. The latter arise due to imperfect information and tagging of individual consumption: this market failure limits the planner's control over the final distribution of outcomes, yet a more accurate prediction helps mitigate that empirical problem (Sallee, 2019).

5.4 The aggregation bias: disposing of high-frequency data matters

In order to correctly infer the price elasticity of fuel demand, the researcher should dispose of three ingredients: (i) exogenous price variations, (ii) high-frequency data, and (iii) a convenient econometric method to control for consumer anticipations. It is perhaps pointless to illustrate how essential the first ingredient is to identification -we have already shown that removing tax changes resulted in an identification failure, both in the local/DinD approach and in the global estimation over the whole period. We have also explained why taking anticipations into account was crucial in order not to confound them with the pure price effect, cf. the downward-biased naive estimations.

Hence we now aggregate our data at the monthly level and show that this aggregation is misleading. By definition, such monthly data miss short-term variations in fuel purchases -though popular in the literature, due to the lack of granular datasets. As made clear by Figure 3, and as confirmed by Figure 28 in Online Appendix, such unobserved variations include dips and spikes consecutive to anticipated tax changes. As a result, it is impossible for the econometrician to isolate the pure price effect, and to disentangle it from short-term intertemporal substitution effects viewed as confounders. This is true even when relying on parametric approaches to control for anticipation effects like, e.g., in Coglianese et al. (2017); in particular, such methods based on monthly-level data cannot control for daily fluctuations which precisely helped us isolate those effects. To quantify the magnitude of that aggregation bias, we replicate our identification strategy presented in Section 4.1 based on monthly data. We obtain a higher price elasticity of demand, in absolute, namely -0.65,[27] see Column V of Table 2. To understand the direction of the bias, it is useful to realize that the spike in fuel purchases arises at the beginning of September 2022, a month during which prices kept on falling; this explains why consumer sensitivity is magnified. It is yet impossible neither to sign, nor to quantify the magnitude of that bias in the general

[27] It is not possible to cluster standard errors in the time dimension in that case, hence we do not comment precision here.

case. When we aggregate our data at the weekly level (Column VI of Table 2), we obtain a point estimate of -0.09, which is yet smaller, in absolute, than the one obtained at the daily level. In our view, this empirical evidence comforts the claim that daily data are truly necessary to properly control for anticipations.

5.5 Counterfactuals and policy implications

Equipped with previous estimates, we proceed to a counterfactual exercise in order to assess both financial and distributive impacts of the fuel tax policy at stake, as well as its effect on CO_2 emissions. To that aim, we first simulate a counterfactual that would have prevailed in the absence of excise tax cuts, i.e. of public policy interventions. In particular, we predict fuel spending $\tilde{q}_{ct}$ at prices $\tilde{p}_{ct} = p_{ct} + \Delta p_t$ for the time period that ranges from January 1st, 2022 ($\underline{t}$) to December 31st, 2022 ($\bar{t}$).[28] The after-tax price differential Δp_t is equal to zero until the end of March, then amounts to +0.18€ per liter after April 1st, and up to +0.30€ per liter from September 1st, onwards; it is then diminished to +0.10€ per liter from November, 16th onwards and vanishes on December 31st, 2022. By focusing on such an experiment, we implicitly assume a full pass-through of tax changes to consumers; we also abstract from decentralized supplementary price reductions like the ones implemented in TotalEnergies gas stations, for instance, when seeking to evaluate the impact of the sole public intervention.

We then evaluate the impact of the policy on consumption, in liters, by computing the difference between observed (ex post) and simulated (ex ante) consumption:

$$\sum_{t=\underline{t}}^{\bar{t}} [q_{ct} - \tilde{q}_{ct}] = \sum_{t=\underline{t}}^{\bar{t}} \hat{\beta}(p_{ct} - \tilde{p}_{ct}) = -\sum_{t=\underline{t}}^{\bar{t}} \hat{\beta}(\Delta p_t) > 0, \tag{16}$$

[28] For each cell of individuals and for each day, we may compute $\tilde{q}_{ct} = \hat{\beta}\tilde{p}_{ct} + \sum_{h=t_0}^{t_a-1} \hat{\gamma}_h^1 \mathbb{1}_{t=h} + \sum_{h=t_a}^{t_a-1+(t_a-t_0)} (-\hat{\gamma}_{t_a-h+t_a-1}^1) \mathbb{1}_{t=h} + \hat{\alpha}_c + \hat{\mu}_t + \hat{\eta}_{ct}$ from previous estimates. Indeed, in the absence of any sharp, policy-driven price change as is the case for the latter three anticipation windows and the second part of the first anticipation window related to the April 1st shock, anticipation effects must be neutralized. During the first anticipation window, we assume that (stored) fuel consumption observed during the period from t_0 to the day before the announcement of the first tax cut, denoted by $(t_a - 1)$, i.e. March 10th, would have been compensated the days after from t_a to $t_a - 1 + (t_a - t_0)$ according to some symmetric, opposite scheme. Note that the latter assumption is yet unimportant to our policy evaluation exercise: it is only required that default purchases during the rest of that window (from t_a to $t_a - 1 + (t_a - t_0)$) exactly compensate excess purchases (from t_0 to $t_a - 1$), corresponding to storage.

due to anticipation effects cancelling out over each anticipation window but the first one. The change in fuel spending is provided by:

$$\sum_{t=\underline{t}}^{\bar{t}}[p_{ct}q_{ct} - \tilde{p}_{ct}\tilde{q}_{ct}] = -\sum_{t=\underline{t}}^{\bar{t}}(\Delta p_t)\tilde{q}_{ct} - \sum_{t=\underline{t}}^{\bar{t}}\hat{\beta}(\Delta p_t)p_{ct} + \sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t p_{ct}, \tag{17}$$

which makes clear that β and $\gamma = (\gamma^1, \gamma^2, \gamma^3, \gamma^4)$ are sufficient statistics for such an evaluation exercise. Three effects are at stake: (i) $-\sum_{t=\underline{t}}^{\bar{t}}[(\Delta p_t)\tilde{q}_{ct}] < 0$ corresponds to the mechanical, or direct effect of the discount on fuel spending, consumption being fixed; (ii) the "behavioral effect" $-\sum_{t=\underline{t}}^{\bar{t}}[(\hat{\beta}\Delta p_t)p_{ct}] > 0$ corresponds to the impact of the increase in consumption (consecutive to reduced prices) on spending; (iii) the "anticipation effect" $\sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t p_{ct}$ is related to the fact that storing (resp. postponing) when prices are low (resp. high) does not alter total consumption but may increase or decrease spending depending on the price variation over time. The latter term rewrites:

$$\sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t p_{ct} = \sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t\tilde{p}_{ct} - \sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t\Delta p_t \approx -\sum_{t=\underline{t}}^{\bar{t}}\hat{\gamma}_t\Delta p_t \tag{18}$$

since (i) there is no anticipation outside anticipation windows, and (ii) counterfactual prices $\tilde{p}_{ct}$ do not vary much during anticipation windows, contrary to observed prices p_{ct}, which means that the first of the two terms in the decomposition (18) is almost equal to the average counterfactual price during each anticipation window times the sum of anticipation effects over that period, i.e. zero, and may thus be neglected. Empirically, the anticipation effect is null outside anticipation windows, and its magnitude is similar to the price effect otherwise: as a result, those effects do not matter much, on the whole, in that specific evaluation exercise -despite their relevance in the estimation as explained before.

Based on previous estimated range of the marginal price effect $\hat{\beta} \in [-0.56, -0.29]$, which yields an average elasticity comprised between -0.4 and -0.21, we first get a sense of how much the policy has absorbed part of the 2022 price shock. Hence we compute the counterfactual fuel spending that households would have faced if prices had maintained at their level at the beginning of the year (about €1.64 per liter). We estimate that households would have then spent €144 to €208 less, on average, compared to the *laissez-faire* (Table 8).

We then estimate that the financial impact of the policy has been to reduce fuel spending by between €51 and €81 per household, on average, in 2022, which represents from 0.15% to 0.24% of the average income: from that viewpoint, the discounts at the pump have only provided a partial compensation to the concerned households. We next allow for $\hat{\beta}$ to vary depending on observed characteristics as in section 5.3, starting with income. Also, to ease exposure, Figure 13 focuses on the more elastic case and quantifies distributive effects at stake: from €29 saved by the bottom 25% of income to €64 saved by the top 25% of income. Those figures represent 0.26% of income for the former,[29] and 0.09% of income for the latter.[30] The mechanical reduction in fuel spending amounts to roughly €110, while the behavioral effect, which induced car drivers to consume more fuel, and thus to spend more, is comprised between €29 and €59: this countervailing response has therefore attenuated the direct effect on fuel spending by between 26% and 54%. Figure 14 then confirms that individuals living in rural areas, whose share of income spent on fuel is higher, benefited more from the policy, in nominal terms -especially for low-income individuals, see Figure 15. Interestingly, those who belong both to the bottom 25% of income and to the top 25% of fuel spending devote about 30% of their income to fuel expenditures: the policy alleviated that share by almost 1.4pp, from 27.8% to 26.4%. Figure 16 further provides counterfactual simulations in which the price elasticity differs according to both location and income.

Last, the impact of the policy on CO_2 emissions has been rather limited. The extra fuel consumption amounts to between 16 and 31 liters per household (i.e. about +2.2% to +4.2%), this effect being heterogeneous: for instance, it is about 45 liters in the top 25% of fuel consumption but 21 liters only in the bottom 25%, those figures being obtained with the upper bound estimate. Based on the observed fuel mix between gasoline and diesel, we estimate that this supplementary consumption represents between 48 and 93 kilograms of CO_2.[31] In 2021, a French household's annual carbon footprint amounted to about 20.3 tons, hence a corresponding increase by 0.24% to 0.46%.

[29] Their observed budget share of fuel expenditures is 8.11%; in the absence of any intervention, that share would have increased to 8.37%.

[30] Respectively 2.7% and 2.79%.

[31] In the polar case of pure diesel, corresponding estimates would range from 51 to 98 kilograms. In the other polar case (pure gasoline), they would range from 44 to 86 kilograms.

6 Conclusion

This paper has shown that the researcher who aims at causally inferring the price elasticity of fuel demand should dispose of granular, high-frequency data, on top of relying on exogenous price variations. We show that daily data allow to take anticipatory behavior into account, combined with an econometric method that is less parametric than other approaches in the literature. Equipped with such ingredients, we build upon previous estimates in the literature, and our findings concur to a short-term price elasticity comprised between -0.4 and -0.21.

We have also documented that the price elasticity exhibits sizeable dispersion, primarily in the fuel spending dimension itself. Individuals who consume more fuel are also more inelastic, especially when they are also liquidity-constrained. By contrast, income and the type of location are not associated with significantly different average price elasticities. From the viewpoint of market design, these results are important to better tailor compensation schemes to car drivers' needs, hereby to improve the targeting of transfer mechanisms.

When evaluating financial and distributive impacts of the current policy as well as its effect on global emissions, we found that concerned households saved between €51 and €81, on average, i.e. from 0.15% to 0.24% of income thanks to this temporary excise tax cut. High-income individuals enjoyed a higher gain (from €64 to €115) in nominal terms, but a smaller one when expressed as a fraction of their income (between 0.09% and 0.17%). Consecutive to that 9-month subsidy of nearly 10.8% of the after-tax price, fuel-related emissions increased by between 2.2% and 4.2%, which leveraged the overall carbon footprint by 0.24%-0.46%. Once again, these short-run effects do not preclude long-term adjustments.

7 Acknowledgements

Data from *Crédit Mutuel Alliance Fédérale*:

Première banque à adopter le statut d'entreprise à mission, Crédit Mutuel Alliance Fédérale a contribué à cette étude par la fourniture de données de comptes bancaires sur la base de deux échantillons : un échantillon d'entreprises et un échantillon de ménages par tirage aléatoire et construit de telle sorte qu'on ne puisse pas identifier les entreprises

(exclusion de sous populations de petite taille) ou les ménages. Toutes les analyses réalisées dans le cadre de cette étude ont été effectuées sur des données strictement anonymisées sur les seuls systèmes d'information sécurisés du Crédit Mutuel en France. Pour Crédit Mutuel Alliance Fédérale, cette démarche s'inscrit dans le cadre des missions qu'il s'est fixées :

- contribuer au bien commun en oeuvrant pour une société plus juste et plus durable : en participant à l'information économique, Crédit Mutuel Alliance Fédérale réaffirme sa volonté de contribuer au débat démocratique ;
- protéger l'intimité numérique et la vie privée de chacun : Crédit Mutuel Alliance Fédérale veille à la protection absolue des données de ses clients.

References

Andersen, A. L., Jensen, A. S., Johannesen, N., Kreiner, C. T., Leth-Petersen, S., and Sheridan, A. (2023). How do households respond to job loss? Lessons from multiple high-frequency data sets. *American Economic Journal: Applied Economics*, forthcoming.

Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.

Baker, S. R. (2018). Debt and the response to household income shocks: Validation and application of linked financial account data. *Journal of Political Economy*, 126(4):1504–1557.

Chernozhukov, V., Demirer, M., Duflo, E., and Fernandez-Val, I. (2018). Generic machine learning inference on heterogeneous treatment effects in randomized experiments, with an application to immunization in india. Technical report, National Bureau of Economic Research.

Coglianese, J., Davis, L. W., Kilian, L., and Stock, J. H. (2017). Anticipation, tax avoidance, and the price elasticity of gasoline demand. *Journal of Applied Econometrics*, 32(1):1–15.

Dahl, C. and Sterner, T. (1991). Analysing gasoline demand elasticities: a survey. *Energy Economics*, 13(3):203–210.

Davis, L. W. and Kilian, L. (2011). Estimating the effect of a gasoline tax on carbon emissions. *Journal of Applied Econometrics*, 26(7):1187–1214.

Deville, J.-C. and Särndal, C.-E. (1992). Calibration estimators in survey sampling. *Journal of the American Statistical Association*, 87(418):376–382.

Espey, M. (1998). Gasoline demand revisited: an international meta-analysis of elasticities. *Energy Economics*, 20(3):273–295.

Fagereng, A., Holm, M. B., Moll, B., and Natvik, G. (2019). Saving behavior across the wealth distribution: The importance of capital gains. NBER Working paper 26588.

Ganong, P. and Noel, P. (2019). Consumer spending during unemployment: Positive and normative implications. *The American Economic Review*, 109(7):2383–2424.

Gautier, E., Marx, M., and Vertier, P. (2022). How do gasoline prices respond to a cost shock? Banque de France Working Paper.

Gelman, M., Gorodnichenko, Y., Kariv, S., Koustas, D., Shapiro, M. D., Silverman, D., and Tadelis, S. (2022). The response of consumer spending to changes in gasoline prices. *American Economic Journal: Macroeconomics*, forthcoming.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673.

Kilian, L. (2022). Understanding the estimation of oil demand and oil supply elasticities. *Energy Economics*, 107:105844.

Kilian, L. and Vigfusson, R. J. (2011). Nonlinearities in the oil price–output relationship. *Macroeconomic Dynamics*, 15(S3):337–363.

Knittel, C. R. and Tanaka, S. (2021). Fuel economy and the price of gasoline: Evidence from fueling-level micro data. *Journal of Public Economics*, 202:104496.

Levin, L., Lewis, M. S., and Wolak, F. A. (2017). High frequency evidence on the demand for gasoline. *American Economic Journal: Economic Policy*, 9(3):314–47.

Levin, L., Lewis, M. S., and Wolak, F. A. (2022). Reference dependence in the demand for gasoline. *Journal of Economic Behavior & Organization*, 197:561–578.

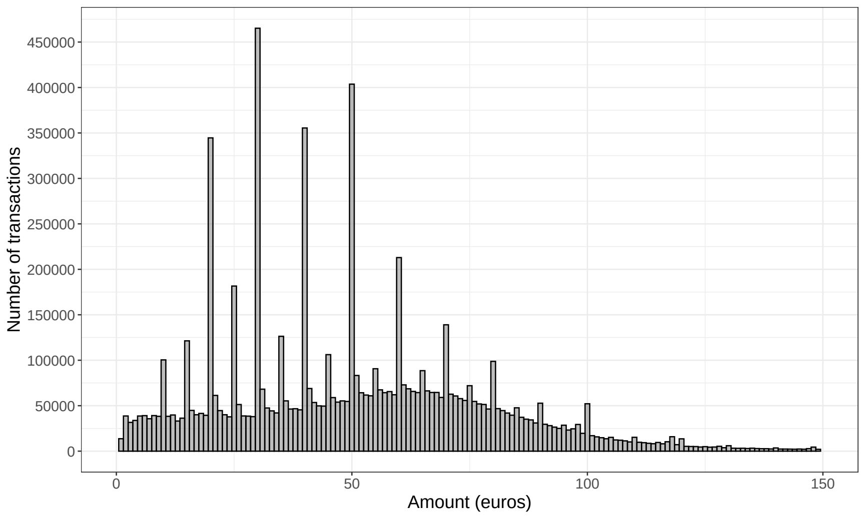
Montag, F., Sagimuldina, A., and Schnitzer, M. (2021). Does tax policy work when consumers have imperfect price information? Theory and evidence. CESifo Working Paper.

Sallee, J. (2019). Pigou creates losers: On the implausibility of achieving pareto improvements from efficiency-enhancing policies. *NBER Working Paper 25831*.

A Figures

A.1 Descriptive evidence

Figure 1: Distribution of fuel expenditures

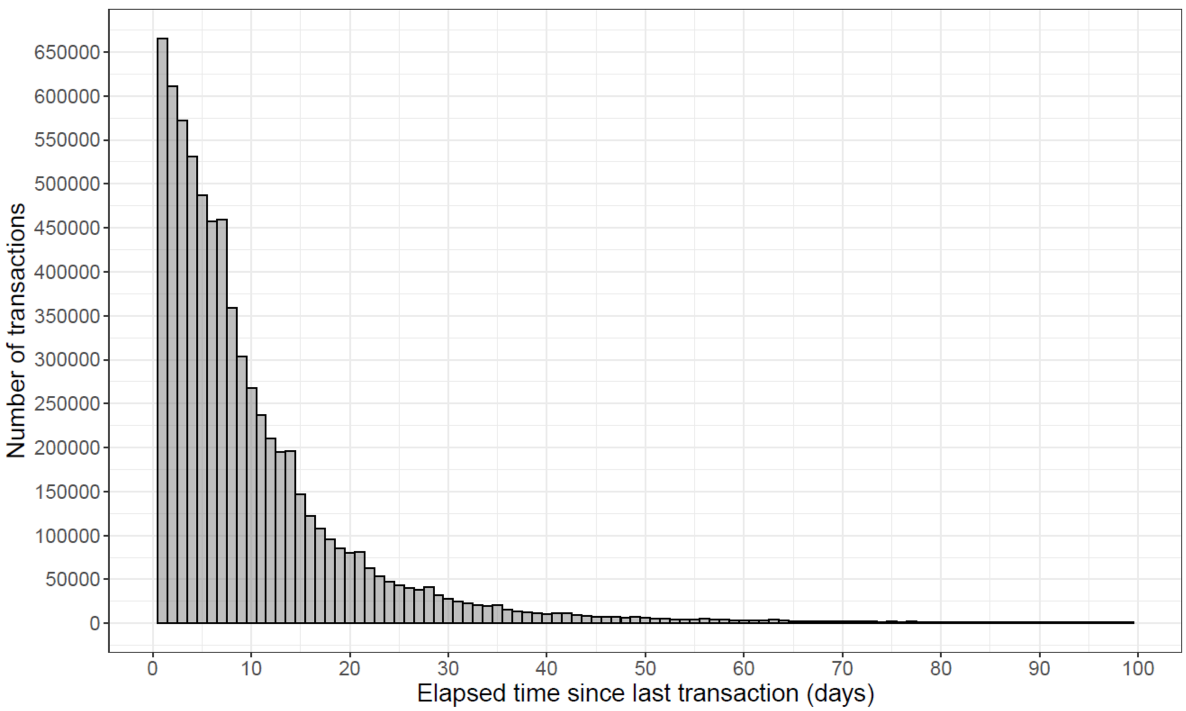


Note. Histogram of transaction-level fuel expenditures (including taxes) from September 2021 to January 2023.

