Pay less, consume more? Estimating the price elasticity of demand for home care services of the disabled elderly*

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Abstract

Although the consumption of home care is increasing with population ageing, little is known about its price sensitivity. This paper estimates the price elasticity of the demand for home care of the disabled elderly. We use an original dataset collected from a French County Council on the beneficiaries of the French home care program (*Allocation personnalisée d'autonomie*, "APA"). This cash–for–care allowance works as an hourly subsidy reducing the price of home care. APA administrative records provide unique information on out–of–pocket payments and home care consumption. Identification primarily relies on inter–individual variations in producer prices. Price endogeneity may arise if APA beneficiaries non–randomly select into a producer; we address this potential issue by exploiting the unequal spatial distribution of producers in the district. Our results point to a price elasticity lower than unity, around -0.4: a 10% increase in the out–of–pocket price is predicted to lower consumption by 4%, or 37 minutes per month for the median consumer. Copayment rates thus matter for allocative and dynamic efficiencies, while the generosity of home care subsidies also entails redistributive effects.

JEL: C24; D12; I18; J14.

Keywords: Long–term care, disabled elderly, price elasticity, public policy, censored regression.

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1 INTRODUCTION

Like most developed countries, France is facing the ageing of its population: due to the increase in life expectancy and the advance in age of baby–boomers, the share of the population above 60 is predicted to grow from 21.5% in 2011 to 32.1% in 2060 (Blanpain and Chardon, 2010). As the rise in disability–free life expectancy falls short of the increase in life expectancy (Sieurin et al., 2011), the number of the elderly needing assistance to perform the activities of daily living is expected to grow substantially. Most disabled elderly keep on living in the community rather than entering specialized institutions (Colombo et al., 2011). Besides medical and nursing care, they are often provided with basic domestic help such as meal preparation, assistance with personal hygiene or house chores. Assistance may be provided by relatives (informal care) and also by professional services (formal care), whose utilization is increasing. In most countries, public policies foster the utilization of formal home care by subsidizing professional home care consumption. These programs, however, only partially cover the cost of professional home care and the disabled elderly often bear non-negligible out–of–pocket (OOP) costs. In France, the average monthly out-of-pocket payment on domestic help utilization for the elderly was estimated to reach €300 in 2011 (Fizzala, 2016), over $1/5^{\text{th}}$ of the average pension benefit (Solard, 2015).

The existence of substantial OOP payments leads to an immediate concern: how sensitive to price are the disabled elderly when consuming home care services? This paper brings empirical evidence on this question by estimating the price elasticity of the demand for non-medical home care services of the disabled elderly, at the intensive margin.

This issue has direct implications for the design of public policies. With a small price elasticity, consumption of domestic help reacts little to changes in the generosity of home care subsidies and such programs work as redistributive transfers (from taxpayers to the disabled elderly). With a non–negligible price elasticity of the compensated demand, home care support programs also have efficiency implications: as in the health care context, generous subsidies may induce over–consumption and a welfare loss, while insufficient coverage could undermine the preventive effects of home care (Barnay and Juin, 2016; Rapp et al., 2015; Stabile et al., 2006).

We focus on the French home care scheme targeted to the disabled elderly, the APA (*Allocation personnalisée d'autonomie*) policy, which counted 738,000 community–dwelling beneficiaries in 2014 and amounted to a spending of 3.1 billion euros in 2013 (0.15% of GDP).[1] Administrative records of the scheme provide detailed information on home care consumption and OOP payments of APA beneficiaries, but they are available only at the local level. We use an original dataset, made of the individual records we collected for the beneficiaries of a given County Council (CC) (*Conseil départemental*). We exploit inter–individual variations in producer prices to identify consumer price elasticity. Price endogeneity may arise if APA beneficiaries non–randomly choose their home care provider. To address this issue empirically, we exploit the unequal spatial distribution of producers in the district. We fit a censored regression model to deal with observational issues and control for disposable income and other individual characteristics likely to affect the consumption of home care.

Our results indicate a negative price elasticity, inferior to one in absolute value. The magnitude is about -0.4, although the significance at conventional thresholds is not systematic. On average, an increase of 10% of the hourly OOP payment would reduce total care hours consumed by 4%, or 37 minutes per month for a beneficiary consuming the median monthly volume of 15.5 hours.

Our paper provides one of the first estimates of the price elasticity of the demand for home care services of the disabled elderly. Despite the growing concern about the financing of long-term care, the impact of OOP payments on the consumption of home care has been little investigated in the economic literature. A few papers tested for the effect of benefiting from subsidies on the utilization of paid domestic help (Coughlin et al., 1992; Ettner, 1994; Pezzin et al., 1996; Stabile et al., 2006; Rapp et al., 2011; Fontaine, 2012); because of data limitations, they were not able to quantify the price sensitivity. To address this gap in the international literature, a research project was built to gather data and design appropriate empirical strategies.[2] Within this project, two companion studies to our own work (Bourreau-Dubois et al., 2014; Hege, 2016) provide the only existing estimations of the consumer price elasticity. Our methodology draws on Bourreau-Dubois et al. (2014) but makes use of a different original data set. In addition, we propose a strategy to deal with the potential price endogeneity stemming from non–random producer selection. Our results entail important policy implications, as home care subsidy schemes are expanding with population ageing.