Lecture. 400, 000 transactions are observed during that period with amounts comprised between 50 and 51 euros.

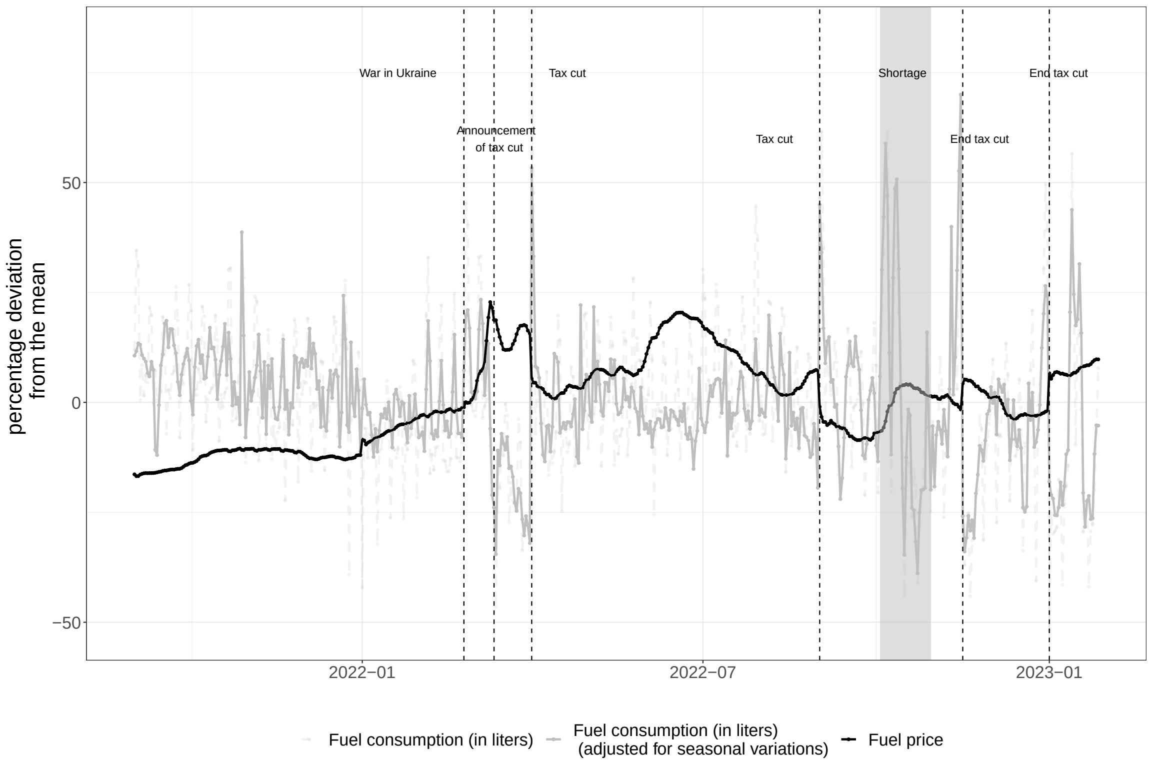
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 2: Interpurchase durations (in days)



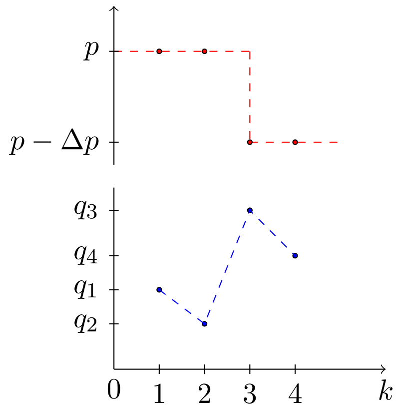
Note. Elapsed time between two transactions from September 2021 to January 2023.
Lecture. 275,000 fuel transactions are observed during that period that occur 10 days after previous purchase.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 3: Fuel prices and purchases



Note. Fuel prices (including taxes) and purchases (in liters). Purchases are adjusted for seasonal variations thanks to GIE CB data from September 2021 to January 2023. Dashed lines correspond to the invasion of Ukraine and policy interventions. Tax cut on April 1st amounts to a 0.18 € per liter price discount (including VAT). Tax cut on September 1st amounts to an extra 0.12 € per liter subsidy, which has prevailed until mid-November 2022. The remaining subsidy was removed on January 1st 2023.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

A.2 Identification

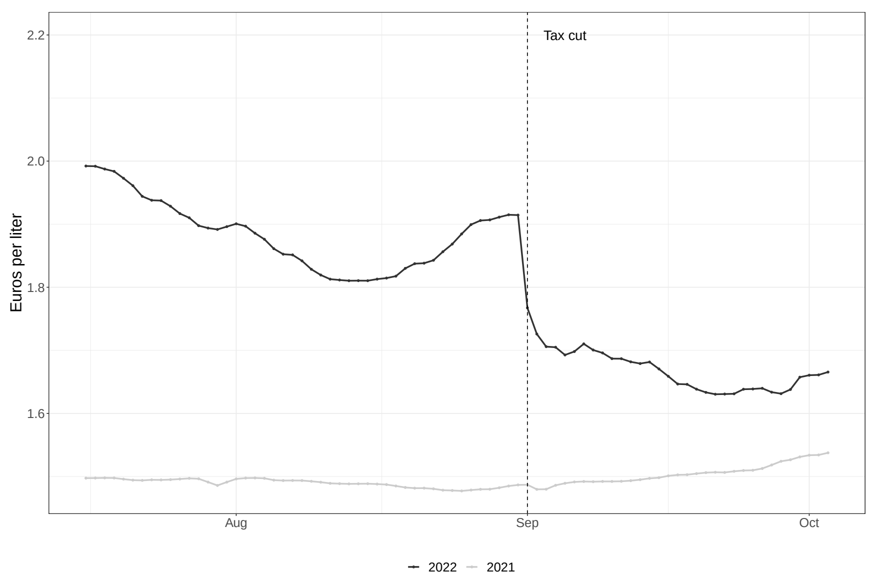


(a) 4-period model

(b) 5-period model

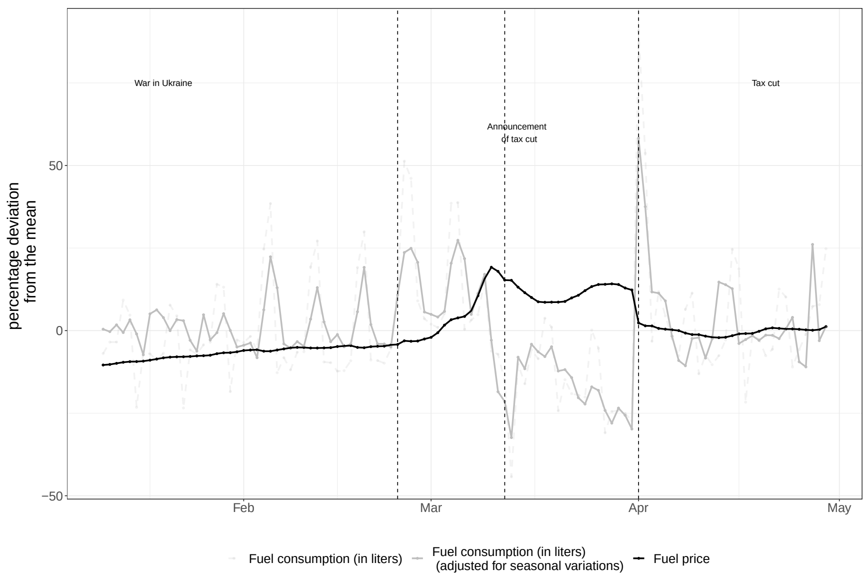
Figure 4: Prices and anticipation effects

Figure 5: Fuel prices around September, 1st (in 2021 and 2022)



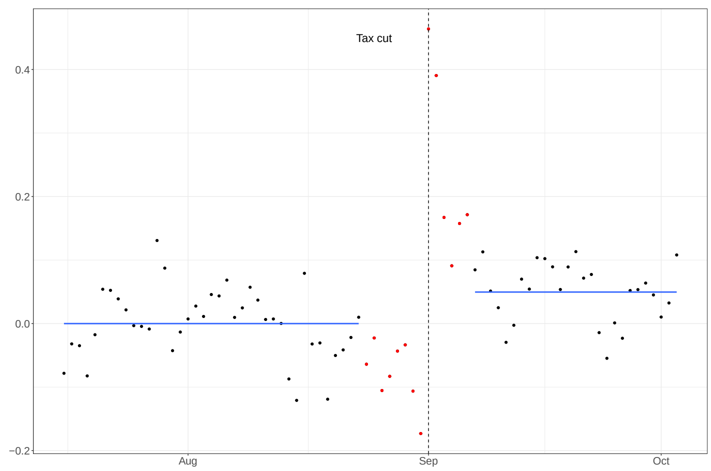
Note. Fuel prices in € per liter (including taxes) in 2021 and 2022. The dashed line corresponds to an extra 0.12 € subsidy for each liter purchased implemented from September 1st 2022.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 6: Fuel prices from January to April 2022



Note. Fuel prices (including taxes) and purchases (in liters). Purchases adjusted for seasonal variations thanks to GIE CB data from January 8th 2022 to April 30th 2022. The first dashed line corresponds to the invasion of Ukraine, the second dashed line refers to the announcement of the first policy intervention, a subsidy of 0.18 € per liter (including VAT), and the last dashed line indicates the effective implementation of the intervention.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 7: Fuel purchases' response to the September 1st anticipated tax cut

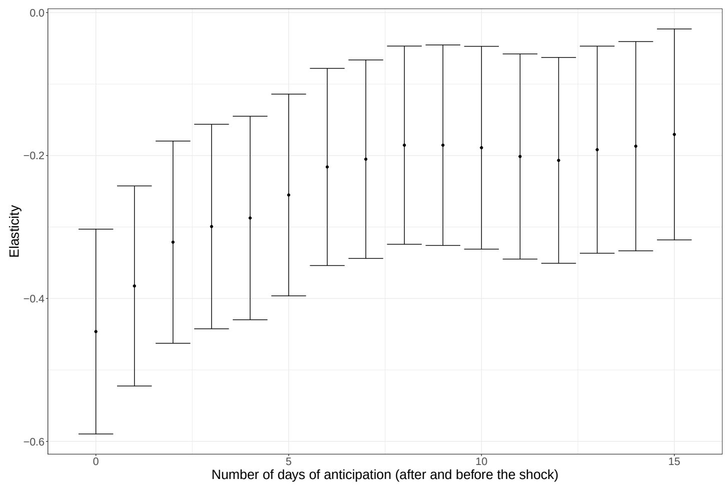


Note. Dots correspond to the difference between average fuel quantity purchased in 2022 and average fuel quantity purchased the same day in 2021 (after adjusting calendar days in 2021 so that weekdays correspond in 2022 and 2021). The average difference is normalized to 0 before the shock and the anticipation period. The dashed line corresponds to an extra €0.12 per liter subsidy starting on September 1st 2022. Red dots correspond to the 7 days before and after the tax cut, which we call the anticipation window. Blue lines correspond to the average difference before and after the tax cut, excluding the 7 days around the policy intervention.

Note:
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

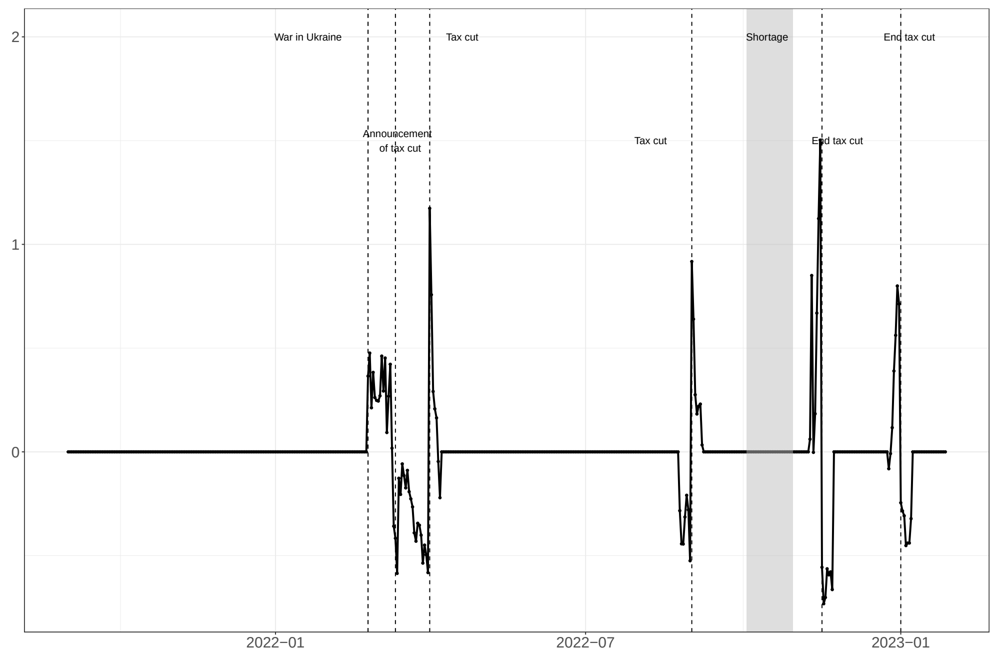
A.3 Estimation results

Figure 8: Estimated price elasticity, depending on the anticipation bandwidth Δ



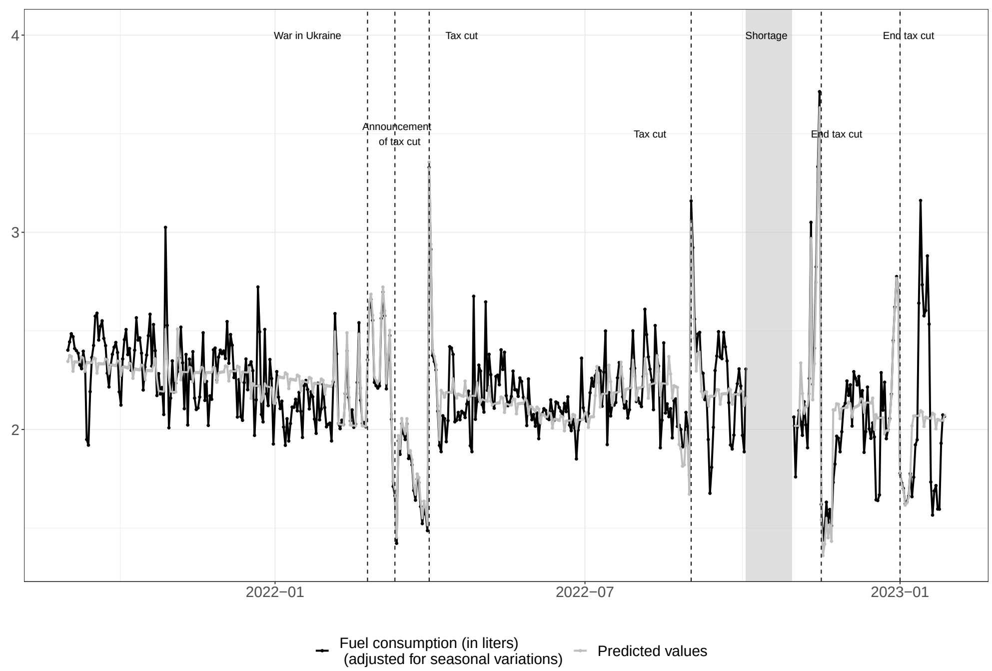
Note. Estimated price elasticity using equation (10) from July 15th to October 4th in 2021 and 2022, depending on the number of days considered for anticipation.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 9: Estimated anticipation parameters (γ coefficients)



Note. The solid line corresponds to the γ coefficients of equation (12) estimated from September to February. These coefficients capture purchases due to anticipatory behavior, in liters; in each anticipation window, the coefficients sum up to 0. Dashed lines correspond to the invasion of Ukraine and policy interventions. Tax cut on April 1st amounts to a 0.18 € per liter price discount (including VAT). Tax cut on September 1st amounts to an extra 0.12 € per liter subsidy, which has prevailed until mid-November 2022. The remaining subsidy was removed on January 1st 2023.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

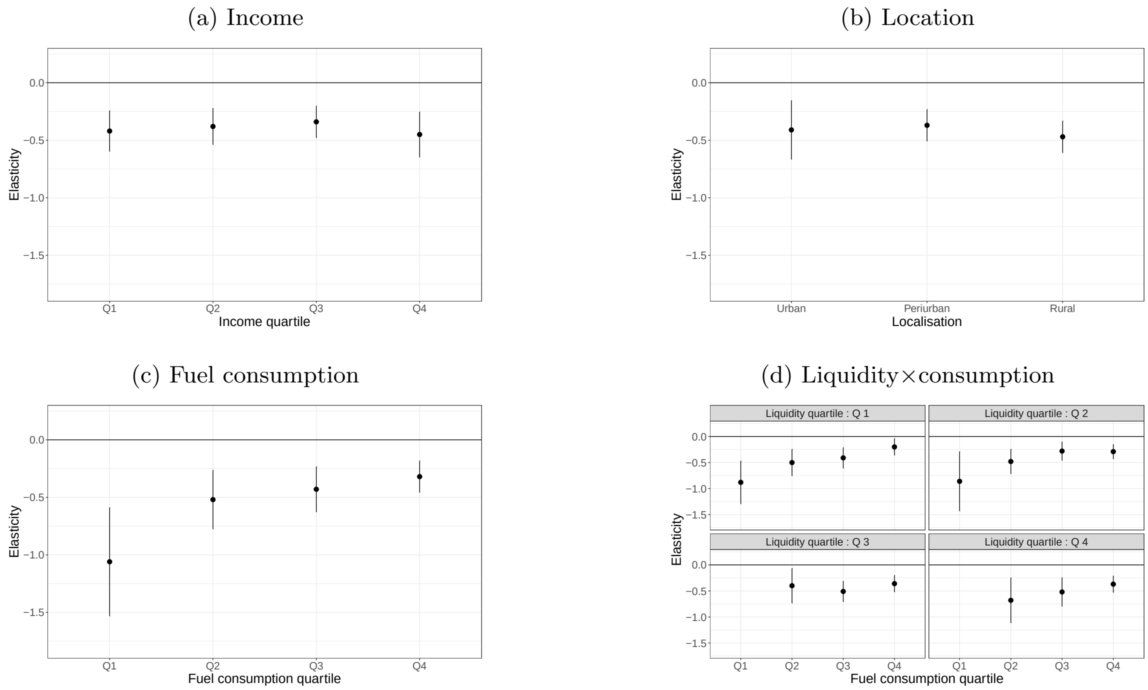
Figure 10: Predicted vs actual demand for fuel



Note. The black line corresponds to observed fuel purchases (in liters) over the period. The grey line corresponds to predicted fuel purchases based on equation (12). Dashed lines correspond to the invasion of Ukraine and policy interventions. Tax cut on April 1st amounts to a 0.18 € per liter price discount (including VAT). Tax cut on September 1st amounts to an extra 0.12 € per liter subsidy, which has prevailed until mid-November 2022. The remaining subsidy was removed on January 1st 2023.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

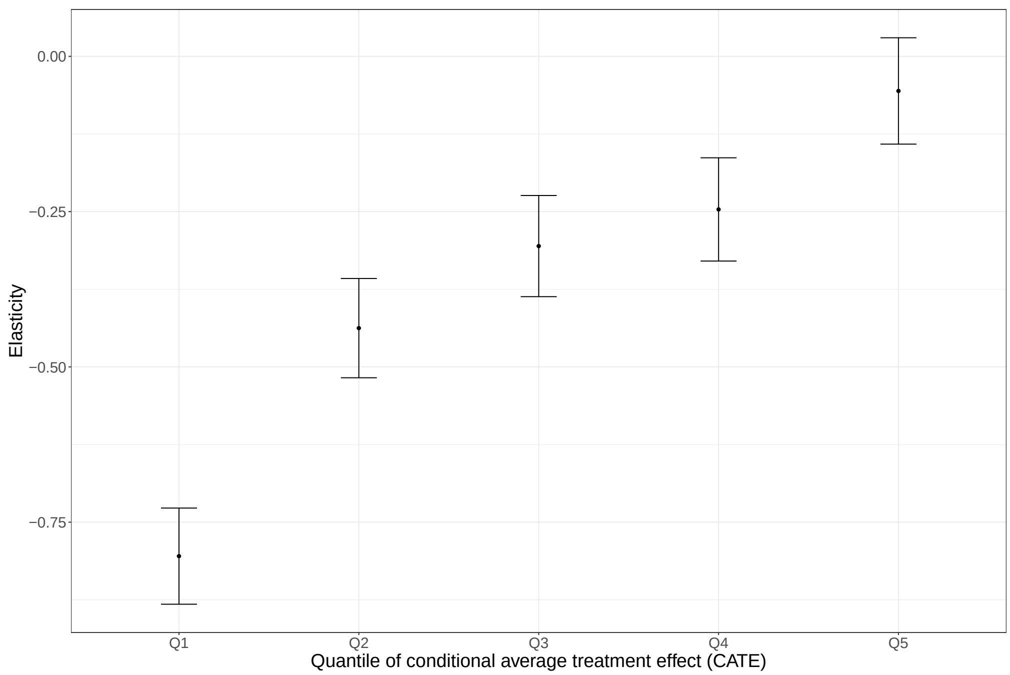
A.4 Heterogeneity of the price elasticity

Figure 11: Heterogeneity along some observed characteristics



Note. Estimated price elasticity using equation (10) from July 15th to October 4th in 2021 and 2022. Corresponding subsamples depend on households' characteristics (observed before the intervention from January to June, for continuous variables, and in June for discrete variables). Two-way clustering of standard errors at cell and year-day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

Figure 12: Sorted Group Average Treatment Effects

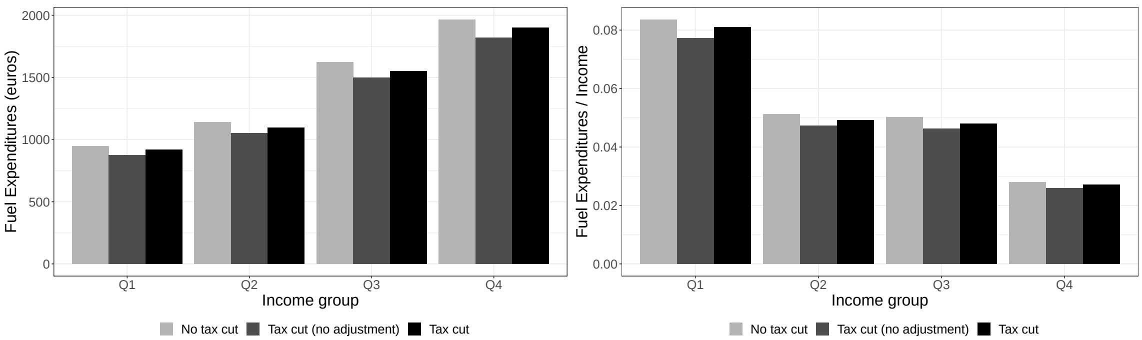


Note. Average elasticity in each quintile of conditional average treatment effect (CATE). Estimation made from July 15th to October 4th in 2021 and 2022 on subsamples (excluding the anticipation window).
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

A.5 Counterfactual simulations

Figure 13: Distributive effects of policy (by income)

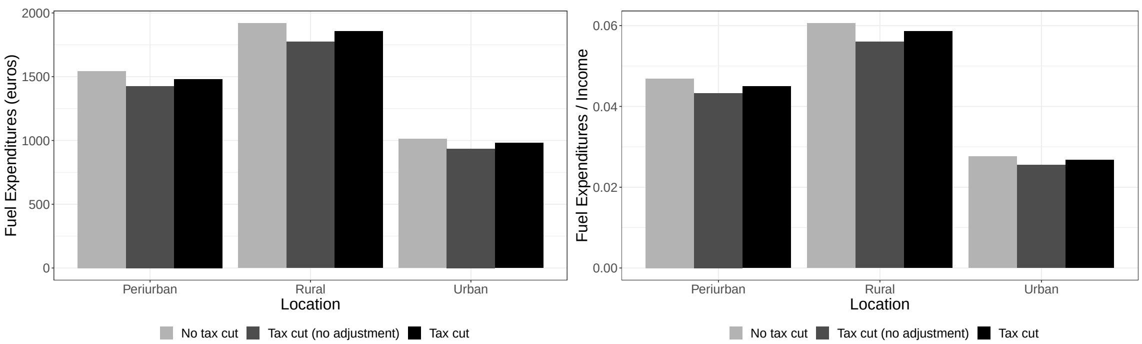
(a) in euros (monthly) (b) in % of income



Note. Estimation period: 2022.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

Figure 14: Distributive effects of policy (by location)

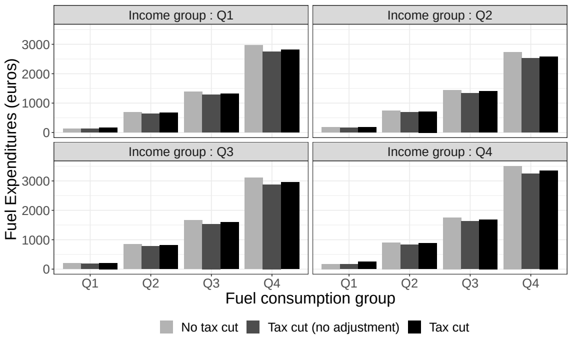
(a) in euros (monthly) (b) in % of income



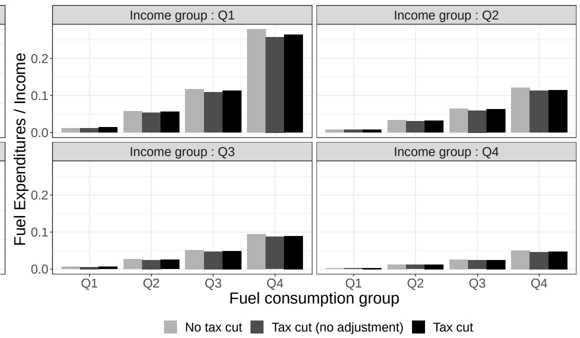
Note. Estimation period: 2022. Location is defined by the bank.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

Figure 15: Distributive effects of policy (by fuel spending × income)

(a) in euros (monthly)



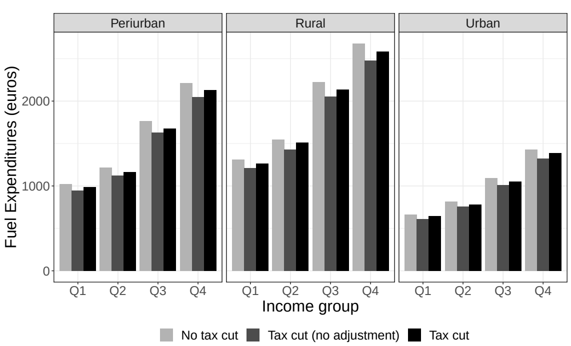
(b) in % of income



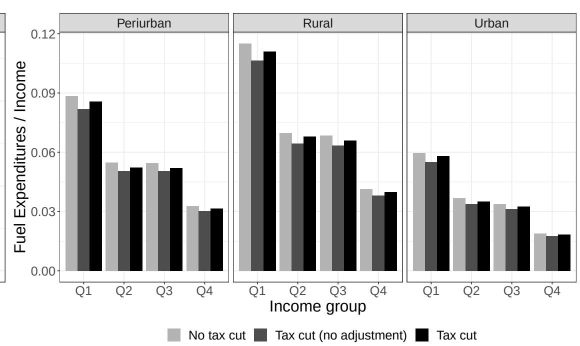
Note. Estimation period: 2022.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 16: Distributive effects of policy (by income × location)

(a) in euros (monthly)



(b) in % of income



Note. Estimation period: 2022.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

B Tables

Table 1: Estimation based on the September 1st tax cut

	I	II	III	IV	V	VI
coefficient	-0.62 (0.10)	-0.29 (0.10)	-0.40 (0.09)	-1.06 (0.18)	-0.56 (0.11)	-0.52 (0.10)
price elasticity	-0.44 (0.07)	-0.21 (0.07)	-0.29 (0.06)	-0.76 (0.13)	-0.40 (0.08)	-0.37 (0.07)
IV (Instrument: post- 9/1 dummy)				✓	✓	✓
Anticipation dummies		✓			✓	
Excluding anticipation window			✓			✓
Cell FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓
# of cells	10777	10777	10777	10777	10777	10777

Note. Estimation of equation (10) with a sample of 10,777 cells of customers observed from July, 15th to October, 4th. Treatment year: 2022, Comparison year: 2021. Two-way clustering of standard errors at cell and year-day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 2: DinD (September 1st): Robustness checks

	I	II	III	IV	V	VI
price elasticity	-0.41 (0.07)	-0.18 (0.07)	-0.23 (0.07)	0.96 (0.38)	-0.65 (.)	-0.09 (.)
Quasi-Poisson regression	✓	✓	✓			
Linear model				✓	✓	✓
Anticipation dummies		✓			✓	
Excluding anticipation window			✓			✓
Falsification test (control for post- 9/1 dummy)				✓		
Monthly aggregation					✓	
Weekly aggregation						✓
Cell FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓		
Week FE						✓
Month FE					✓	
# of cells	10,777	10,777	10,777	10,777	10,777	10,777

Note. Estimation of equation (10) with a sample of 10,777 cells of customers observed from July, 15th to October, 4th. Treatment year: 2022, Comparison year: 2021. Two-way clustering of standard errors at cell and year-day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 3: Estimation based on the price surge (war) + tax cut (April 1st)

	I	II	III
price elasticity	-0.72 (0.16)	-0.18 (0.06)	-0.31 (0.24)
Anticipation dummies		✓	
Excluding anticipation window			✓
Cell FE	✓	✓	✓
# of cells	10,826	10,826	10,826

Note. Estimation sample: 10,826 cells of customers observed from January, 10th to April, 30th 2022. Two-way clustering of standard errors at cell and day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 4: Estimations based on the whole period (September 2021-February 2023)

	I	II	III	IV	V	VI
coefficient	-0.54 (0.06)	-0.61 (0.06)	-0.57 (0.08)	-0.39 (0.04)	-0.47 (0.05)	-0.32 (0.04)
price elasticity	-0.44 (0.05)	-0.50 (0.05)	-0.47 (0.07)	-0.32 (0.03)	-0.38 (0.04)	-0.26 (0.03)
Anticipation dummies				✓	✓	✓
Seasonality controls		✓	✓		✓	✓
Linear trend			✓			✓
Cell FE	✓	✓	✓	✓	✓	✓
# of cells	7,000	7,000	7,000	7,000	7,000	7,000

Note. Estimation of equation (12) with a sample of $7,000$ cells of customers observed from September 2021 to February 2023. Two-way clustering of standard errors at cell and day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 5: Robustness checks (September 2021-February 2023)

	I	II	III	IV	V	VI
Main estimates	-0.44 (0.05)	-0.50 (0.05)	-0.47 (0.07)	-0.32 (0.03)	-0.38 (0.04)	-0.26 (0.03)
IV estimates	-0.34 (0.06)	-0.38 (0.06)	-0.42 (0.08)	-0.25 (0.04)	-0.33 (0.04)	-0.24 (0.04)
Quasi-Poisson regression	-0.43 (0.05)	-0.50 (0.05)	-0.48 (0.07)	-0.34 (0.04)	-0.42 (0.04)	-0.29 (0.04)
Removing June and July	-0.57 (0.06)	-0.65 (0.07)	-0.65 (0.09)	-0.40 (0.05)	-0.46 (0.06)	-0.32 (0.05)
January-September 2022	-0.38 (0.08)	-0.40 (0.08)	-0.39 (0.08)	-0.04 (0.0)	-0.11 (0.05)	-0.11 (0.05)
Before war (2022-02-24)	-0.80 (0.11)	-1.04 (0.11)	-0.33 (0.26)	-0.80 (0.11)	-1.04 (0.11)	-0.33 (0.26)
Pure Diesel prices	-0.49 (0.04)	-0.54 (0.05)	-0.45 (0.07)	-0.38 (0.03)	-0.45 (0.03)	-0.24 (0.03)
Monthly estimates	-0.20 (0.31)					
Anticipation dummies				✓	✓	✓
Seasonality controls		✓	✓		✓	✓
Linear trend			✓			✓
Cell FE	✓	✓	✓	✓	✓	✓

Note. Estimation with a sample of $7,000$ cells of customers observed from September 2021 to February 2023. Two-way clustering of standard errors at cell and day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 6: Heterogeneity of elasticities

	OLS	**IV**
Average	-0.21 (0.07)	-0.40 ((0.08))
Income group		
1st quarter	-0.26 (0.08)	-0.42 (0.09)
2nd quarter	-0.21 (0.07)	-0.38 (0.08)
3rd quarter	-0.19 (0.07)	-0.34 (0.07)
4th quarter	-0.21 (0.09)	-0.45 (0.1)
Past fuel consumption group		
1st quarter	-0.62 (0.22)	-1.06 (0.24)
2nd quarter	-0.25 (0.12)	-0.52 (0.13)
3rd quarter	-0.25 (0.08)	-0.43 (0.1)
4th quarter	-0.19 (0.06)	-0.32 (0.07)
Location		
Periurban	-0.32 (0.05)	-0.47 (0.07)
Urban	-0.24 (0.12)	-0.41 (0.13)
Rural	-0.22 (0.06)	-0.37 (0.07)

Note. Two-way clustering of standard errors at cell and day levels.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 7: Socio-economic characteristics (by elasticity group)

	All		20 % most elastic		20 % least elastic	
	Avg.	Sd.	Avg.	Sd.	Avg.	Sd.
Age	52	0.03	58	0.07	42	0.08
Monthly fuel consumption (euros)	106	0.18	77	0.38	122	0.40
Monthly income	3014	4.72	2850	10.24	3143	10.94
Liquid wealth	42,165	214	43,518	465	42,118	497
Periurban	0.45	0	0.39	0	0.50	0
Rural	0.23	0	0.29	0	0.15	0
Urban	0.32	0	0.33	0	0.34	0
Consumption unit	1.29	0	1.33	0	1.22	0

Note. Average characteristics in each quintile of conditional average treatment effect (CATE). Estimation period: from July 15th to October 4th (without the anticipation window). Treatment group: 2022. Control year: 2021.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Table 8: Counterfactual spending

	I	II	III	IV	V	VI	VII
	Observed	**Simulations**					
		OLS estimations			**IV estimations**		
		Fixed price in 2022	Without discount	With discount (no adjustment)	Fixed price in 2022	Without discount	With discount (no adjustment)
Average	1368	1241	1449	1338	1275	1419	1311
Income group							
1st quarter	920	842	968	894	863	949	877
2nd quarter	1096	995	1161	1071	1019	1139	1052
3rd quarter	1552	1401	1650	1523	1431	1623	1499
4th quarter	1903	1726	2018	1864	1782	1967	1818
Past fuel consumption group							
1st quarter	187	193	180	163	211	162	147
2nd quarter	761	700	808	742	724	785	722
3rd quarter	1513	1379	1602	1478	1410	1575	1454
4th quarter	3013	2709	3202	2964	2753	3164	2930
Location							
Periurban	1480	1347	1568	1447	1373	1544	1426
Urban	981	902	1034	955	924	1012	936
Rural	1855	1695	1948	1800	1728	1919	1774

Note. Fuel spending (in €) in 2022 based on various scenarios and estimations. Column I: observed spending. Column II: simulated spending if prices had remained fixed and equal to their level on January 8th. Column III: simulated spending in the absence of any discount at the pump. Column IV: simulated spending with discounts, holding quantity constant and equal to its level in the no-discount scenario (no adjustment: null price-elasticity). Columns V, VI and VI: same scenarios as Columns II, III and IV based on IV estimations (instead of OLS).
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

Online Appendix

C Toy econometric models: details

In this Appendix, we first consider an econometric specification that extends the toy model presented in section 3.2 in that period k may last T_k days, which encompasses the case where $T_k = T, \forall k$. We then present a model suited to the case of a tax cut that exactly compensates a price surge.

C.1 A single price reduction (4-period model)

C.1.1 Unconstrained estimator

Program:

$$\min_{(q_0,\beta,\gamma_2,\gamma_3)} \sum_{k=1}^{4} T_k \left(q_k - q_0 - \beta p_k - \sum_{k=2}^{3} \gamma_k \right)^2$$

FOC:

$$q_0 + \beta \bar{p} = \bar{q} - \sum_{k=2}^{3} \gamma_k \frac{T_k}{T} \tag{19}$$

$$q_0 \bar{p} + \beta \overline{p^2} = \overline{pq} - \sum_{k=2}^{3} \gamma_k p_k \frac{T_k}{T} \tag{20}$$

$$q_k - q_0 - \beta p_k = \gamma_k, \ \forall k = 2, 3 \tag{21}$$

Plugging (21) into (19) yields $q_0(T_1 + T_4) + \beta(T_1 p_1 + T_4 p_4) = T_1 q_1 + T_4 q_4$

Plugging (21) into (20) yields $q_0(T_1 p_1 + T_4 p_4) + \beta(T_1 p_1^2 + T_4 p_4^2) = T_1 p_1 q_1 + T_4 p_4 q_4$

Thus

$$\boxed{\hat{\beta}^u = \frac{q_1 - q_4}{p_1 - p_4} < 0}$$

$$\hat{q}_0^u = \frac{p_1 q_4 - p_4 q_1}{p_1 - p_4}$$

$$\hat{\gamma}_k^u = q_k - q_1 - (q_4 - q_1)\frac{p}{\Delta p} - p_k \frac{q_1 - q_k}{\Delta p} \quad \forall k = 2, 3$$

that is,

$$\hat{\gamma}_2^u = q_2 - q_1 < 0, \hat{\gamma}_3^u = q_3 - q_4 > 0$$

C.1.2 Constrained estimator

Under the constraint $\sum_{k=2}^{3} T_k \gamma_k = 0$, FOC now write:

$$q_0 + \beta \bar{p} = \bar{q} \tag{22}$$

$$q_0 \bar{p} + \beta \overline{p^2} = \overline{pq} - \sum_{k=2}^{3} \gamma_k p_k \frac{T_k}{T} \tag{23}$$

$$\gamma_2 (T_2 + T_3) = T_3 [q_2 - q_3 - \beta(p_2 - p_3)] \tag{24}$$

Plugging the latter into (23) and using (22) combined with the constraint yields

$$\boxed{\hat{\beta}^c = \frac{(T_2 + T_3)[T_1 q_1 (T_3 + T_4) - T_4 q_4 (T_1 + T_2)] + (T_2 T_4 - T_1 T_3)(T_2 q_2 + T_3 q_3)}{[T_2 T_4 (T_1 + T_2) + T_1 T_3 (T_3 + T_4)] \Delta p}}$$

When the episode is symmetric with respect to the moment when prices fall, i.e. $T_1 = T_4$ and $T_2 = T_3$, the latter formula boils down to

$$\boxed{\hat{\beta}^c = \frac{q_1 - q_4}{\Delta p}}$$

In the absence of symmetry, the information about purchases during the anticipation window may be used to infer β.

$$\hat{\gamma}_2^c = T_3 \frac{T_1 (T_3 + T_4)(q_2 - q_1) + T_4 (T_1 + T_2)(q_4 - q_3)}{T_2 T_4 (T_1 + T_2) + T_1 T_3 (T_3 + T_4)} < 0$$

Under symmetry, the latter expression boils down to $\hat{\gamma}_2^c = (q_2 - q_1)/2 + (q_4 - q_3)/2$.