[1] Drees (2015, 2016). The APA program also has a component for the elderly living in nursing homes we leave aside here.

[2] Details at: www.modapa.cnrs.fr.

2 THE APA POLICY AND DEMAND FOR HOME CARE

2.1 The APA program

The French APA program aims at fostering the utilization of professional care services by the elderly requiring assistance in the activities of daily living (household chores, meal preparation, personal hygiene, ...). The APA policy is established at the national level and implemented at the county level.[3] To be eligible, an individual must be at least 60 years–old and be recognized as disabled. This second condition requires a specific assessment from a team managed by the CC, called the evaluation team, made of medical professionals (nurses, doctors) and/or social workers. The evaluation team visits each APA applicant to evaluate her needs of assistance using a national standardized scale. The applicant is thus assigned a disability group (*Groupe Iso-Ressources*, or GIR). There are six disability groups, going from the group of non-disabled individuals (GIR–6) to the group of extremely disabled individuals (GIR–1). Only individuals found to be moderately to extremely disabled (GIR–4 to GIR–1) are eligible for APA.

The evaluation team then establishes a "personalized care plan". This document lists the activities for which the individual needs assistance and sets the number of hours necessary to their realization. It gives the maximum number of hours eligible for APA subsidies of each beneficiary, called the care plan volume.[4] Up to the care plan volume, the consumer price of each hour of care is lowered by the APA subsidy. For hours beyond the care plan volume, there are no more subsidies: the consumer bears the full producer price.

2.2 Computation rules of APA subsidies

Up to the care plan volume, the APA beneficiary is charged an hourly OOP price that depends on both the producer price and a copayment rate, increasing with disposable income. For low-income individuals (below €739 per month in October 2014), the copayment rate is null while it reaches 90% for the richest beneficiaries (monthly income above €2,945). In between the

[3] Mainland France is divided into 95 counties (*départements*), with a median population of 550,000 inhabitants (Insee, 2013).

[4] The monetary valuation of the care plan volume must not exceed a legal ceiling which depends on the disability level. In October 2014, the ceiling was €1,313 (resp. €563) per month for GIR–1 (resp. GIR–4). The evaluation team is supposed to set the care plan volume before computing the monetary equivalent but it might, in fact, retroactively change the number of hours or the chosen producer (price) with respect to the legal ceiling.

two, the copayment rate is an increasing linear function of disposable income.

The copayment rate usually applies to the producer price to obtain the hourly OOP payment: if the copayment rate is 50%, the beneficiary will pay out–of–pocket half of the producer price for each hour of care. This computation rule is used by most CCs when the producer chosen by the beneficiary is an "authorized" structure (*service autorisé*), whose price is generally directly administrated by the CC. If the producer chosen by the individual is not authorized ("non-authorized" structure or over-the-counter worker), the copayment rate applies to a lump–sum price. This distinction has important implications for what can be known of APA beneficiaries' OOP payments, as CCs usually keep track only of the prices of authorized producers.

2.3 Modeling demand for home care with APA

We write the marshallian demand for home care services under the general form:

$$h_i^* = g_i(CP_i, \hat{I}_i; X_i) \tag{1}$$

With:
h_i^* the number of hours of home care consumed by individual i;
$g_i(.)$ the individual demand function for home care;
CP_i individual i's consumer price for one hour of home care;
$\hat{I}_i$ the total disposable income available to i for consumption;
X_i a set of individual sociodemographic characteristics.

Following Moffitt (1986), we assume a heterogeneity-only model such that:

$$g_i(CP_i, \hat{I}_i; X_i) = g(CP_i, \hat{I}_i; X_i) + \nu_i$$

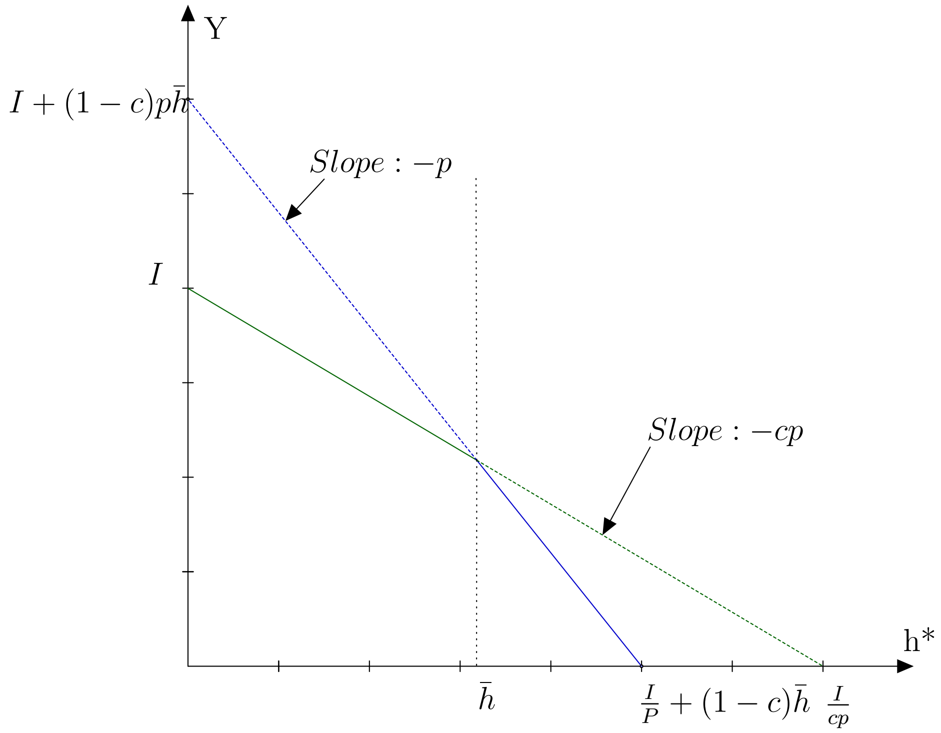
where ν_i is an individual preference shifter.

With the APA policy, the beneficiary receives an hourly subsidy reducing the price she has to pay: the consumer price corresponds to the proportion of the producer price set by the copayment rate. The copayment rate, denoted c_i, is a function of individual i's disposable income. We have: $c_i = c(I_i)$, where $c(.)$ is a linear function, and thus: $CP_i = c(I_i)p_i$. But for hours consumed beyond the care plan volume, the consumer price goes back to the full producer price and the total disposable income available to consumption now integrates subsidies on the previous subsidized hours consumed. Denoting $\bar{h}_i$ the care plan volume of individual i, the budget constraint writes as:

$$\begin{cases} I_i = c_i p_i h_i^* + Y_i & \text{if} \quad h_i^* \leq \bar{h}_i \\ I_i = c_i p_i \bar{h}_i + p_i(h_i^* - \bar{h}_i) + Y_i \iff I_i + (1-c_i)p_i\bar{h}_i = p_i h_i^* + Y_i & \text{if} \quad h_i^* > \bar{h}_i \end{cases}$$

where Y denotes the composite good, with price set to 1. The APA program creates a kink in the budget constraint of the beneficiary (Figure 1).

Figure 1: Demand for home care services with APA: a kinked budget constraint



Denoting $\tilde{I}_i = I_i + (1-c_i)p_i\bar{h}_i$ the virtual income of individual i (Moffitt, 1986, 1990), we rewrite the demand function specified in Equation (1) as follows:

$$\begin{cases} h_i^* = g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* < \bar{h}_i \\ g(p_i, \tilde{I}_i; X_i) + \nu_i < \bar{h}_i < g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* = \bar{h}_i \\ h_i^* = g(p_i, \tilde{I}_i; X_i) + \nu_i & \text{if } h_i^* > \bar{h}_i \end{cases}$$

The objective of the paper is to get an empirical estimate of the following quantity, which is the point price elasticity:

$$\frac{\mathrm{d}g(CP, \tilde{I}; X)}{\mathrm{d}CP} \frac{CP}{g(CP, \tilde{I}; X)}$$

3 DATA

3.1 Administrative data from a County Council

As of today, in France, there is no national survey or administrative data set providing precise information on both the OOP payments and the professional home care consumption of the disabled elderly. To get round data limitations, we use the administrative records CCs keep on their APA recipients. We collected data from a CC using the most frequent OOP computation rule: the OOP price is computed using the provider price when home care is provided by an authorized producer, while a lump–sum price is used when the producer is not authorized.

We selected a county whose demographic characteristics are close to national figures, with respect to several indicators: share of population aged 60 and more in total population (around 25%), proportion of community–dwelling APA beneficiaries in the 60+ population (about 5%). In terms of income, county indicators are slightly higher than national averages, with a higher ratio of households subject to the income tax (70% of households, against 64% nationwide) and a lower poverty rate (less than 10%, against 15% at the national level).[5]

Data were collected for every month of 2012 to 2014. Infra–yearly variation in producer prices being negligible, we pick up a single month by year[6] and retain the month of October, when home care consumption is less likely to be affected by temporary shocks (like holidays and visits from children). Results obtained on October 2014 are presented as the baseline results; panel analysis including October 2012 and 2013 are used as robustness checks.

3.2 Sample selection

To ensure clear identification, we focus on APA beneficiaries served by an authorized home care provider. With non-authorized caregivers, the producer price (and thus the OOP price) cannot be observed: we exclude from our sample beneficiaries receiving care from over-the-counter employees (17% of initial sample) and non–authorized structures (6%). We also drop the 8 individuals receiving care simultaneously from several authorized providers to avoid any potential bias arising from the simultaneity of consumption decisions.

Secondly, we exclude beneficiaries whose copayment rate is null: their OOP price on subsidized hours is null. We also exclude beneficiaries whose copay-

[5] National figures come from Drees (2015); Insee (2014); Insee-DGFiP-Cnaf-Cnav-Ccmsa (2015).

[6] Averaging consumption and OOP prices on an annual basis would hamper identification by blurring the true empirical relationship between price and consumption.

ment is equal to 90%: the relationship between their disposable income and their copayment rate is not linear and this makes identification more complex. We end up with a sample of 2,862 individuals, representing 52.2% of initial sample (Appendix A).