C.1.3 Naive estimator

Under $\gamma_k = 0, \forall k = 2, 3$, FOC now write:

$$q_0 + \beta\bar{p} = \bar{q}$$

$$q_0\bar{p} + \beta\overline{p^2} = \overline{pq}$$

It follows that

$$\boxed{\hat{\beta}^n = \frac{\overline{pq} - \bar{p}\bar{q}}{\overline{p^2} - \bar{p}^2} = \frac{T}{T_1 + T_2}\frac{\bar{q} - \bar{q}^{34}}{\Delta p} < 0}$$

C.2 Price surge + compensatory tax cut (5-period model)

The main advantage of our estimation procedure (namely, the fact of imposing a zero-sum for the γ coefficients all over the anticipation window) is even more salient when we consider a rise in prices followed by a price cut that brings prices back to their original level. Though simplified, this framework once again resembles the situation that prevailed at the beginning of the war, followed a few weeks later by the first excise tax cut announced on March 11th and implemented on April 1st. We then resort to a 5-period model as described by Figure 4b: $\forall k \neq 3,\ p_k = p$, and $p_3 = p + \Delta p$. Here the researcher expects that $q_3 < q_1 = q_5 < q_2 = q_4$, due to positive anticipation effects in period 2 (consecutive to the anticipated price increase in period 3) and to negative anticipation effects (or postponement effects) in period 3 (as a consequence of the latter, but also consecutive to the expected price cut in period 4), on top of the (negative) price effect since $p_3 > p$. Consumption in period 4 should be higher due to consumers refraining from buying in period 3. We then consider a similar linear specification as before:[32]

$$q_t = q_0 + \beta p_t + \gamma_2 \mathbb{1}_{t\in 2} + \gamma_3 \mathbb{1}_{t\in 3} + \gamma_4 \mathbb{1}_{t\in 4} + u_t. \tag{25}$$

[32] Again, the inventory model would impose further constraints: $\gamma_2 = \lambda\frac{\Delta p}{2\theta} = \gamma_4 > 0$ and $\gamma_3 = -\lambda\frac{\Delta p}{\theta} < 0$. The model would then predict that $i_1 = i_4 = i_5 = 0, i_2 = \lambda\frac{\Delta p}{2\theta}, i_3 = -\lambda\frac{\Delta p}{2\theta}$, and that $c_3 - \lambda\frac{\Delta p}{\theta} = q_3 < q_1 = q_5 = c_1 < q_2 = q_4 = c_1 + \lambda\frac{\Delta p}{2\theta}$. Consistently with the econometric model, $\gamma_2 = q_2 - c_2 = \lambda\frac{\Delta p}{2\theta} = q_2 - q_1 = \gamma_4 = q_4 - c_4 = q_4 - q_5, \gamma_3 = q_3 - c_3 = -\lambda\frac{\Delta p}{\theta} = (q_3 - q_1) - \left(\frac{q_2+q_3+q_4}{3} - \frac{q_1+q_2+q_3+q_4+q_5}{5}\right)\frac{15}{2}$, such that $\gamma_2 + \gamma_3 + \gamma_4 = 0$.

Not imposing $T_2\gamma_2 + T_3\gamma_3 + T_4\gamma_4 = 0$ would be equivalent to dismiss the whole episode from $k = 1$ to $k = 5$ when inferring price sensitivity: indeed, since the price is the same in periods 1 and 5, the unconstrained estimator is infeasible here (cf. Appendix C.2.2). In practice, it means that the imprecision, i.e. the standard errors, should dramatically increase. Under the naive approach, that is, when $\gamma_k = 0, \forall k = 2, \ldots, 4$, one has $\hat{\beta}^n = \frac{T}{T-T_3}\frac{q_3-\bar{q}}{\Delta p} < 0$ (cf. Appendix C.2): this estimator mostly relies on the sole time period when the price effectively varies, and compares the demand in that period with the average demand over the whole episode. By definition, such an approach does not account for any short-term intertemporal substitution. Under the assumption that anticipation effects exactly compensate over the anticipation window, i.e. $T_2\gamma_2 + T_3\gamma_3 + T_4\gamma_4 = 0$, one obtains $\hat{\beta}^c = \frac{T}{T_3}\frac{T_2+T_3+T_4}{T_1+T_5}\frac{\bar{q}^{234}-\bar{q}}{\Delta p}$ (see Appendix C.2.3). Interestingly, this estimator exploits the information contained in the anticipation window to infer the price effect, while adjusting for anticipatory behavior. A numerical example based on observed prices and purchases during that episode suggests that the anticipation bias would be even more pronounced here, the naive elasticity being as high as 1.49, in absolute (see Appendix C.3). Yet the constrained estimation yields -0.3. On the whole, this example also suggests that the estimation procedure is perhaps more fragile when relying on that price surge episode (compared with the one based on the single price reduction).

C.2.1 Testing the model

Though it is not possible to test the model in the sense that, by construction, $T_2\gamma_2 + T_3\gamma_3 + T_4\gamma_4 = 0$ holds, it is yet possible to first test whether $q_1 = q_5$ and $q_2 = q_4$ on the data. From Table 10, $q_1 \approx 2.414$ liters per day, $q_5 \approx 2.388$ liters per day -a tiny 1.1% difference; similarly, $q_2 \approx 2.739$ liters per day, $q_4 \approx 2.773$ liters per day -a 1.2% gap. Second, it would be possible to reject the model if the condition $q_1 - q_3 > (q_2 - q_1) + (q_4 - q_5)$ was not met. Once those periods have been appropriately weighted, it is not possible to reject the model.[33]

[33] $9.306 \approx 22(0.423) \approx T_3(q_1 - q_3) > T_2(q_2 - q_1) + T_4(q_4 - q_5) \approx 13(0.325) + 7(0.385) \approx 6.92.$

C.2.2 Unconstrained estimator

Program:

$$\min_{(q_0,\beta,\gamma_2,\gamma_3,\gamma_4)} \sum_{k=1}^{5} T_k \left(q_k - q_0 - \beta p_k - \sum_{k=2}^{4} \gamma_k \right)^2$$

FOC:

$$q_0 + \beta \bar{p} = \bar{q} - \sum_{k=2}^{4} \gamma_k \frac{T_k}{T} \tag{26}$$

$$q_0 \bar{p} + \beta \overline{p^2} = \overline{pq} - \sum_{k=2}^{4} \gamma_k p_k \frac{T_k}{T} \tag{27}$$

$$q_k - q_0 - \beta p_k = \gamma_k, \ \forall k = 2, \ldots, 4 \tag{28}$$

Plugging (28) into (26) yields $q_0(T_1 + T_5) + \beta(T_1 p_1 + T_5 p_5) = T_1 q_1 + T_5 q_5$

Plugging (28) into (27) yields $q_0(T_1 p_1 + T_5 p_5) + \beta(T_1 p_1^2 + T_5 p_5^2) = T_1 p_1 q_1 + T_5 p_5 q_5$

Thus

$$\boxed{\hat{\beta}^u = \frac{q_1 - q_5}{p_1 - p_5}}$$

infeasible since $p_1 = p_5$.

$$\hat{q}_0^u = \frac{p_1 q_5 - p_5 q_1}{p_1 - p_5}$$

$$\hat{\gamma}_k^u = \frac{[q_k(p_1 - p_5) - p_k(q_1 - q_5)] - (p_1 q_5 - p_5 q_1)}{p_1 - p_5} \quad \forall k = 2, \ldots, 4$$

C.2.3 Constrained estimator

Under the constraint $\sum_{k=2}^{4} T_k \gamma_k = 0$, FOC now write:

$$q_0 + \beta \bar{p} = \bar{q} \tag{29}$$

$$q_0 \bar{p} + \beta \overline{p^2} = \overline{pq} - \sum_{k=2}^{4} \gamma_k p_k \frac{T_k}{T} \tag{30}$$

$$\gamma_2(T_2+T_3)+\gamma_4 T_4 = T_3[q_2-q_3-\beta(p_2-p_3)] \tag{31}$$

$$\gamma_2 T_2+\gamma_4(T_3+T_4) = T_3[q_4-q_3-\beta(p_4-p_3)] \tag{32}$$

It follows from (31) and (32) that

$$\gamma_2 = \frac{[(T_3+T_4)q_2-T_3q_3-T_4q_4]-\beta[(T_3+T_4)p_2-T_3p_3-T_4p_4]}{T_2+T_3+T_4}$$

$$\gamma_4 = \frac{[(T_2+T_3)q_4-T_2q_2-T_3q_3]-\beta[(T_2+T_3)p_4-T_2p_2-T_3p_3]}{T_2+T_3+T_4}$$

Plugging the latter into (30) and using (29) combined with the constraint yields

$$\boxed{\hat{\beta}^c = \frac{T}{T_3}\frac{T_2+T_3+T_4}{T_1+T_5}\frac{\bar{q}^{234}-\bar{q}}{\Delta p} < 0}$$

N.B. $\hat{\beta}^c < 0$ because $\bar{q}^{234} < \bar{q}$ due to $\bar{p}^{234} > \bar{p}$.

$$\hat{q}_0^c = \bar{q}^{15} - (\bar{q}^{234}-\bar{q})\frac{p}{\Delta p}\frac{T}{T_3}\frac{T_2+T_3+T_4}{T_1+T_5}$$

$$\hat{\gamma}_k^c = q_k - \bar{q}^{15} + (\bar{q}^{234}-\bar{q})\frac{p-p_k}{\Delta p}\frac{T}{T_3}\frac{T_2+T_3+T_4}{T_1+T_5} \quad \forall k=2,\ldots,4$$

hence

$$\hat{\gamma}_k^c = q_k - \bar{q}^{15} > 0 \quad \forall k = 2,4$$

and

$$\hat{\gamma}_3^c = q_3 - \bar{q}^{15} - (\bar{q}^{234}-\bar{q})\frac{T}{T_3}\frac{T_2+T_3+T_4}{T_1+T_5} < 0$$

C.2.4 Naive estimator

Under $\gamma_k = 0, \quad \forall k = 2,\ldots,4$, FOC now write:

$$q_0 + \beta \bar{p} = \bar{q}$$

$$q_0 \bar{p} + \beta \overline{p^2} = \overline{pq}$$

It follows that

$$\boxed{\hat{\beta}^n = \frac{\overline{pq} - \bar{p}\bar{q}}{\overline{p^2} - \bar{p}^2} = \frac{T}{T - T_3} \frac{q_3 - \bar{q}}{\Delta p} < 0}$$

C.3 Numerical examples

4-period model Cf. DinD strategy from section 4.1.

Table 9: Consumption around September 1st

Period	07-15 to 08-24	08-25 to 08-31	09-01 to 09-07	09-08 to 10-04
Liters per day (2021)	2.815	2.854	2.734	2.607
Liters per day (2022)	2.503	2.344	2.973	2.420
Price in € (2021)	1.491	1.481	1.486	1.509
Price in € (2022)	1.881	1.905	1.715	1.656
Length of period (days)	42	7	7	28

Unconstrained estimator: $\hat{\varepsilon}^u \approx -0.38$ (linear), $\hat{\varepsilon}^u \approx -0.21$ (log-log).

Constrained estimator: $\hat{\varepsilon}^c \approx -0.4$ (linear), $\hat{\varepsilon}^c \approx -0.22$ (log-log).

Naive estimator: $\hat{\varepsilon}^n \approx -0.73$ (linear), $\hat{\varepsilon}^n \approx -0.42$ (log-log).

Table 10: Consumption during the war

Period	01-10 to 02-24	02-25 to 03-09	03-10 to 03-31	04-01 to 04-07	04-08 to 04-30
Liters per day	2.283	2.702	1.955	2.805	2.344
Liters per day (adjusted)	2.373	2.694	1.962	2.746	2.361
Price in €	1.712	1.870	2.063	1.853	1.827
Length of period (days)	46	13	22	7	23

5-period model Constrained estimator: $\hat{\varepsilon}^c \approx -0.3$ (linear), $\hat{\varepsilon}^c \approx -0.35$ (log-log).

Naive estimator: $\hat{\varepsilon}^n \approx -1.49$ (linear), $\hat{\varepsilon}^n \approx -1.13$ (log-log).

D Data details

Two concerns have been raised by the literature as regards the external validity of bank account data (Baker, 2018): representativeness and completeness. We therefore resort to several external sources to assess both representativeness and completeness of our databases.

Representativeness To alleviate concerns about representativeness, and to build upon previous works afore mentioned, we proceed to calibration weighting using the method proposed by Deville and Särndal (1992). We compute weights that exactly reproduce some targets for auxiliary variables, related to the whole population, while ensuring that these calibrated weights are as close as possible to original sampling weights. By construction, the weighted sample has the same distribution as regards the corresponding variables as the whole population. We consider the following dimensions, called margins: age, sex and *département*, for that auxiliary information.

The distribution of household expenditures with respect to their position in the standard of living distribution obtained in transaction data matches closely the one issued from the representative consumption survey *Budget des Familles* (Figure 19). In particular, putting aside both ends of the income distribution, spending-to-income ratios look remarkably similar, decreasing from 1 to 0.75, which mitigates previous concerns related to measurement error on income. If anything, our data overestimate spending, probably because Crédit Mutuel customers tend to be richer. This is confirmed by Table 11 which suggests that Crédit Mutuel customers are wealthier: they dispose of higher income (Figure 17), detain more assets (Figure 18), and spend more than the average (Figure 19). The pregnancy of liquidity constraints can be assessed by looking at the liquid wealth-to-income ratio, about 10.5, meaning that, on average, households dispose of liquidity equivalent to 10.5 months of income. It decomposes into a 3.1 ratio of liquid assets over end-of-month balances on deposit accounts (this number compares well with the one documented in the U.S. by Baker (2018)), and another 3.4 ratio of end-of-month balances on deposit accounts over monthly income. Finally, these customers are younger, on average, and tend to live in more peripheral areas. Figure 20 focuses on the sole fuel category: it can be verified that our sample spends systematically a bit more, probably because it is composed of richer customers. Reassuringly, the evolution of fuel spending looks yet quite identical (Figure 22) to the one issued from the comprehensive *Groupement des Cartes Bancaires CB* (GIE CB) dataset, with a 0.99 correlation. On top of supporting external validity, this empirical evidence provides some grounds for a seasonal adjustment based on the data issued from the French card and mobile payment system. More generally, we believe that it alleviates legitimate concerns about selection bias.

Completeness First, our measure of spending exhibits quite the same evolution as the one issued from the *Groupement des Cartes Bancaires CB*, the leading domestic card and mobile payment system in France (Figure 21).

Second, our measure of income is more volatile (Figure 23) than the one measured by Insee.[34] This higher dispersion is rather expected: it is intrinsically related to the fact that we do not observe income directly, but rather all incoming transfers. Yet it is reassuring to see that the magnitude of possible measurement error is limited.

Third, our measure of liquid assets is slightly more dynamic than the one reported by *Banque de France* that centralizes information from all other bank networks (Figure 24). If anything, Crédit Mutuel customers likely enjoy higher capital gains (Fagereng et al., 2019) but that composition effect looks again rather limited.

On the whole, these comparisons with external sources suggest (i) that representativeness is not too much of a concern, (ii) that the calibration weighting contributes to alleviate this problem, and (iii) that the remaining differences on earnings and assets are mostly due to differences in concepts, rather than to incompleteness.

[34]namely, the gross standard of living as the ratio of gross disposable income over the number of consumption units.

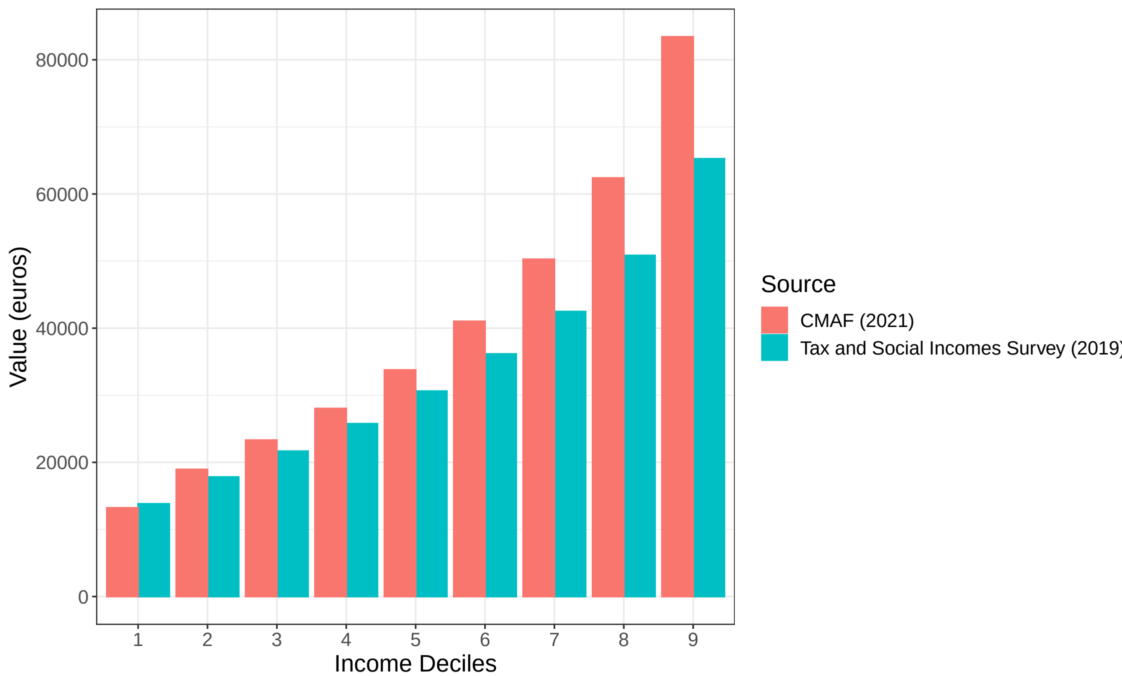
D.1 Data: External validity

Table 11: Summary statistics

	Weighted sample
# of observations	181,527
	Banking variables (sample means)
Monthly Spending	2,721
Fuel (cards)	94
Income	3,622
Financial Assets	
Liquid financial Assets	38,116
Illiquid financial Assets	23,469
Ratio liquid assets/deposit account	3.1
	Household head characteristics (sample means)
Age	53
Female	0.41
Craftsmen, merchants and business owners	0.08
Managerial and professional occupations	0.13
Technicians and associate professionals	0.12
Employees	0.17
Workers	0.11
Periphery areas	0.41
Rural areas	0.37
Urban areas	0.19

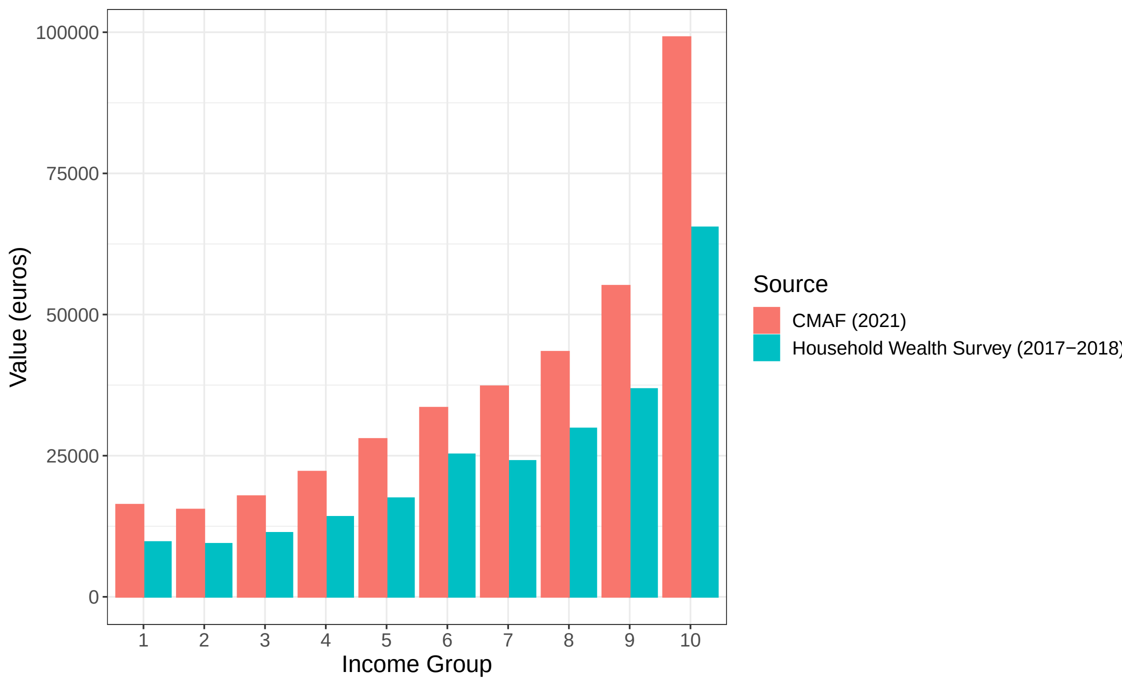
Note. Estimation period: 2021 for transactions (spending, income), January 2021 for assets and socio-demographics. Pecuniary amounts in €. The oldest member of the household is the head of the household.
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 17: Distribution of income (transaction data vs. survey data from *ERFS*, Insee)