3.3 Descriptive statistics

Table I describes the final sample used in the econometric analysis. Its sociodemographic structure can be compared with national data on APA recipients. The typical individual in our sample is a woman, in her mid-80s and living alone, in line with the sociodemographic characteristics of the French disabled elderly population. Strongly disabled individual are slightly less represented in our sample than at the national level. The average copayment rate on APA is slightly higher than the national average, reflecting the fact that individuals in our county tend to be richer. Six APA beneficiaries out of ten do not consume the maximum number of hours for which they are entitled to a subsidy; price sensitivity of the disabled elderly is one possible candidate to explain part of this high figure.

[Table I (p. 9) about here]

3.4 A censored measure of home care consumption

The dataset contains the individual number of home care hours that are charged by the producer to the CC or, equivalently, the *subsidized* hours of home care. However, we do not observe the *total* volume of home care consumed by each APA beneficiary, who is free to consume home care beyond her care plan volume. For 40% of our sample, our measure of home care consumption is then possibly right–censored. Appropriate econometric methods are needed.

Table I: General descriptive statistics

	National population of APA recipients	*County baseline sample*	
Variable	Mean	Mean	Std-dev.
Care plan volume [a]	*n.a.*	20.5	10.7
Care plan monetary value [b]	€489[b]	€455.5	238.3€
Hours effectively subsidized [c]	*n.a.*	17.7	10.8
Amount of effective subsidies [d]	€392[b]	€300.8	201.4€
Underconsumption of care plan	*n.a.*	59.8%	-
Ratio [c]/[a]	-	84.9%	20.7 pp.
Ratio [d]/[b]	-	65.1%	22.2 pp.
Individualized income	*n.a.*	€1,315	€423
Copayment rate	20%[b]	23.7%	17.3 pp.
Producer price	*n.a.*	€22.2	€1.3
Hourly OOP price	*n.a.*	€5.2	€3.8
Total OOP payments on subsidized hours	*n.a.*	€91.3	€98.6
Age	*n.a.*	84.2	7.5
Women	73.0%[a]	73.9%	-
Disability level 1 (most severe)	2%[a]	1.2%	-
Disability level 2	17%[a]	12.5%	-
Disability level 3	23%[a]	19.6%	-
Disability level 4 (least severe)	58%[a]	65.7%	-
	100%	*100%*	-
Living with a spouse	*n.a.*	33.8%	-
Living alone	*n.a.*	66.6%	-
Spouse in institution	*n.a.*	0.6%	-
	-	*100%*	-
Number of individuals	721,000[a]	2,862	
Number of households	*n.a.*	2,785	

NOTES: "pp." stands for percentage points, "*n.a.*" for "not available". Care plan volume and effective home care consumption are expressed in hours per month, income, subsidies and total OOP payments are expressed in euros per month. National data from [a] 2013 (Borderies and Trespeux, 2015) and [b] 4th quarter of 2011 (Drees, 2012). County statistics computed on the baseline sample from October 2014.

4 EMPIRICAL STRATEGY

4.1 Econometric specification

Denote h_i the number of home care hours billed to the CC for beneficiary i. Only effectively–consumed hours can be billed, and this within the limit of the care plan volume $\bar{h}_i$. Thus, $h_i \leq h_i^*$ and $h_i \leq \bar{h}_i$. If the individual consumes less than the care plan volume, the consumption registered by the CC is equal to her effective consumption ($h_i = h_i^*$ if $h_i^* \leq \bar{h}_i$): there is no censoring issue. If the individual consumes more than the care plan volume, the consumption registered by the CC will systematically be equal to her individual ceiling ($h_i = \bar{h}_i$ if $h_i^* > \bar{h}_i$). Consequently, when $h_i = \bar{h}_i$ is observed, we either have $h_i^* = \bar{h}_i$, or $h_i^* > \bar{h}_i$ (right-censored consumption).

The estimation of the parameters of the demand function $g(.)$ can only rely on information relating to the first segment of the budget constraint. For individuals consuming $\bar{h}_i$ or more, the only information we can use is that $g(c_i p_i, I_i; X_i) + \nu_i > \bar{h}_i$, whether i is exactly at the kink or actually consumes more than $\bar{h}_i$.[7] The *observed* consumption of home care rewrites as:

$$\begin{cases} h_i = g(c_i p_i, I_i; X_i) + \nu_i & \text{if} \quad g(c_i p_i, I_i; X_i) + \nu_i < \bar{h}_i \\ h_i = \bar{h}_i & \text{if} \quad g(c_i p_i, I_i; X_i) + \nu_i \geq \bar{h}_i \end{cases} \tag{2}$$

Given that the distribution of home care consumption is slightly skewed, we assume a log-linear specification of $g(c_i p_i, I_i; X_i) + \nu_i$:

$$ln(h_i^*) = \beta_0 + \beta_1.ln(c_i p_i) + \beta_2.ln(I_i) + X_i'.\theta + \epsilon_i$$

Both the consumer price and income are included in log so that β_1 represents the consumer price elasticity and β_2 represents the income elasticity of the uncompensated demand for home care service.