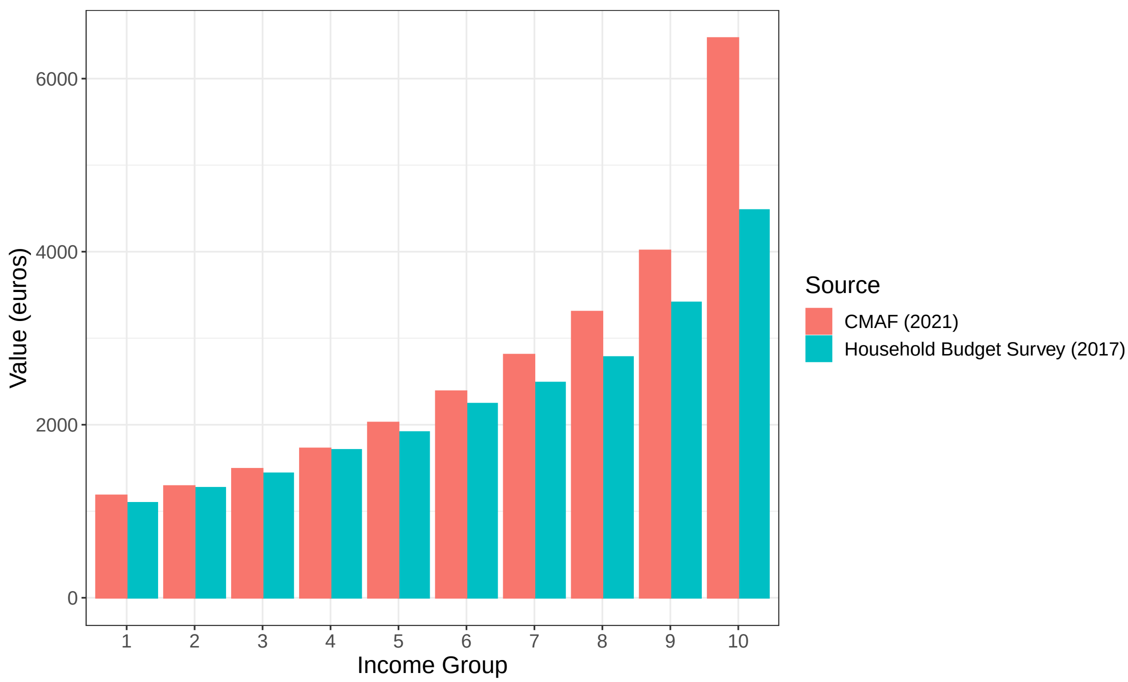
Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *Enquête sur les Revenus Fiscaux et Sociaux* (ERFS) survey.

Figure 18: Household financial wealth by income (transaction data vs. survey data from *Histoire de Vie et Patrimoine*, Insee)



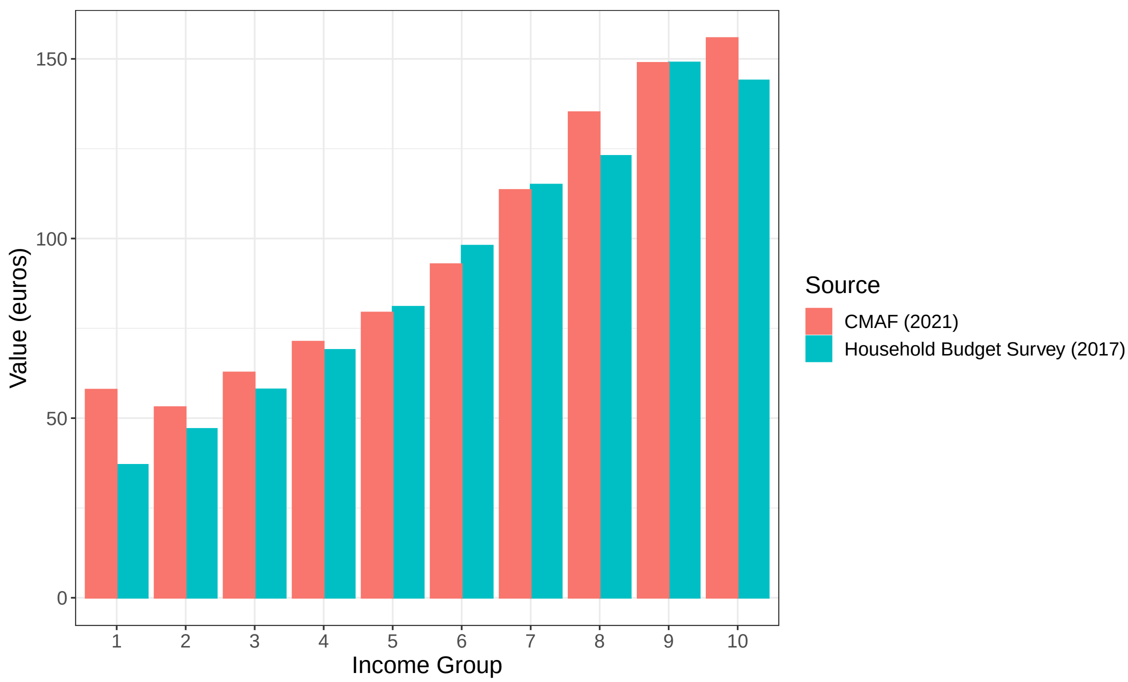
Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *Patrimoine* survey.

Figure 19: Household monthly expenditures by income (transaction data vs. survey data from *Budget des Familles*, Insee)



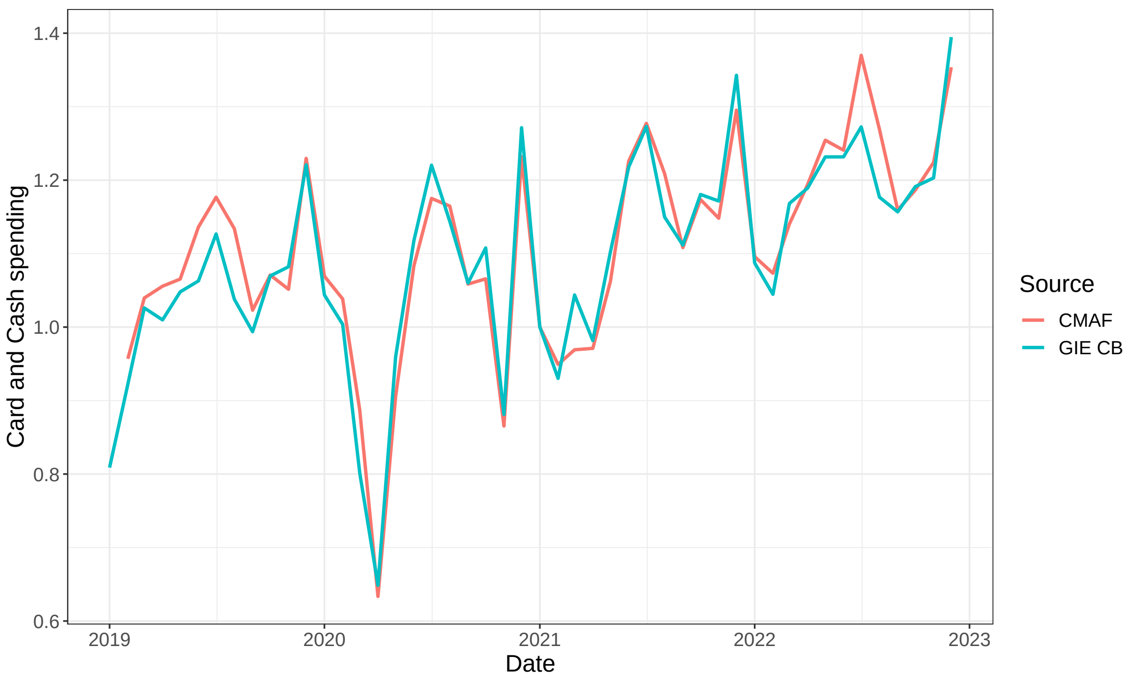
Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *Budget des Familles* survey.

Figure 20: Distribution of monthly fuel spending, by income (transaction data vs. survey data from *Budget des Familles*, Insee)



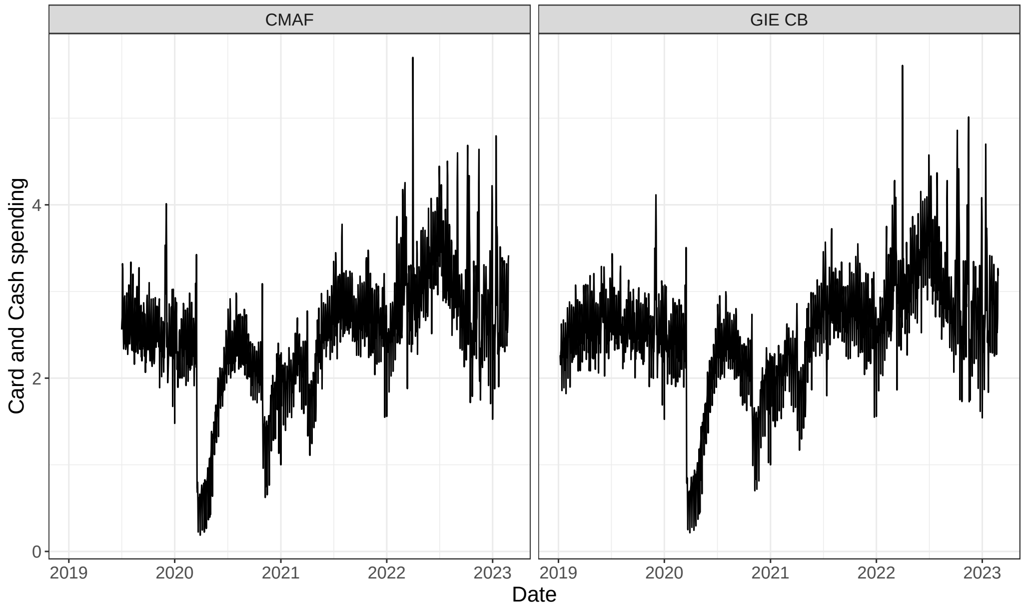
Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *Budget des Familles* survey.

Figure 21: Evolution of spending (transaction data vs. aggregate data from the French card and mobile payment system)



Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *GIE CB* data.

Figure 22: Evolution of fuel spending (transaction data vs. aggregate data from the French card and mobile payment system)

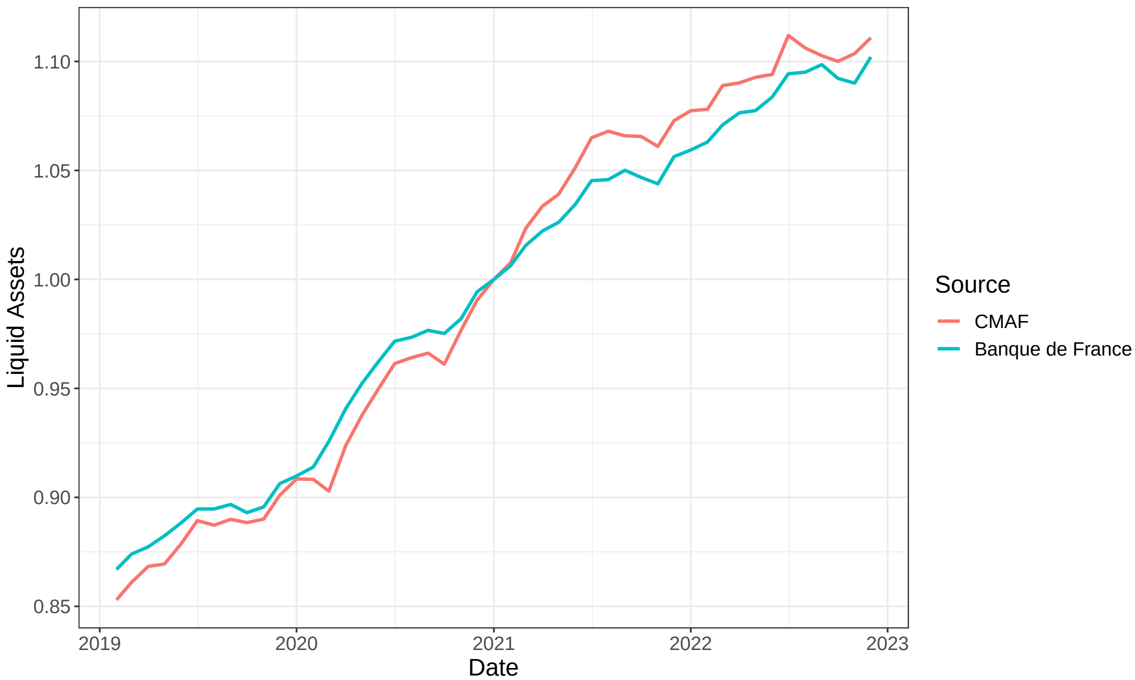


Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *GIE CB* data.

Figure 23: Income (transaction data vs. aggregate data from national accounts, Insee)

Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; French National Accounts.

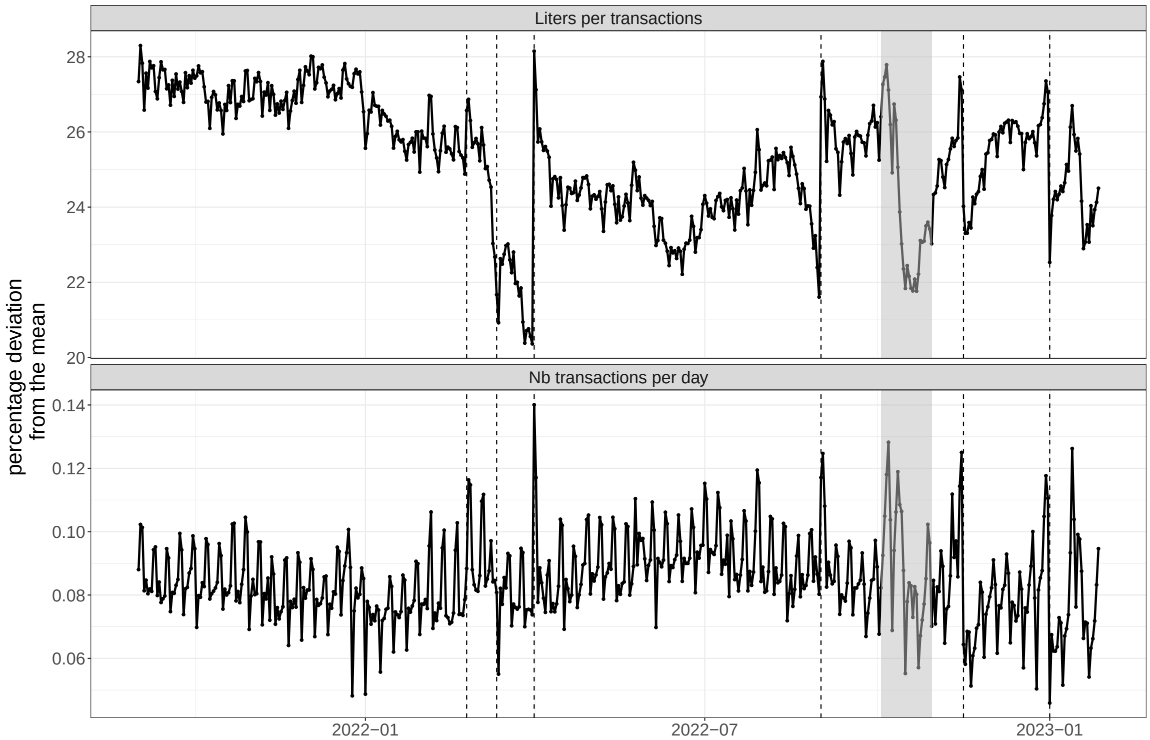
Figure 24: Liquid Assets (transaction data vs. aggregate data from Banque de France)



Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*; *Banque de France*.

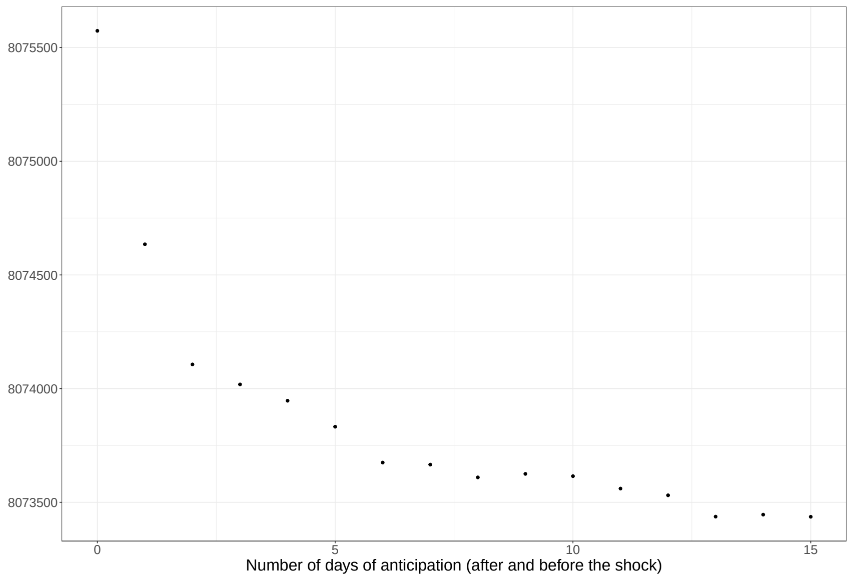
E Supplementary figures and tables

Figure 25: Intensive vs extensive margins (quantity per transaction vs # of transactions)



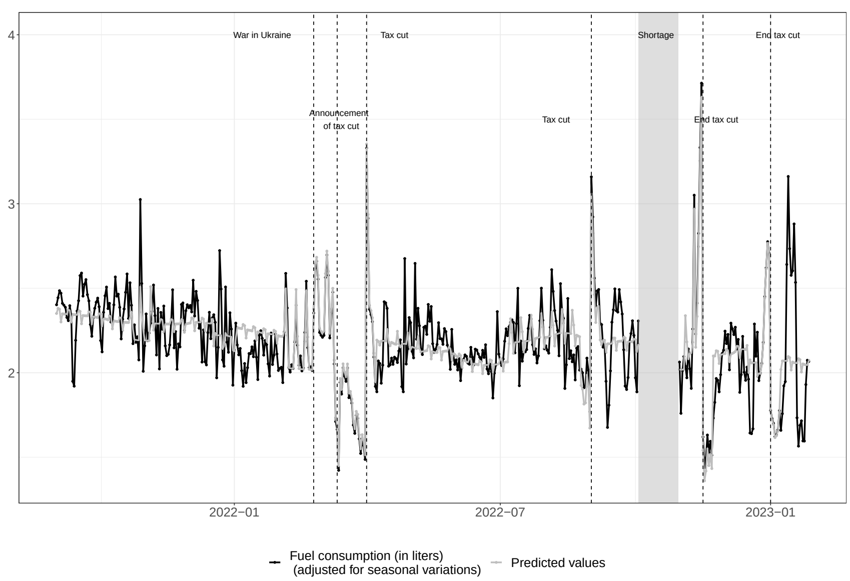
Sources. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 26: The BIC as a function of the anticipation bandwidth Δ



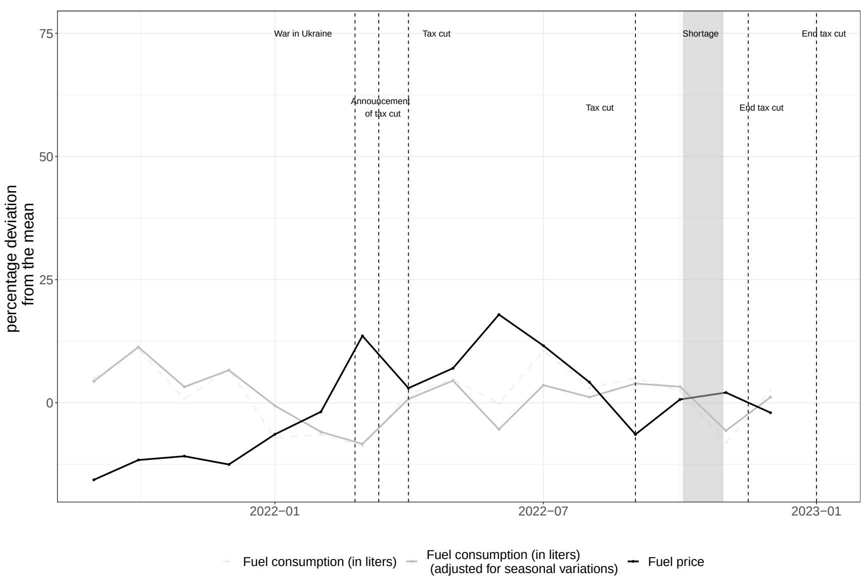
Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 27: Fit of the model (quasi-Poisson regression)



Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale.*

Figure 28: Fuel prices and purchases (monthly aggregation)



Source. Sample of households who primarily bank at *Crédit Mutuel Alliance Fédérale*.