In the data, the record of disposable income is not the current value of income, but the income when the copayment rate was computed or last revised, denoted I_i^{obs}. We express current disposable income as: $I_i = I_i^{obs}\gamma_i$, with γ_i the rate of increase of individual disposable income since i's last copayment rate was computed. As the rate of increase in disposable income γ_i is not directly observable, we write:

$$ln(h_i^*) = \beta_0 + \beta_1.ln(c_i p_i) + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \lambda^d.1_i^d + X_i'.\theta + \epsilon_i \tag{3}$$

[7] Appendix C provides more details.

where 1_i^d is a dummy equal to one when i's copayment rate was last revised in year d ($1^d, d = 2009, ..., 2014$) and coefficients λ^d should capture the rate of increase in income since year d.[8]

Together with the observational scheme summed up by System (2), Equation (3) corresponds to a censored regression model. Estimation of parameters β and θ is done by Maximum Likelihood, after making the following parametric assumption:

$$\epsilon \quad | \quad p_i, I^{obs}, X, 1 \sim \mathcal{N}(0, \sigma^2). \tag{4}$$

4.2 Identification using cross-sectional variations in prices

Variations in the consumer price $c_i p_i$ come from a variation either in the producer price p_i or in the copayment rate c_i that directly depends on the disposable income I_i^D. As we control for disposable income, any variation in the consumer price arises from a variation in the producer price. The *consumer price* elasticity of demand is thus identified by the cross-sectional variation in *producer prices*.[9] In 2014, there are 27 producers in the county, offering 23 different prices. Producer prices range from €19.7 to €23.5, with an average of €22.2 and a standard-deviation of €1.3.

For our estimation to give unbiased coefficients, the producer price charged to individual i must be uncorrelated with the unobserved factors affecting her home care consumption, ϵ_i. Supply-demand simultaneity may violate this condition (Zhen et al., 2014), but it should be negligible with our data. Indeed, each producer is priced by the CC on the basis of its average production cost two years earlier and the pricing process largely depends on administrative and political considerations (Gramain and Xing, 2012).

Omitted variables could also bias our estimation. Beneficiaries may non-randomly select their producer (price) on the basis of some unobservable individual characteristics such as quality expectations, unobserved health condition or informal care provision (Billaud et al., 2012). Although we can document some sources of price variations, unlikely to be correlated with unobserved determinants of home care consumption (Appendix D), it is insufficient to rule out any price endogeneity induced by non–random producer choice.

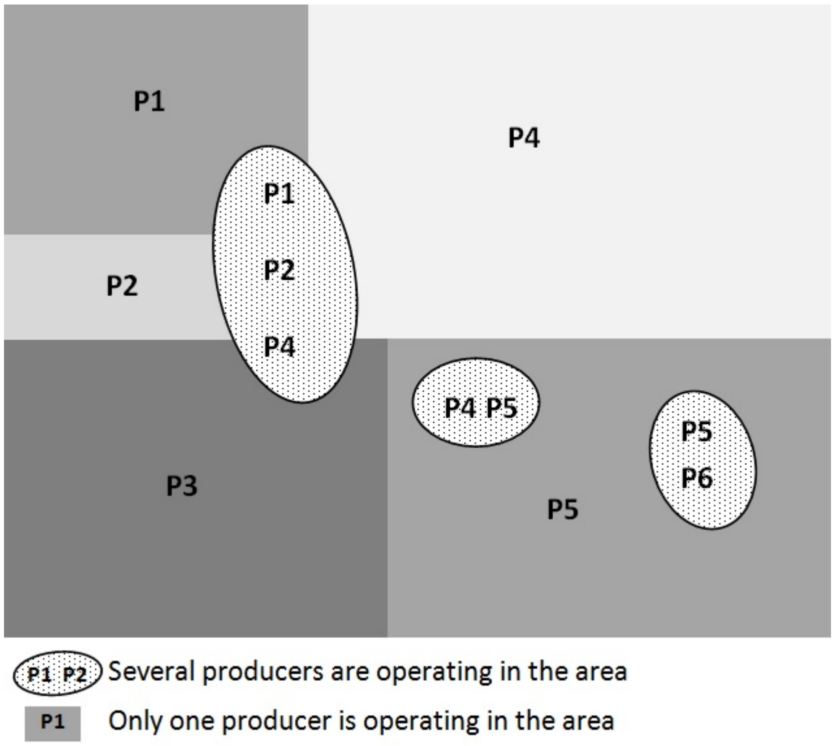
To address this issue empirically, we make use of the unequal distribution of producers over space in the county. We divide our sample into two

[8] We implicitly assume the rate of increase in disposable income to be identical for two individuals whose personalized plans were decided upon the same year d. Retirees' income is mostly made of pension benefits (Deloffre, 2009), which are reevaluated every year following the inflation rate. It remains a strong assumption given the heterogeneity in income composition across the income distribution.

[9] Appendix B provides more details on identification.

sub–populations (Figure 2): on the one side, beneficiaries living in a municipality where a single producer is found to operate, or single–producer area denoted "SPA" (areas in plain color). On the other hand, individuals living in a municipality where two or more authorized producers have customers, or non single–producer area denoted "non-SPA" (dotted areas). Selection into a producer should be negligible in the first sub–sample (35% of baseline sample) while it may arise in the second (65%).