Estimation based on August 2022-February 2023 Local estimations primarily based on the end of the temporary excise tax cut enable us to empirically investigate whether the response of fuel demand to a price change is asymmetric or not, i.e. whether it has the same magnitude with respect to either downwards or upwards shocks (Table 12). The naive estimator, -0.73 (0.10), still suffers from an anticipation bias. As expected, both constrained and unconstrained estimators are close, amounting respectively to -0.4 (0.08) and -0.35 (0.08): they are not significantly different from each other at 5%. They both lie at the lower bound of previous range of estimates: we therefore conclude to no (or limited) asymmetry in consumer response to price changes.

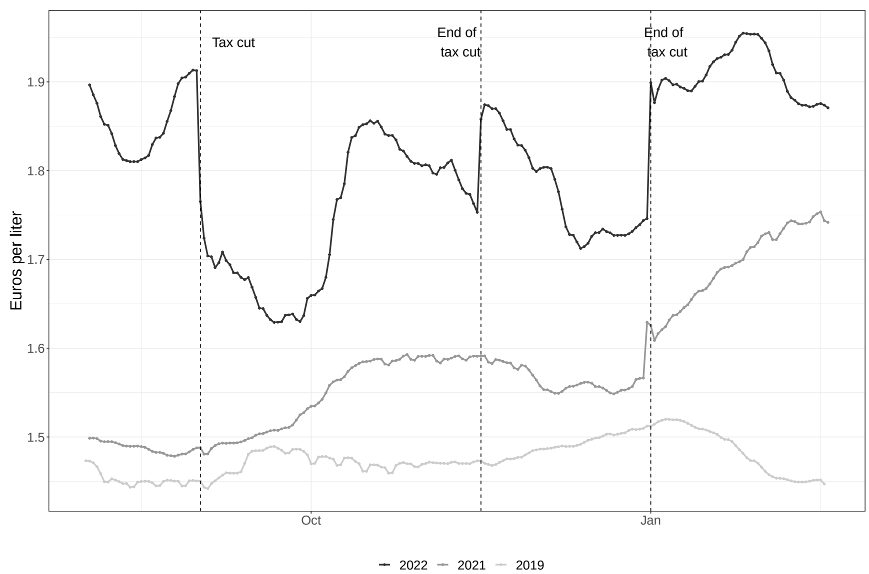


Figure 29: Fuel prices (August 2022-February 2023)

Table 12: Estimation based on the period from August 2022 to February 2023

	I	II	III
price elasticity	-0.76 (0.12)	-0.29 (0.07)	-0.34 (0.07)
Anticipation dummies		✓	
Excluding anticipation window			✓
Cell FE	✓	✓	✓
Day FE	✓	✓	✓
# of cells	10,938	10,938	10,938

Note. Estimation sample: 10,938 cells of customers.

3 observation windows: (i) from August 4th, 2019 to February, 22nd 2020,

(ii) from August 2nd, 2021 to February 20th, 2022,

and (iii) from August 1st 2022 to February 19th 2023

Two-way clustering of standard errors at cell and year-day levels.

Liste des documents de travail de la Direction des Études et Synthèses Économiques

G 9607 N. GREENAN - D. GUELLEC
La théorie coopérative de la firme

G 9608 N. GREENAN - D. GUELLEC
Technological innovation and employment reallocation

G 9609 Ph. COUR - F. RUPPRECHT
L'intégration asymétrique au sein du continent américain : un essai de modélisation

G 9610 S. DUCHENE - G. FORGEOT - A. JACQUOT
Analyse des évolutions récentes de la productivité apparente du travail

G 9611 X. BONNET - S. MAHFOUZ
The influence of different specifications of wages-prices spirals on the measure of the NAIRU: the case of France

G 9612 PH. COUR - E. DUBOIS, S. MAHFOUZ, J. PISANI-FERRY
The cost of fiscal retrenchment revisited: how strong is the evidence?

G 9613 A. JACQUOT
Les flexions des taux d'activité sont-elles seulement conjoncturelles ?

G 9614 ZHANG Yingxiang - SONG Xueqing
Lexique macroéconomique Français-Chinois

G 9701 J.L. SCHNEIDER
La taxe professionnelle : éléments de cadrage économique

G 9702 J.L. SCHNEIDER
Transition et stabilité politique d'un système redistributif

G 9703 D. GOUX - E. MAURIN
Train or Pay: Does it Reduce Inequalities to Encourage Firms to Train their Workers?

G 9704 P. GENIER
Deux contributions sur dépendance et équité

G 9705 E. DUGUET - N. IUNG
R & D Investment, Patent Life and Patent Value
An Econometric Analysis at the Firm Level

G 9706 M. HOUDEBINE - A. TOPIOL-BENSAÏD
Les entreprises internationales en France : une analyse à partir de données individuelles

G 9707 M. HOUDEBINE
Polarisation des activités et spécialisation des départements en France

G 9708 E. DUGUET - N. GREENAN
Le biais technologique : une analyse sur données individuelles

G 9709 J.L. BRILLET
Analyzing a small French ECM Model

G 9710 J.L. BRILLET
Formalizing the transition process: scenarios for capital accumulation

G 9711 G. FORGEOT - J. GAUTIÉ
Insertion professionnelle des jeunes et processus de déclassement

G 9712 E. DUBOIS
High Real Interest Rates: the Consequence of a Saving Investment Disequilibrium or of an insufficient Credibility of Monetary Authorities?

G 9713 Bilan des activités de la Direction des Études et Synthèses Économiques - 1996

G 9714 F. LEQUILLER
Does the French Consumer Price Index Overstate Inflation?

G 9715 X. BONNET
Peut-on mettre en évidence les rigidités à la baisse des salaires nominaux ?
Une étude sur quelques grands pays de l'OCDE

G 9716 N. IUNG - F. RUPPRECHT
Productivité de la recherche et rendements d'échelle dans le secteur pharmaceutique français

G 9717 E. DUGUET - I. KABLA
Appropriation strategy and the motivations to use the patent system in France - An econometric analysis at the firm level

G 9718 L.P. PELÉ - P. RALLE
Âge de la retraite : les aspects incitatifs du régime général

G 9719 ZHANG Yingxiang - SONG Xueqing
Lexique macroéconomique français-chinois, chinois-français

G 9720 M. HOUDEBINE - J.L. SCHNEIDER
Mesurer l'influence de la fiscalité sur la localisation des entreprises

G 9721 A. MOUROUGANE
Crédibilité, indépendance et politique monétaire
Une revue de la littérature

G 9722 P. AUGERAUD - L. BRIOT
Les données comptables d'entreprises
Le système intermédiaire d'entreprises
Passage des données individuelles aux données sectorielles

G 9723 P. AUGERAUD - J.E. CHAPRON
Using Business Accounts for Compiling National Accounts: the French Experience

G 9724 P. AUGERAUD
Les comptes d'entreprise par activités - Le passage aux comptes - De la comptabilité d'entreprise à la comptabilité nationale - *A paraître*

G 9801 H. MICHAUDON - C. PRIGENT
Présentation du modèle AMADEUS

G 9802 J. ACCARDO
Une étude de comptabilité générationnelle pour la France en 1996

G 9803 X. BONNET - S. DUCHÊNE
Apports et limites de la modélisation « Real Business Cycles »

G 9804 C. BARLET - C. DUGUET - D. ENCAOUA - J. PRADEL
The Commercial Success of Innovations
An econometric analysis at the firm level in French manufacturing

G 9805 P. CAHUC - Ch. GIANELLA - D. GOUX - A. ZILBERBERG
Equalizing Wage Differences and Bargaining Power - Evidence form a Panel of French Firms

G 9806 J. ACCARDO - M. JLASSI
La productivité globale des facteurs entre 1975 et 1996

G 9807 Bilan des activités de la Direction des Études et Synthèses Économiques - 1997

G 9808 A. MOUROUGANE
Can a Conservative Governor Conduct an Accomodative Monetary Policy?

G 9809 X. BONNET - E. DUBOIS - L. FAUVET
Asymétrie des inflations relatives et menus costs : tests sur l'inflation française

G 9810 E. DUGUET - N. IUNG
Sales and Advertising with Spillovers at the firm level: Estimation of a Dynamic Structural Model on Panel Data

G 9811 J.P. BERTHIER
Congestion urbaine : un modèle de trafic de pointe à courbe débit-vitesse et demande élastique

G 9812 C. PRIGENT
La part des salaires dans la valeur ajoutée : une approche macroéconomique

G 9813 A.Th. AERTS
L'évolution de la part des salaires dans la valeur ajoutée en France reflète-t-elle les évolutions individuelles sur la période 1979-1994 ?

G 9814 B. SALANIÉ
Guide pratique des séries non-stationnaires

G 9901 S. DUCHÊNE - A. JACQUOT
Une croissance plus riche en emplois depuis le début de la décennie ? Une analyse en comparaison internationale

G 9902 Ch. COLIN
Modélisation des carrières dans Destinie

G 9903 Ch. COLIN
Évolution de la dispersion des salaires : un essai de prospective par microsimulation

G 9904 B. CREPON - N. IUNG
Innovation, emploi et performances

G 9905 B. CREPON - Ch. GIANELLA
Wages inequalities in France 1969-1992
An application of quantile regression techniques

G 9906 C. BONNET - R. MAHIEU
Microsimulation techniques applied to intergenerational transfers - Pensions in a dynamic framework: the case of France

G 9907 F. ROSENWALD
L'impact des contraintes financières dans la décision d'investissement

G 9908 Bilan des activités de la DESE - 1998

G 9909 J.P. ZOYEM
Contrat d'insertion et sortie du RMI
Évaluation des effets d'une politique sociale

G 9910 Ch. COLIN - Fl. LEGROS - R. MAHIEU
Bilans contributifs comparés des régimes de retraite du secteur privé et de la fonction publique

G 9911 G. LAROQUE - B. SALANIÉ
Une décomposition du non-emploi en France

G 9912 B. SALANIÉ
Une maquette analytique de long terme du marché du travail

G 9912 Bis Ch. GIANELLA
Une estimation de l'élasticité de l'emploi peu qualifié à son coût

G 9913 Division « Redistribution et Politiques Sociales »
Le modèle de microsimulation dynamique DESTINIE

G 9914 E. DUGUET
Macro-commandes SAS pour l'économétrie des panels et des variables qualitatives

G 9915 R. DUHAUTOIS
Évolution des flux d'emplois en France entre 1990 et 1996 : une étude empirique à partir du fichier des bénéfices réels normaux (BRN)

G 9916 J.Y. FOURNIER
Extraction du cycle des affaires : la méthode de Baxter et King

G 9917 B. CRÉPON - R. DESPLATZ - J. MAIRESSE
Estimating price cost margins, scale economies and workers' bargaining power at the firm level

G 9918 Ch. GIANELLA - Ph. LAGARDE
Productivity of hours in the aggregate production function: an evaluation on a panel of French firms from the manufacturing sector

G 9919 S. AUDRIC - P. GIVORD - C. PROST
Évolution de l'emploi et des coûts par qualification entre 1982 et 1996

G 2000/01 R. MAHIEU
Les déterminants des dépenses de santé : une approche macroéconomique

G 2000/02 C. ALLARD-PRIGENT - H. GUILMEAU - A. QUINET
The real exchange rate as the relative price of nontrables in terms of tradables: theoretical investigation and empirical study on French data

G 2000/03 J.-Y. FOURNIER
L'approximation du filtre passe-bande proposée par Christiano et Fitzgerald

G 2000/04 Bilan des activités de la DESE - 1999

G 2000/05 B. CREPON - F. ROSENWALD
Investissement et contraintes de financement : le poids du cycle
Une estimation sur données françaises

G 2000/06 A. FLIPO
Les comportements matrimoniaux de fait

G 2000/07 R. MAHIEU - B. SÉDILLOT
Microsimulations of the retirement decision: a supply side approach

G 2000/08 C. AUDENIS - C. PROST
Déficit conjoncturel : une prise en compte des conjonctures passées

G 2000/09 R. MAHIEU - B. SÉDILLOT
Équivalent patrimonial de la rente et souscription de retraite complémentaire

G 2000/10 R. DUHAUTOIS
Ralentissement de l'investissement : petites ou grandes entreprises ? industrie ou tertiaire ?

G 2000/11 G. LAROQUE - B. SALANIÉ
Temps partiel féminin et incitations financières à l'emploi

G2000/12 Ch. GIANELLA
Local unemployment and wages

G2000/13 B. CREPON - Th. HECKEL
- Informatisation en France : une évaluation à partir de données individuelles
- Computerization in France: an evaluation based on individual company data

G2001/01 F. LEQUILLER
- La nouvelle économie et la mesure de la croissance du PIB
- The new economy and the measure ment of GDP growth

G2001/02 S. AUDRIC
La reprise de la croissance de l'emploi profite-t-elle aussi aux non-diplômés ?

G2001/03 I. BRAUN-LEMAIRE
Évolution et répartition du surplus de productivité

G2001/04 A. BEAUDU - Th. HECKEL
Le canal du crédit fonctionne-t-il en Europe ? Une étude de l'hétérogénéité des comportements d'investissement à partir de données de bilan agrégées

G2001/05 C. AUDENIS - P. BISCOURP - N. FOURCADE - O. LOISEL
Testing the augmented Solow growth model: An empirical reassessment using panel data

G2001/06 R. MAHIEU - B. SÉDILLOT
Départ à la retraite, irréversibilité et incertitude

G2001/07 Bilan des activités de la DESE - 2000

G2001/08 J. Ph. GAUDEMET
Les dispositifs d'acquisition à titre facultatif d'annuités viagères de retraite

G2001/09 B. CRÉPON - Ch. GIANELLA
Fiscalité, coût d'usage du capital et demande de facteurs : une analyse sur données individuelles

G2001/10 B. CRÉPON - R. DESPLATZ
Évaluation des effets des dispositifs d'allégements de charges sociales sur les bas salaires

G2001/11 J.-Y. FOURNIER
Comparaison des salaires des secteurs public et privé

G2001/12 J.-P. BERTHIER - C. JAULENT
R. CONVENEVOLE - S. PISANI
Une méthodologie de comparaison entre consommations intermédiaires de source fiscale et de comptabilité nationale

G2001/13 P. BISCOURP - Ch. GIANELLA
Substitution and complementarity between capital, skilled and less skilled workers: an analysis at the firm level in the French manufacturing industry

G2001/14 I. ROBERT-BOBEE
Modelling demographic behaviours in the French microsimulation model Destinie: An analysis of future change in completed fertility

G2001/15 J.-P. ZOYEM
Diagnostic sur la pauvreté et calendrier de revenus : le cas du "Panel européen des ménages »

G2001/16 J.-Y. FOURNIER - P. GIVORD
La réduction des taux d'activité aux âges extrêmes, une spécificité française ?

G2001/17 C. AUDENIS - P. BISCOURP - N. RIEDINGER
Existe-t-il une asymétrie dans la transmission du prix du brut aux prix des carburants ?

G2002/01 F. MAGNIEN - J.-L. TAVERNIER - D. THESMAR
Les statistiques internationales de PIB par habitant en standard de pouvoir d'achat : une analyse des résultats

G2002/02 Bilan des activités de la DESE - 2001

G2002/03 B. SÉDILLOT - E. WALRAET
La cessation d'activité au sein des couples : y a-t-il interdépendance des choix ?

G2002/04 G. BRILHAULT
- Rétropolation des séries de FBCF et calcul du capital fixe en SEC-95 dans les comptes nationaux français
- Retropolation of the investment series (GFCF) and estimation of fixed capital stocks on the ESA-95 basis for the French balance sheets

G2002/05 P. BISCOURP - B. CRÉPON - T. HECKEL - N. RIEDINGER
How do firms respond to cheaper computers? Microeconometric evidence for France based on a production function approach

G2002/06 C. AUDENIS - J. DEROYON - N. FOURCADE
L'impact des nouvelles technologies de l'information et de la communication sur l'économie française - un bouclage macro-économique

G2002/07 J. BARDAJI - B. SÉDILLOT - E. WALRAET
Évaluation de trois réformes du Régime Général d'assurance vieillesse à l'aide du modèle de microsimulation DESTINIE

G2002/08 J.-P. BERTHIER
Réflexions sur les différentes notions de volume dans les comptes nationaux : comptes aux prix d'une année fixe ou aux prix de l'année précédente, séries chaînées

G2002/09 F. HILD
Les soldes d'opinion résument-ils au mieux les réponses des entreprises aux enquêtes de conjoncture ?

G2002/10 I. ROBERT-BOBÉE
Les comportements démographiques dans le modèle de microsimulation Destinie - Une comparaison des estimations issues des enquêtes Jeunes et Carrières 1997 et Histoire Familiale 1999

G2002/11 J.-P. ZOYEM
La dynamique des bas revenus : une analyse des entrées-sorties de pauvreté

G2002/12 F. HILD
Prévisions d'inflation pour la France

G2002/13 M. LECLAIR
Réduction du temps de travail et tensions sur les facteurs de production

G2002/14 E. WALRAET - A. VINCENT
- Analyse de la redistribution intragénérationnelle dans le système de retraite des salariés du privé - Une approche par microsimulation
- Intragenerational distributional analysis in the french private sector pension scheme - A microsimulation approach

G2002/15 P. CHONE - D. LE BLANC - I. ROBERT-BOBEE
Offre de travail féminine et garde des jeunes enfants

G2002/16 F. MAUREL - S. GREGOIR
Les indices de compétitivité des pays : interprétation et limites

G2003/01 N. RIEDINGER - E.HAUVY
Le coût de dépollution atmosphérique pour les entreprises françaises : Une estimation à partir de données individuelles

G2003/02 P. BISCOURP et F. KRAMARZ
Création d'emplois, destruction d'emplois et internationalisation des entreprises industrielles françaises : une analyse sur la période 1986-1992

G2003/03 Bilan des activités de la DESE - 2002

G2003/04 P.-O. BEFFY - J. DEROYON - N. FOURCADE - S. GREGOIR - N. LAÏB - B. MONFORT
Évolutions démographiques et croissance : une projection macro-économique à l'horizon 2020

G2003/05 P. AUBERT
La situation des salariés de plus de cinquante ans dans le secteur privé

G2003/06 P. AUBERT - B. CRÉPON
Age, salaire et productivité
La productivité des salariés décline-t-elle en fin de carrière ?