Figure 2: Distribution of producers in the county – Schematic representation



NOTES: We provide only a schematic representation to preserve the anonymity of the CC our data come from. Different shades of plain grey indicate different areas served by a unique authorized service (single–producer areas, or SPA), each being served by a different producer with a given price level. The dotted areas correspond to multiple–producer municipalities, or non–SPA.

Overall, the two sub–samples do not differ in terms of consumption and explaining observables (Appendix D). Living in a SPA does not affect significantly home care consumption nor its estimated price elasticity. Estimating our model on the two sub–samples can then be interpreted as a test of price endogeneity.

5 RESULTS AND DISCUSSION

5.1 Main results

As we estimate a censored regression model, the coefficients displayed in the tables give the predicted impact of a marginal (or 0/1) change in a given explaining variable on the total, uncensored home care consumption. Table II presents our baseline results, obtained on the data from 2014. Column (1) does not include sociodemographic controls, while the others do. Estimations (1) to (3) are run on the entire sample while Estimations (4) and (5) are respectively run on the subsamples of SPA beneficiaries and non–SPA beneficiaries. With the entire sample, standard errors are clustered at the producer level to deal with potential correlation across the error terms of observations with the same producer. With subsamples, standard errors are clustered at the (producer) price level, as the construction of the two subsamples artificially increases the empirical variance in prices.

[Table II (p. 14) about here]

With no controls whatsoever, a 1% increase in the consumer price is associated with a very small variation of -0.05% in the hours of home care consumed. Comparison of Specifications (1) and (2) evidences a negative correlation between income and producer price. The estimated coefficient increases (in absolute value) to -0.709 when we include disposable income and sociodemographic controls. The price elasticity coefficient is negative, statistically significant, in Columns (3) and (4), suggesting that the disabled elderly are sensitive to the consumer price of home care.

Restricting the sample to individuals who have no producer choice, the point estimate of the price elasticity is reduced to around -0.34. Given the smaller sample size and reduced identifying variation in prices, precision is low and we cannot formally reject that the price elasticity is zero at conventional statistical significance levels. The point estimate is higher when we run the estimation on the subpopulation of individuals who can choose between different providers: the estimator is significantly different from zero at the 1% level, with a point value of -1.05. As the selection effect is inflationary, on average, individuals willing to consume more hours go for relatively cheap services when they can choose between several producers. This value thus captures what we may call the overall price sensitivity of consumption, which includes both an *ex ante* selection into a producer on the basis of expected consumption ("pay less to consume more") and the real price elasticity ("consuming more when paying less").

Table II: Consumer price elasticity estimations (October 2014)

	Dependent variable: hours consumed during the week h^* (log)				
	(1)	(2)	(3)	(4)	(5)
Consumer price (log)	-0.050**	-0.268	-0.709**	-0.344	-1.054***
	(0.024)	(0.394)	(0.290)	(0.608)	(0.391)
Disposable income (log)		0.220	0.660**	0.296	1.009***
		(0.395)	(0.291)	(0.609)	(0.382)
Woman			0.065**	0.106***	0.046
			(0.026)	(0.034)	(0.039)
Age: 60-69			-0.265***	-0.168***	-0.292***
			(0.079)	(0.063)	(0.102)
Age: 70-79			-0.070**	-0.082**	-0.058
			(0.032)	(0.032)	(0.044)
Age: 80-89			*Ref.*	*Ref.*	*Ref.*
Age: 90 or older			0.072**	0.065**	0.077
			(0.032)	(0.031)	(0.049)
Disability group: 1			0.729***	0.719***	0.779***
			(0.128)	(0.112)	(0.177)
Disability group: 2			0.433***	0.530***	0.388***
			(0.045)	(0.059)	(0.050)
Disability group: 3			*Ref.*	*Ref.*	*Ref.*
Disability group: 4			-0.523***	-0.470***	-0.551***
			(0.023)	(0.026)	(0.033)
Living with no spouse			0.317***	0.371***	0.289***
			(0.032)	(0.042)	(0.056)
Spouse receives APA			0.031	0.163*	-0.045
			(0.059)	(0.095)	(0.090)
Spouse in institution			0.570***	1.282***	0.313
			(0.127)	(0.334)	(0.197)
Living with non-APA spouse			*Ref.*	*Ref.*	*Ref.*
Constant	3.046***	3.954***	5.320***	3.902**	6.532***
	(0.037)	(1.235)	(0.890)	(1.892)	(1.248)
σ	0.871***	0.870***	0.725***	0.705***	0.732***
	(0.015)	(0.015)	(0.015)	(0.018)	(0.016)
Sample	All	All	All	SPA	Non–SPA
Observations	2,862	2,862	2,862	997	1,865
Censored observations	40.2%	40.2%	40.2%	40.8%	38.8%
Number of clusters	27	27	27	14	23
AIC	5,946.561	5,951.525	5,355.001	1,803.185	3,560.903
BIC	5,964.439	5,993.240	5,468.227	1,866.947	3,665.993

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the producer level in Specifications (1) to (3) and at the producer price level in Specifications (4) and (5). Data from October 2014. Estimation of a Tobit model by Maximum Likelihood. SPA stands for “single–producer area” beneficiaries. Specifications (3) to (5) include as controls sociodemographic variables, dummies for the year the latest plan was decided upon as well as dummies for the year in which the copayment rate was computed.