G2003/07 H. BARON - P.O. BEFFY - N. FOURCADE - R. MAHIEU
Le ralentissement de la productivité du travail au cours des années 1990

G2003/08 P.-O. BEFFY - B. MONFORT
Patrimoine des ménages, dynamique d'allocation et comportement de consommation

G2003/09 P. BISCOURP - N. FOURCADE
Peut-on mettre en évidence l'existence de rigidités à la baisse des salaires à partir de données individuelles ? Le cas de la France à la fin des années 90

G2003/10 M. LECLAIR - P. PETIT
Présence syndicale dans les firmes : quel impact sur les inégalités salariales entre les hommes et les femmes ?

G2003/11 P.-O. BEFFY - X. BONNET - M. DARRACQ-PARIES - B. MONFORT
MZE: a small macro-model for the euro area

G2004/01 P. AUBERT - M. LECLAIR
La compétitivité exprimée dans les enquêtes trimestrielles sur la situation et les perspectives dans l'industrie

G2004/02 M. DUÉE - C. REBILLARD
La dépendance des personnes âgées : une projection à long terme

G2004/03 S. RASPILLER - N. RIEDINGER
Régulation environnementale et choix de localisation des groupes français

G2004/04 A. NABOULET - S. RASPILLER
Les déterminants de la décision d'investir : une approche par les perceptions subjectives des firmes

G2004/05 N. RAGACHE
La déclaration des enfants par les couples non mariés est-elle fiscalement optimale ?

G2004/06 M. DUÉE
L'impact du chômage des parents sur le devenir scolaire des enfants

G2004/07 P. AUBERT - E. CAROLI - M. ROGER
New Technologies, Workplace Organisation and the Age Structure of the Workforce: Firm-Level Evidence

G2004/08 E. DUGUET - C. LELARGE
Les brevets accroissent-ils les incitations privées à innover ? Un examen microéconométrique

G2004/09 S. RASPILLER - P. SILLARD
Affiliating versus Subcontracting:
the Case of Multinationals

G2004/10 J. BOISSINOT - C. L'ANGEVIN - B. MONFORT
Public Debt Sustainability: Some Results on the French Case

G2004/11 S. ANANIAN - P. AUBERT
Travailleurs âgés, nouvelles technologies et changements organisationnels : un réexamen à partir de l'enquête « REPONSE »

G2004/12 X. BONNET - H. PONCET
Structures de revenus et propensions différentes à consommer - Vers une équation de consommation des ménages plus robuste en prévision pour la France

G2004/13 C. PICART
Évaluer la rentabilité des sociétés non financières

G2004/14 J. BARDAJI - B. SÉDILLOT - E. WALRAET
Les retraites du secteur public : projections à l'horizon 2040 à l'aide du modèle de microsimulation DESTINIE

G2005/01 S. BUFFETEAU - P. GODEFROY
Conditions de départ en retraite selon l'âge de fin d'études : analyse prospective pour les générations 1945 à1974

G2005/02 C. AFSA - S. BUFFETEAU
L'évolution de l'activité féminine en France : une approche par pseudo-panel

G2005/03 P. AUBERT - P. SILLARD
Délocalisations et réductions d'effectifs dans l'industrie française

G2005/04 M. LECLAIR - S. ROUX
Mesure et utilisation des emplois instables dans les entreprises

G2005/05 C. L'ANGEVIN - S. SERRAVALLE
Performances à l'exportation de la France et de l'Allemagne - Une analyse par secteur et destination géographique

G2005/06 Bilan des activités de la Direction des Études et Synthèses Économiques - 2004

G2005/07 S. RASPILLER
La concurrence fiscale : principaux enseignements de l'analyse économique

G2005/08 C. L'ANGEVIN - N. LAÏB
Éducation et croissance en France et dans un panel de 21 pays de l'OCDE

G2005/09 N. FERRARI
Prévoir l'investissement des entreprises
Un indicateur des révisions dans l'enquête de conjoncture sur les investissements dans l'industrie.

G2005/10 P.-O. BEFFY - C. L'ANGEVIN
Chômage et boucle prix-salaires :
apport d'un modèle « qualifiés/peu qualifiés »

G2005/11 B. HEITZ
A two-states Markov-switching model of inflation in France and the USA: credible target VS inflation spiral

G2005/12 O. BIAU - H. ERKEL-ROUSSE - N. FERRARI
Réponses individuelles aux enquêtes de conjoncture et prévision macroéconomiques :
Exemple de la prévision de la production manufacturière

G2005/13 P. AUBERT - D. BLANCHET - D. BLAU
The labour market after age 50: some elements of a Franco-American comparison

G2005/14 D. BLANCHET - T. DEBRAND -
P. DOURGNON - P. POLLET
L'enquête SHARE : présentation et premiers résultats de l'édition française

G2005/15 M. DUÉE
La modélisation des comportements démographiques dans le modèle de microsimulation DESTINIE

G2005/16 H. RAOUI - S. ROUX
Étude de simulation sur la participation versée aux salariés par les entreprises

G2006/01 C. BONNET - S. BUFFETEAU - P. GODEFROY
Disparités de retraite de droit direct entre hommes et femmes : quelles évolutions ?

G2006/02 C. PICART
Les gazelles en France

G2006/03 P. AUBERT - B. CRÉPON -P. ZAMORA
Le rendement apparent de la formation continue dans les entreprises : effets sur la productivité et les salaires

G2006/04 J.-F. OUVRARD - R. RATHELOT
Demographic change and unemployment:
what do macroeconometric models predict?

G2006/05 D. BLANCHET - J.-F. OUVRARD
Indicateurs d'engagements implicites des systèmes de retraite : chiffrages, propriétés analytiques et réactions à des chocs démographiques types

G2006/06 G. BIAU - O. BIAU - L. ROUVIERE
Nonparametric Forecasting of the Manufacturing Output Growth with Firm-level Survey Data

G2006/07 C. AFSA - P. GIVORD
Le rôle des conditions de travail dans les absences pour maladie

G2006/08 P. SILLARD - C. L'ANGEVIN - S. SERRAVALLE
Performances comparées à l'exportation de la France et de ses principaux partenaires
Une analyse structurelle sur 12 ans

G2006/09 X. BOUTIN - S. QUANTIN
Une méthodologie d'évaluation comptable du coût du capital des entreprises françaises : 1984-2002

G2006/10 C. AFSA
L'estimation d'un coût implicite de la pénibilité du travail chez les travailleurs âgés

G2006/11 C. LELARGE
Les entreprises (industrielles) françaises sont-elles à la frontière technologique ?

G2006/12 O. BIAU - N. FERRARI
Théorie de l'opinion
Faut-il pondérer les réponses individuelles ?

G2006/13 A. KOUBI - S. ROUX
Une réinterprétation de la relation entre productivité et inégalités salariales dans les entreprises

G2006/14 R. RATHELOT - P. SILLARD
The impact of local taxes on plants location decision

G2006/15 L. GONZALEZ - C. PICART
Diversification, recentrage et poids des activités de support dans les groupes (1993-2000)

G2007/01 D. SRAER
Allègements de cotisations patronales et dynamique salariale

G2007/02 V. ALBOUY - L. LEQUIEN
Les rendements non monétaires de l'éducation : le cas de la santé

G2007/03 D. BLANCHET - T. DEBRAND
Aspiration à la retraite, santé et satisfaction au travail : une comparaison européenne

G2007/04 M. BARLET - L. CRUSSON
Quel impact des variations du prix du pétrole sur la croissance française ?

G2007/05 C. PICART
Flux d'emploi et de main-d'œuvre en France : un réexamen

G2007/06 V. ALBOUY - C. TAVAN
Massification et démocratisation de l'enseignement supérieur en France

G2007/07 T. LE BARBANCHON
The Changing response to oil price shocks in France: a DSGE type approach

G2007/08 T. CHANEY - D. SRAER - D. THESMAR
Collateral Value and Corporate Investment
Evidence from the French Real Estate Market

G2007/09 J. BOISSINOT
Consumption over the Life Cycle: Facts for France

G2007/10 C. AFSA
Interpréter les variables de satisfaction : l'exemple de la durée du travail

G2007/11 R. RATHELOT - P. SILLARD
Zones Franches Urbaines : quels effets sur l'emploi salarié et les créations d'établissements ?

G2007/12 V. ALBOUY - B. CRÉPON
Aléa moral en santé : une évaluation dans le cadre du modèle causal de Rubin

G2008/01 C. PICART
Les PME françaises : rentables mais peu dynamiques

G2008/02 P. BISCOURP - X. BOUTIN - T. VERGÉ
The Effects of Retail Regulations on Prices
Evidence form the Loi Galland

G2008/03 Y. BARBESOL - A. BRIANT
Économies d'agglomération et productivité des entreprises : estimation sur données individuelles françaises

G2008/04 D. BLANCHET - F. LE GALLO
Les projections démographiques : principaux mécanismes et retour sur l'expérience française

G2008/05 D. BLANCHET - F. TOUTLEMONDE
Évolutions démographiques et déformation du cycle de vie active : quelles relations ?

G2008/06 M. BARLET - D. BLANCHET - L. CRUSSON
Internationalisation et flux d'emplois : que dit une approche comptable ?

G2008/07 C. LELARGE - D. SRAER - D. THESMAR
Entrepreneurship and Credit Constraints - Evidence from a French Loan Guarantee Program

G2008/08 X. BOUTIN - L. JANIN
Are Prices Really Affected by Mergers?

G2008/09 M. BARLET - A. BRIANT - L. CRUSSON
Concentration géographique dans l'industrie manufacturière et dans les services en France : une approche par un indicateur en continu

G2008/10 M. BEFFY - É. COUDIN - R. RATHELOT
Who is confronted to insecure labor market histories? Some evidence based on the French labor market transition

G2008/11 M. ROGER - E. WALRAET
Social Security and Well-Being of the Elderly: the Case of France

G2008/12 C. AFSA
Analyser les composantes du bien-être et de son évolution
Une approche empirique sur données individuelles

G2008/13 M. BARLET - D. BLANCHET -
T. LE BARBANCHON
Microsimuler le marché du travail : un prototype

G2009/01 P.-A. PIONNIER
Le partage de la valeur ajoutée en France, 1949-2007

G2009/02 Laurent CLAVEL - Christelle MINODIER
A Monthly Indicator of the French Business Climate

G2009/03 H. ERKEL-ROUSSE - C. MINODIER
Do Business Tendency Surveys in Industry and Services Help in Forecasting GDP Growth?
A Real-Time Analysis on French Data

G2009/04 P. GIVORD - L. WILNER
Les contrats temporaires : trappe ou marchepied vers l'emploi stable ?

G2009/05 G. LALANNE - P.-A. PIONNIER - O. SIMON
Le partage des fruits de la croissance de 1950 à 2008 : une approche par les comptes de surplus

G2009/06 L. DAVEZIES - X. D'HAULTFOEUILLE
Faut-il pondérer ?… Ou l'éternelle question de l'économètre confronté à des données d'enquête

G2009/07 S. QUANTIN - S. RASPILLER - S. SERRAVALLE
Commerce intragroupe, fiscalité et prix de transferts : une analyse sur données françaises

G2009/08 M. CLERC - V. MARCUS
Élasticités-prix des consommations énergétiques des ménages

G2009/09 G. LALANNE - E. POULIQUEN - O. SIMON
Prix du pétrole et croissance potentielle à long terme

G2009/10 D. BLANCHET - J. LE CACHEUX - V. MARCUS
Adjusted net savings and other approaches to sustainability: some theoretical background

G2009/11 V. BELLAMY - G. CONSALES - M. FESSEAU - S. LE LAIDIER - É. RAYNAUD
Une décomposition du compte des ménages de la comptabilité nationale par catégorie de ménage en 2003

G2009/12 J. BARDAJI - F. TALLET
Detecting Economic Regimes in France: a Qualitative Markov-Switching Indicator Using Mixed Frequency Data

G2009/13 R. AEBERHARDT - D. FOUGÈRE - R. RATHELOT
Discrimination à l'embauche : comment exploiter les procédures de *testing* ?

G2009/14 Y. BARBESOL - P. GIVORD - S. QUANTIN
Partage de la valeur ajoutée, approche par données microéconomiques

G2009/15 I. BUONO - G. LALANNE
The Effect of the Uruguay round on the Intensive and Extensive Margins of Trade

G2010/01 C. MINODIER
Avantages comparés des séries des premières valeurs publiées et des séries des valeurs révisées - Un exercice de prévision en temps réel de la croissance trimestrielle du PIB en France

G2010/02 V. ALBOUY - L. DAVEZIES - T. DEBRAND
Health Expenditure Models: a Comparison of Five Specifications using Panel Data

G2010/03 C. KLEIN - O. SIMON
Le modèle MÉSANGE réestimé en base 2000
Tome 1 – Version avec volumes à prix constants

G2010/04 M.-É. CLERC - É. COUDIN
L'IPC, miroir de l'évolution du coût de la vie en France ? Ce qu'apporte l'analyse des courbes d'Engel

G2010/05 N. CECI-RENAUD - P.-A. CHEVALIER
Les seuils de 10, 20 et 50 salariés : impact sur la taille des entreprises françaises

G2010/06 R. AEBERHARDT - J. POUGET
National Origin Differences in Wages and Hierarchical Positions - Evidence on French Full-Time Male Workers from a matched Employer-Employee Dataset

G2010/07 S. BLASCO - P. GIVORD
Les trajectoires professionnelles en début de vie active : quel impact des contrats temporaires ?

G2010/08 P. GIVORD
Méthodes économétriques pour l'évaluation de politiques publiques

G2010/09 P.-Y. CABANNES - V. LAPÈGUE - E. POULIQUEN - M. BEFFY - M. GAINI
Quelle croissance de moyen terme après la crise ?

G2010/10 I. BUONO - G. LALANNE
La réaction des entreprises françaises à la baisse des tarifs douaniers étrangers

G2010/11 R. RATHELOT - P. SILLARD
L'apport des méthodes à noyaux pour mesurer la concentration géographique - Application à la concentration des immigrés en France de 1968 à 1999

G2010/12 M. BARATON - M. BEFFY - D. FOUGÈRE
Une évaluation de l'effet de la réforme de 2003 sur les départs en retraite - Le cas des enseignants du second degré public

G2010/13 D. BLANCHET - S. BUFFETEAU - E. CRENNER S. LE MINEZ
Le modèle de microsimulation Destinie 2 : principales caractéristiques et premiers résultats

G2010/14 D. BLANCHET - E. CRENNER
Le bloc retraites du modèle Destinie 2 : guide de l'utilisateur

G2010/15 M. BARLET - L. CRUSSON - S. DUPUCH - F. PUECH
Des services échangés aux services échangeables : une application sur données françaises

G2010/16 M. BEFFY - T. KAMIONKA
Public-private wage gaps: is civil-servant human capital sector-specific?

G2010/17 P.-Y. CABANNES - H. ERKEL-ROUSSE - G. LALANNE - O. MONSO - E. POULIQUEN
Le modèle Mésange réestimé en base 2000
Tome 2 - Version avec volumes à prix chaînés

G2010/18 R. AEBERHARDT - L. DAVEZIES
Conditional Logit with one Binary Covariate: Link between the Static and Dynamic Cases

G2011/01 T. LE BARBANCHON - B. OURLIAC - O. SIMON
Les marchés du travail français et américain face aux chocs conjoncturels des années 1986 à 2007 : une modélisation DSGE

G2011/02 C. MARBOT
Une évaluation de la réduction d'impôt pour l'emploi de salariés à domicile

G2011/03 L. DAVEZIES
Modèles à effets fixes, à effets aléatoires, modèles mixtes ou multi-niveaux : propriétés et mises en œuvre des modélisations de l'hétérogénéité dans le cas de données groupées

G2011/04 M. ROGER - M. WASMER
Heterogeneity matters: labour productivity differentiated by age and skills

G2011/05 J.-C. BRICONGNE - J.-M. FOURNIER V. LAPÈGUE - O. MONSO
De la crise financière à la crise économique L'impact des perturbations financières de 2007 et 2008 sur la croissance de sept pays industrialisés

G2011/06 P. CHARNOZ - É. COUDIN - M. GAINI
Wage inequalities in France 1976-2004: a quantile regression analysis

G2011/07 M. CLERC - M. GAINI - D. BLANCHET
Recommendations of the Stiglitz-Sen-Fitoussi Report: A few illustrations

G2011/08 M. BACHELET - M. BEFFY - D. BLANCHET
Projeter l'impact des réformes des retraites sur l'activité des 55 ans et plus : une comparaison de trois modèles

G2011/09 C. LOUVOT-RUNAVOT
L'évaluation de l'activité dissimulée des entreprises sur la base des contrôles fiscaux et son insertion dans les comptes nationaux

G2011/10 A. SCHREIBER - A. VICARD
La tertiarisation de l'économie française et le ralentissement de la productivité entre 1978 et 2008

G2011/11 M.-É. CLERC - O. MONSO - E. POULIQUEN
Les inégalités entre générations depuis le baby-boom

G2011/12 C. MARBOT - D. ROY
Évaluation de la transformation de la réduction d'impôt en crédit d'impôt pour l'emploi de salariés à domicile en 2007

G2011/13 P. GIVORD - R. RATHELOT - P. SILLARD
Place-based tax exemptions and displacement effects: An evaluation of the Zones Franches Urbaines program

G2011/14 X. D'HAULTFOEUILLE - P. GIVORD - X. BOUTIN
The Environmental Effect of Green Taxation: the Case of the French "Bonus/Malus"

G2011/15 M. BARLET - M. CLERC - M. GARNEO - V. LAPÈGUE - V. MARCUS
La nouvelle version du modèle MZE, modèle macroéconométrique pour la zone euro

G2011/16 R. AEBERHARDT - I. BUONO - H. FADINGER
Learning, Incomplete Contracts and Export Dynamics: Theory and Evidence form French Firms

G2011/17 C. KERDRAIN - V. LAPÈGUE
Restrictive Fiscal Policies in Europe: What are the Likely Effects?

G2012/01 P. GIVORD - S. QUANTIN - C. TREVIEN
A Long-Term Evaluation of the First Generation of the French Urban Enterprise Zones

G2012/02 N. CECI-RENAUD - V. COTTET
Politique salariale et performance des entreprises

G2012/03 P. FÉVRIER - L. WILNER
Do Consumers Correctly Expect Price Reductions? Testing Dynamic Behavior

G2012/04 M. GAINI - A. LEDUC - A. VICARD
School as a shelter? School leaving-age and the business cycle in France

G2012/05 M. GAINI - A. LEDUC - A. VICARD
A scarred generation? French evidence on young people entering into a tough labour market

G2012/06 P. AUBERT - M. BACHELET
Disparités de montant de pension et redistribution dans le système de retraite français

G2012/07 R. AEBERHARDT - P GIVORD - C. MARBOT
Spillover Effect of the Minimum Wage in France: An Unconditional Quantile Regression Approach

G2012/08 A. EIDELMAN - F. LANGUMIER - A. VICARD
Prélèvements obligatoires reposant sur les ménages : des canaux redistributifs différents en 1990 et 2010

G2012/09 O. BARGAIN - A. VICARD
Le RMI et son successeur le RSA découragent-ils certains jeunes de travailler ? Une analyse sur les jeunes autour de 25 ans

G2012/10 C. MARBOT - D. ROY
Projections du coût de l'APA et des caractéristiques de ses bénéficiaires à l'horizon 2040 à l'aide du modèle Destinie

G2012/11 A. MAUROUX
Le crédit d'impôt dédié au développement durable : une évaluation économétrique

G2012/12 V. COTTET - S. QUANTIN - V. RÉGNIER
Coût du travail et allègements de charges : une estimation au niveau établissement de 1996 à 2008

G2012/13 X. D'HAULTFOEUILLE - P. FÉVRIER - L. WILNER
Demand Estimation in the Presence of Revenue Management

G2012/14 D. BLANCHET - S. LE MINEZ
Joint macro/micro evaluations of accrued-to-date pension liabilities: an application to French reforms

G2013/01-F1301 T. DEROYON - A. MONTAUT - P-A PIONNIER
Utilisation rétrospective de l'enquête Emploi à une fréquence mensuelle : apport d'une modélisation espace-état

G2013/02-F1302 C. TREVIEN
Habiter en HLM : quel avantage monétaire et quel impact sur les conditions de logement ?