Turning to the effects of control variables, the marshallian income effect is positive and inferior to 1 in our preferred estimation (Column (4)), though not statistically significant. β_2 captures the effect of an increase in income when the copayment rate is fixed, which is likely to be the case in the short-run. In the medium-run, any marginal increase in disposable income entails two effects: (i) an income effect, through which the increase in the individual's budget set makes the consumption of all normal goods increase, (ii) a price effect playing in the opposite direction, as an income increase will induce the APA copayment rate to rise. Our estimations suggest that the overall effect of an income change within the APA scheme, $\beta_1 + \beta_2$, is zero. Given the specific schedule of APA copayments, the final impact of a marginal increase in the OOP price within APA corresponds to the substitution effect.

As expected, the heavier the disability level, the higher the predicted consumption, all other factors being equal. Even when controlling for disability level, age retains a significant effect on the consumption on home care services. Being a woman increases the consumption of professional home care by a small but statistically significant amount. Living alone (spouse in institution or no spouse) increases the amount of professional assistance received, consistently with previous works showing the importance of the co-residing spouse in providing informal care substituting partly for formal home care services.

5.2 Further results and robustness checks

Table III gives the results of the estimations on SPA beneficiaries using 2012 and 2013 data. We also exploit the panel dimension of our data, by estimating population-average and random-effect models on the pooled observations from 2012, 2013 and 2014 (same Table). Panel estimations increase precision by providing an additional source of variation for identification: as the administrated price of each producer is re-evaluated every year, we observe some intra-individual variations in the producer price over time.[10] Overall, further results are consistent with our baseline cross-sectional estimates. Some estimations even makes it possible to conclude to the significance of the price elasticity estimator at the 1% level.

[Tables III and IV (p. 16) about here]

[10] On average, producer prices have increased by 1.9% between October 2012 and 2013 and by 1.3% between 2013 and 2014.

Table III: Cross-sectional and panel estimations (SPA, October 2012-2014)

	Dependent variable: hours consumed during the week h^* (log)				
	2012	2013	2014	—— 2012–14 ——	
	CS	CS	CS	PA	RE
	(1)	(2)	(3)	(4)	(5)
Consumer price (log)	-0.730*	-0.372***	-0.344	-0.452***	-0.229
	(0.441)	(0.002)	(0.608)	(0.001)	(0.503)
p-value	*0.098*	*0.000*	*0.572*	*0.000*	*0.649*
Observations	738	756	997	2,491	2,491
Censored observations	39.7%	38.6%	42.8%	40.6%	40.6%
Number of clusters	16	15	14	37	–

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the price level in cross–sectional (CS) or population–average (PA) estimations or bootstrapped in the random-effect (RE) model (25 replications). Both PA and RE are estimated on the unbalanced panel sample. Data from October 2012, 2013 and 2014, subsample of single-producer area (SPA) residents. Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls sociodemographic variables, dummies for the year the latest plan was decided upon as well as dummies for the year in which the copayment rate was computed. Specifications (4) and (5) also include year fixed effects.

Table IV: Price elasticity by disability level (SPA, October 2012-2014)

	Dependent variable: hours consumed during the week h^* (log)		
	Disability group: 1 & 2	*Disability group: 3*	*Disability group: 4*
	(1)	(2)	(3)
Consumer price (log)	0.945	0.047***	-0.865**
	(0.951)	(0.001)	(0.414)
Observations	371	518	1,602
Censored observations	45.0%	34.9%	41.5%
Number of clusters	27	32	35

NOTES: Standard errors in parentheses; *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the price level. Pooled data from October 2012, October 2013 and October 2014 (population–average model), subsample of single–producer area (SPA) residents. Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls sociodemographic variables, dummies for the year the latest plan was decided upon, dummies for the year in which the copayment rate was computed and year fixed effects.

To investigate the potential heterogeneity in price sensitivity, we estimate the model on three subsamples corresponding to different disability levels (Table IV). We find that the lower the disability level is, the higher the price sensitivity. It echoes the findings of previous works showing that poorer health status is associated with a lower price elasticity of healthcare consumption (Fukushima et al., 2016). In addition, price sensitivity is found to increase with income quartile (Appendix E.1).

Our Tobit model assumes the individual–specific censoring point is uncorrelated with the unobserved determinants of professional home care consumption. It also relies on the homoscedasticity and normality of the error term. We investigate the robustness of our results by estimating an alternative specification, using as the latent dependent variable the (log) ratio of home care consumption relative to the personalized care plan, $h_i^*/\bar{h}_i$. With a fixed censoring point, this transformation opens the way for semi–parametric models. Estimations by Tobit, Censored Least Absolute Deviation (Powell, 1984) and censored quantile regressions (Chernozhukov et al., 2015) provide statistically significant estimates ranging from -0.5 to -0.2, in line with our baseline results (Appendices E.2 and E.3).