G2013/03 A. POISSONNIER
Temporal disaggregation of stock variables - The Chow-Lin method extended to dynamic models

G2013/04 P. GIVORD - C. MARBOT
Does the cost of child care affect female labor market participation? An evaluation of a French reform of childcare subsidies

G2013/05 G. LAME - M. LEQUIEN - P.-A. PIONNIER
Interpretation and limits of sustainability tests in public finance

G2013/06 C. BELLEGO - V. DORTET-BERNADET
La participation aux pôles de compétitivité : quelle incidence sur les dépenses de R&D et l'activité des PME et ETI ?

G2013/07 P.-Y. CABANNES - A. MONTAUT - P.-A. PIONNIER
Évaluer la productivité globale des facteurs en France : l'apport d'une mesure de la qualité du capital et du travail

G2013/08 R. AEBERHARDT - C. MARBOT
Evolution of Instability on the French Labour Market During the Last Thirty Years

G2013/09 J-B. BERNARD - G. CLÉAUD
Oil price: the nature of the shocks and the impact on the French economy

G2013/10 G. LAME
Was there a « Greenspan Conundrum » in the Euro area?

G2013/11 P. CHONÉ - F. EVAIN - L. WILNER - E. YILMAZ
Introducing activity-based payment in the hospital industry : Evidence from French data

G2013/12 C. GRISLAIN-LETRÉMY
Natural Disasters: Exposure and Underinsurance

G2013/13 P.-Y. CABANNES - V. COTTET - Y. DUBOIS - C. LELARGE - M. SICSIC
French Firms in the Face of the 2008/2009 Crisis

G2013/14 A. POISSONNIER - D. ROY
Households Satellite Account for France in 2010. Methodological issues on the assessment of domestic production

G2013/15 G. CLÉAUD - M. LEMOINE - P.-A. PIONNIER
Which size and evolution of the government expenditure multiplier in France (1980-2010)?

G2014/01 M. BACHELET - A. LEDUC - A. MARINO
Les biographies du modèle Destinie II : rebasage et projection

G2014/02 B. GARBINTI
L'achat de la résidence principale et la création d'entreprises sont-ils favorisés par les donations et héritages ?

G2014/03 N. CECI-RENAUD - P. CHARNOZ - M. GAINI
Évolution de la volatilité des revenus salariaux du secteur privé en France depuis 1968

G2014/04 P. AUBERT
Modalités d'application des réformes des retraites et prévisibilité du montant de pension

G2014/05 C. GRISLAIN-LETRÉMY - A. KATOSSKY
The Impact of Hazardous Industrial Facilities on Housing Prices: A Comparison of Parametric and Semiparametric Hedonic Price Models

G2014//06 J.-M. DAUSSIN-BENICHOU - A. MAUROUX
Turning the heat up. How sensitive are households to fiscal incentives on energy efficiency investments?

G2014/07 C. LABONNE - G. LAMÉ
Credit Growth and Capital Requirements: Binding or Not?

G2014/08 C. GRISLAIN-LETRÉMY et C. TREVIEN
The Impact of Housing Subsidies on the Rental Sector: the French Example

G2014/09 M. LEQUIEN et A. MONTAUT
Croissance potentielle en France et en zone euro : un tour d'horizon des méthodes d'estimation

G2014/10 B. GARBINTI - P. LAMARCHE
Les hauts revenus épargnent-ils davantage ?

G2014/11 D. AUDENAERT - J. BARDAJI - R. LARDEUX - M. ORAND - M. SICSIC
Wage Resilience in France since the Great Recession

G2014/12 F. ARNAUD - J. BOUSSARD - A. POISSONNIER - H. SOUAL

Computing additive contributions to growth and other issues for chain-linked quarterly aggregates

G2014/13 H. FRAISSE - F. KRAMARZ - C. PROST
Labor Disputes and Job Flows

G2014/14 P. GIVORD - C. GRISLAIN-LETRÉMY - H. NAEGELE
How does fuel taxation impact new car purchases? An evaluation using French consumer-level dataset

G2014/15 P. AUBERT - S. RABATÉ
Durée passée en carrière et durée de vie en retraite : quel partage des gains d'espérance de vie ?

G2015/01 A. POISSONNIER
The walking dead Euler equation
Addressing a challenge to monetary policy models

G2015/02 Y. DUBOIS - A. MARINO
Indicateurs de rendement du système de retraite français

G2015/03 T. MAYER - C. TREVIEN
The impacts of Urban Public Transportation: Evidence from the Paris Region

G2015/04 S.T. LY - A. RIEGERT
Measuring Social Environment Mobility

G2015/05 M. A. BEN HALIMA - V. HYAFIL-SOLELHAC
M. KOUBI - C. REGAERT
Quel est l'impact du système d'indemnisation maladie sur la durée des arrêts de travail pour maladie ?

G2015/06 Y. DUBOIS - A. MARINO
Disparités de rendement du système de retraite dans le secteur privé : approches intergénérationnelle et intragénérationnelle

G2015/07 B. CAMPAGNE - V. ALHENC-GELAS - J.-B. BERNARD
No evidence of financial accelerator in France

G2015/08 Q. LAFFÉTER - M. PAK
Élasticités des recettes fiscales au cycle économique : étude de trois impôts sur la période 1979-2013 en France

G2015/09 J.-M. DAUSSIN-BENICHOU, S. IDMACHICHE, A. LEDUC et E. POULIQUEN
Les déterminants de l'attractivité de la fonction publique de l'État

G2015/10 P. AUBERT
La modulation du montant de pension selon la durée de carrière et l'âge de la retraite : quelles disparités entre assurés ?

G2015/11 V. DORTET-BERNADET - M. SICSIC
Effet des aides publiques sur l'emploi en R&D dans les petites entreprises

G2015/12 S. GEORGES-KOT
Annual and lifetime incidence of the value-added tax in France

G2015/13 M. POULHÈS
Are Enterprise Zones Benefits Capitalized into Commercial Property Values? The French Case

G2015/14 J.-B. BERNARD - Q. LAFFÉTER
Effet de l'activité et des prix sur le revenu salarial des différentes catégories socioprofessionnelles

G2015/15 C. GEAY - M. KOUBI - G de LAGASNERIE
Projections des dépenses de soins de ville, construction d'un module pour Destinie

G2015/16 J. BARDAJI - J.-C. BRICONGNE - B. CAMPAGNE - G. GAULIER
Compared performances of French companies on the domestic and foreign markets

G2015/17 C. BELLÉGO - R. DE NIJS
The redistributive effect of online piracy on the box office performance of American movies in foreign markets

G2015/18 J.-B. BERNARD - L. BERTHET
French households financial wealth: which changes in 20 years?

G2015/19 M. POULHÈS
Fenêtre sur Cour ou *Chambre avec Vue* ?
Les prix hédoniques de l'immobilier parisien

G2016/01 B. GARBINTI - S. GEORGES-KOT
Time to smell the roses? Risk aversion, the timing of inheritance receipt, and retirement

G2016/02 P. CHARNOZ - C. LELARGE - C. TREVIEN
Communication Costs and the Internal Organization of Multi-Plant Businesses: Evidence from the Impact of the French High-Speed Rail

G2016/03 C. BONNET - B. GARBINTI - A. SOLAZ
Gender Inequality after Divorce: The Flip Side of Marital Specialization - Evidence from a French Administrative Database

G2016/04 D. BLANCHET - E. CAROLI - C. PROST - M. ROGER
Health capacity to work at older ages in France

G2016/05 B. CAMPAGNE - A. POISSONNIER
MELEZE: A DSGE model for France within the Euro Area

G2016/06 B. CAMPAGNE - A. POISSONNIER
Laffer curves and fiscal multipliers: lessons from Mélèze model

G2016/07 B. CAMPAGNE - A. POISSONNIER
Structural reforms in DSGE models: a case for sensitivity analyses

G2016/08 Y. DUBOIS et M. KOUBI
Relèvement de l'âge de départ à la retraite : quel impact sur l'activité des séniors de la réforme des retraites de 2010 ?

G2016/09 A. NAOUAS - M. ORAND - I. SLIMANI HOUTI
Les entreprises employant des salariés au Smic : quelles caractéristiques et quelle rentabilité ?

G2016/10 T. BLANCHET - Y. DUBOIS - A. MARINO - M. ROGER
Patrimoine privé et retraite en France

G2016/11 M. PAK - A. POISSONNIER
Accounting for technology, trade and final consumption in employment: an Input-Output decomposition

G2017/01 D. FOUGÈRE - E. GAUTIER - S. ROUX
Understanding Wage Floor Setting in Industry-Level Agreements: Evidence from France

G2017/02 Y. DUBOIS - M. KOUBI
Règles d'indexation des pensions et sensibilité des dépenses de retraites à la croissance économique et aux chocs démographiques

G2017/03 A. CAZENAVE-LACROUTZ - F. GODET
L'espérance de vie en retraite sans incapacité sévère des générations nées entre 1960 et 1990 : une projection à partir du modèle Destinie

G2017/04 J. BARDAJI - B. CAMPAGNE - M.-B. KHDER - Q. LAFFÉTER - O. SIMON (Insee)
A.-S. DUFERNEZ - C. ELEZAAR - P. LEBLANC - E. MASSON - H. PARTOUCHE (DG-Trésor)
Le modèle macroéconométrique Mésange : réestimation et nouveautés

G2017/05 J. BOUSSARD - B. CAMPAGNE
Fiscal Policy Coordination in a Monetary Union at the Zero-Lower-Bound

G2017/06 A. CAZENAVE-LACROUTZ - A. GODZINSKI
Effects of the one-day waiting period for sick leave on health-related absences in the French central civil service

G2017/07 P. CHARNOZ - M. ORAND
Qualification, progrès technique et marchés du travail locaux en France, 1990-2011

G2017/08 K. MILIN
Modélisation de l'inflation en France par une approche macrosectorielle

G2017/09 C.-M. CHEVALIER - R. LARDEUX
Homeownership and labor market outcomes: disentangling externality and composition effects

G2017/10 P. BEAUMONT
Time is Money: Cash-Flow Risk and Export Market Behavior

G2018/01 S. ROUX - F. SAVIGNAC
SMEs' financing: Divergence across Euro area countries?

G2018/02 C.-M. CHEVALIER - A. LUCIANI
Computerization, labor productivity and employment: impacts across industries vary with technological level

G2018/03 R.MONIN - M. SUAREZ CASTILLO
L'effet du CICE sur les prix : une double analyse sur données sectorielles et individuelles

G2018/04 R. LARDEUX
Who Understands The French Income Tax? Bunching Where Tax Liabilities Start

G2018/05 C.-M. CHEVALIER
Financial constraints of innovative firms and sectoral growth

G2018/06 R. S.-H. LEE - M. PAK
Pro-competitive effects of globalisation on prices, productivity and markups: Evidence in the Euro Area

G2018/07 C.-M. CHEVALIER
Consumption inequality in France between 1995 and 2011

G2018/08 A. BAUER - B. GARBINTI - S. GEORGES-KOT
Financial Constraints and Self-Employment in France, 1945-2014

G2018/09 P. BEAUMONT – A. LUCIANI
Prime à l'embauche dans les PME : évaluation à partir des déclarations d'embauche

G2018/10 C BELLÉGO – V. DORTET-BERNADET - M. TÉPAUT
Comparaison de deux dispositifs d'aide à la R&D collaborative public-privé

G2018/11 R. MONIN – M. SUAREZ CASTILLO
Réplication et rapprochement des travaux d'évaluation de l'effet du CICE sur l'emploi en 2013 et 2014

G2018/12 A. CAZENAVE-LACROUTZ - F. GODET – V. LIN
L'introduction d'un gradient social dans la mortalité au sein du modèle Destinie 2

G2019/01 F1901 M. ANDRÉ – A.-L. BIOTTEAU
Effets de moyen terme d'une hausse de TVA sur le niveau de vie et les inégalités : une approche par microsimulation

G2019/02 A. BOURGEOIS – A. BRIAND
Le modèle Avionic : la modélisation Input/Output des comptes nationaux

G2019/03 A. GODZINSKI – M. SUAREZ CASTILLO
Short-term health effects of public transport disruptions: air pollution and viral spread channels

G2019/04 F1903 L. AEBERHARDT - F. HATIER - M. LECLAIR - B. PENTINAT - J.-D. ZAFAR
L'économie numérique fausse-t-elle le partage volume-prix du PIB ?

G2019/05 A. CAZENAVE-LACROUTZ – E. YILMAZ
Dans quelle mesure les incitations tarifaires et la procédure de mise sous accord préalable ont-elles contribué au développement de la chirurgie ambulatoire ?

G2019/06 J.-P. CLING – S. EGHBAL-TEHERANI – M. ORZONI – C. PLATEAU
The Differences between EU Countries for Sustainable Development Indicators:
It is (mainly) the Economy!

G2019/07 P. CHONÉ – L. WILNER
Competition on Unobserved Attributes: The Case of the Hospital Industry

G2019/08 P. PORA – L. WILNER
Child Penalties and Financial Incentives: Exploiting Variation along the Wage Distribution

G2019/09 E. GAUTIER – S. ROUX – M. SUAREZ CASTILLO
Do Minimum Wages make Wages more Rigid ? Evidence from French Micro Data

G2019/10 M. ANDRÉ – A. SIREYJOL

Imposition des couples et des familles : effets budgétaires et redistributifs de l'impôt sur le revenu

G2019/11 K. MOHKAM – O. SIMON
L'empreinte matière de l'économie française : une analyse par matière et catégorie de produits

G2019/12 S. BUNEL – B. HADJIBEYLI
Évaluation du crédit d'impôt innovation

G2019/13 C. BONNET – F. GODET – A. SOLAZ
Gendered economic determinants of couple formation over 50 in France

G2019/14 P. GIVORD – M. SUAREZ CASTILLO
Excellence for all? Heterogeneity in high schools' value-added

G2019/15 G. CETTE – L. KOEHL – T. PHILIPPON
Labor Share in Some Advanced Countries

G2020/01 J. SILHOL – B. VENTELOU
Les zones d'intervention prioritaire reflètent-elles des écarts de pratiques des médecins généralistes ?

G2020/02 B. BOUCHTENIK – R. LARDEUX
The Take-Up of Unemployment Benefit Extensions

G2020/03 J-M. GERMAIN
A Welfare Based Estimate of "Real Feel GDP" for Europe and the USA

G2020/04 J. BOUSSARD – R. LEE
Competition, Profit Share and Concentration

G2020/05 P. PORA
Keep Working and Spend Less?
Collective Childcare and Parental Earnings in France

G2020/06 R. MONIN – M. SUAREZ CASTILLO
Product Switching, market power and distance to core competency

G2020/07 L. WILNER
How do citizens perceive centralization reforms? Evidence from the merger of French regions

G2020/08 L. WILNER
The persistence of subjective well-being: permanent happiness, transitory misery?

G2020/09 J-M. GERMAIN – T. LELLOUCH
Comptabilité économique de la soutenabilité climatique

G2020/10 A. BAUER – M. ROTEMBERG
Tax avoidance in French Firms:
Evidence from the Introduction of a Tax Notch

G2020/11 P. AGHION – A. BERGEAUD
M. LEQUIEN – M. J. MELITZ
The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports

G2020/12 L. GALIANA – B. SAKAROVITCH
F. SÉMÉCURBE – Z. SMOREDA
Residential segregation, daytime segregation and spatial frictions : an analysis

G2020/13 A. BAUER – J. BOUSSARD
Market Power and Labor Share

G2020/14 A. BAUER – J. BOUSSARD – D. LASHKARI
Information Technology and Returns to Scale

G2020/15 V. LIN – O. MESLIN
Hausse des prix immobiliers et mesure du niveau de vie

G2021/01 N. BECHICHI – G. THEBAULT
Students' Preferences, Capacity Constraints and Post-Secondary Achievements in a Non-Selective System

G2021/02 B. BUREAU – A. DUQUERROY
J. GIORGI – M. LÉ – S. SCOTT – F. VINAS
Une année de crise COVID : impact sur la dymanique des entreprises en France
Une évaluation sur données individuelles

G2021/03 B. BUREAU – A. DUQUERROY
J. GIORGI – M. LÉ – S. SCOTT – F. VINAS
L'impact de la crise sanitaire sur la situation financière des entreprises en 2020 : une analyse sur données individuelles

G2021/04 A. GODZINSKI – M.SUAREZ CASTILLO
Disentangling the effects of air pollutants with many instruments

2021/01 S.QUANTIN – S.BUNEL – C.LENOIR
Évaluation du dispositif Jeune entreprise innovante (JEI) Un exemple d'application du modèle d'analyse de sensibilité de Rosenbaum

2021/02 L. GOBILLON – D. MEURS – S. ROUX
Differences in positions along a hierarchy : Counterfactuals based on an assignment model

2021/03 N. BECHICHI – J. GRENET – G. THEBAULT
Ségrégation à l'entrée des études supérieures en France et en région parisienne : quels effets du passage à Parcoursup ?

2021/04 M. ANDRÉ – O. MESLIN
Et pour quelques appartements de plus :Étude de la propriété immobilière des ménages et du profil redistributif de la taxe foncière

2022/05 S. GEORGES-KOT – D. GOUX – E. MAURIN
The value of leisure synchronozation

2022/06 N. BECHICHI – M. FABRE – T. OLIVIA
Projections de la population active à l'horizon 2080

2022/11 S. QUANTIN – C. WELTER-MÉDÉE
Estimation des montants manquants de versements de TVA :exploitation des données du contrôle fiscal

2022/14 L. BLOCH – B. FAVETTO – A. LAGOUGE – F. SÉDILLOT
Inégalités de rendements et de patrimoine en France en 2017

2022/15 H. GENIN – S. SCOTT
Un portrait de la r´etention de main-d'oeuvre dans l'industrie française : analyse à partir des enquêtes mensuelles de conjoncture

2023/02 D. GOUX – E. MAURIN
On the seventh day you shall do not any work : the winners and losers of Sunday work deregulation

2023/03 P. AGHION – A. BERGEAUD – M. LEQUIEN – M. MELITZ – T. ZUBER
Opposing firm-level responses to the China shock: Output competition versus input supply

2023/04 L. GALIANA – L. WILNER
Private Wealth over the Life-Cycle:
A Meeting between Microsimulation and Structural Approaches

2023/06 M. HILLION – E. MAUGENDRE
L'effet du « jour de carence » sur les absences pour maladie ordinaire, la santé perçue et le recours aux soins à court- terme

2023/07 M.ANDRÉ- J-M GERMAIN – M. SICSIC
'Do I get my money back?': A Broader Approach to Inequality and Redistribution in France With a Monetary Valuation of Public Services

2023/08 R. LAFROGNE-JOUSSIER – J. MARTIN – I. MEJEAN
Supply shocks in supply chains: Evidence from the early lockdown in China

2023/09 J. SILHOL – L. WILNER
Teachers' desired mobility to disadvantaged schools: Do financial incentives matter?

2023/12 P. AGHION - C. ANTONIN - S. BUNEL - X. JARAVEL
Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France

2023/13 R. LAFROGNE-JOUSSIER – J. MARTIN – I. MEJEAN
Cost Pass-Through and the Rise of Inflation

2023/14 A. BOURGEOIS – F. GERVOIS - R. LAFROGNE-JOUSSIER
Forces et fragilités des tableaux internationaux entrées-sorties pour le calcul de l'empreinte carbone

2023/17 M. ADAM – O. BONNET – E. FIZE
T.LOISEL – M. RAULT – L. WILNER
How does fuel demand respond to price changes?
Quasi-experimental evidence based on high-frequency data