5.3 Discussion

Our results confirm that the consumption of home care of the disabled elderly is sensitive to its OOP cost. Decisions relating to home care consumption are influenced by a trade-off between the OOP price of an extra hour and its marginal value. Such a pecuniary trade–off was highlighted at the extensive margin, as the take–up of APA benefits is affected by the average subsidy rate in the county (Arrighi et al., 2015). More originally, we find evidence that the price elasticity of the demand for domestic help is seemingly lower than unity at the intensive margin. This result is in line with the estimates of the average price elasticity of demand of -0.5 and -0.15 respectively found by Bourreau-Dubois et al. (2014) and Hege (2016). Home care services should be regarded as necessary goods, in the sense that adjustment of consumption is proportionally lower than a given change in price.

We retrieve the price elasticity of home care *expenditures* to compare our results with estimates obtained in the literature on the demand for medical services. Manning et al. (1987); Keeler and Rolph (1988) found a price elasticity of medical spending of -0.2; although its magnitude is subject to discussion, its negative sign was found to be robust (Aron-Dine et al., 2013). With a price elasticity of *demand* of -0.4, the price elasticity of *expenditures* is positive: an increase in the unit OOP payment of formal care will lead to a less than proportional decrease in consumption, and thus to an *increase* in OOP and total expenditures.

Our OOP price measure does not take into account possible tax reductions on home care services, unobserved in the data. Given we lack sufficient information to simulate them, we implicitly assume APA beneficiaries to be sensitive to the "spot" price (Geoffard, 2000). We also assume that APA recipients react in the same way to variations in the copayment rate and in the producer price. If salience differs (Chetty et al., 2009), implications for the design of the copayment schedule are less straightforward.

In our administrative data, information on family characteristics is poor. Receiving more informal care has been found to decrease formal care use, both at the extensive and intensive margins (Van Houtven and Norton, 2004; Bonsang, 2009). Omitting informal care provision could bias the estimates of our entire set of coefficients. As a robustness check, we include as a control whether the individual receives formal home care during the weekend and public holidays. We hypothesize that individuals not receiving care over the weekend are more likely to receive assistance from their relatives. Receiving home care during the weekend is associated with more hours consumed during working days (Table E.I) but does not significantly affect the price elasticity estimate.

[Table E.I (p. 44) about here]

Finally, external validity of our results should be qualified. Without data covering the entire population eligible to APA, the potential bias induced by the differential take–up of APA subsidies (Chauveaud and Warin, 2005) cannot be dealt with. Our sample is not nationally representative and we focus on APA recipients who consume home care from authorized services. Yet the county was selected to be "average" in terms of socio-economic and demographic characteristics. In addition, customers of authorized home care services represent a large share of APA beneficiaries in France.

Table V: Inclusion of home care received on weekends (SPA, October 2012-2014)

	Dependent variable: hours consumed during the week h^* (log)		
	(1)	(2)	(3)
Consumer price (log)	-0.452***	-0.637***	-0.604***
	(0.001)	(0.001)	(0.001)
Consumes care on weekends		0.502***	-0.095***
		(0.008)	(0.008)
Number of hours received on weekends			0.189***
			(0.002)
Observations	2,491	2,491	2,491
Censored observations	40.6%	40.6%	40.6%
Number of clusters	37	37	37
AIC	4,454.546	4,389.963	4,364.021
BIC	4,600.057	4,541.294	4,521.173

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard-errors are clustered at the price level. Pooled data from October 2012, 2013 and 2014 (population–average model), subsample of single–producer area (SPA) residents. Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls sociodemographic variables, dummies for the year the latest plan was decided upon, dummies for the year in which the copayment rate was computed and year fixed effects.
The latent dependent variable is the number of hours consumed between Monday and Saturday, except for public holidays. APA beneficiaries may also receive a subsidy for a few hours of care to be received during weekends and public holidays, which are set separately in the personalized care plan. We did not include the home care hours received on weekends as a control in our baseline specifications because of a simultaneity concern. Only 7.5% of our baseline sample has weekend hours included in her personalized care plan, for a median volume of about 5 hours a month.

6 CONCLUSION

This paper estimates the consumer price elasticity of the demand for home care services of the disabled elderly living in the community and benefiting from the French APA program. Our results suggest this parameter is, in absolute value, inferior to one. Although the significance at conventional thresholds is not systematic, the point estimate of -0.4 we obtain is roughly stable across estimations.

Our findings pave the way for several public policy implications. As the disabled elderly are sensitive to the price of care, the copayment rates in home care subsidies programs entail allocative and dynamic efficiency issues. The specific schedule of APA copayments makes the price elasticity we estimate a sufficient statistics for the substitution effect in home care subsidy schemes. Given the low value of the price elasticity (among the most severely disabled individuals notably), the generosity of home care subsidies also has substantial redistributive effects from taxpayers to the disabled elderly. In the case of APA, the linear copayment schedule actually cancels out the effect of recipients' income on home care consumption. Our estimates can also be used to discuss the effects of potential reforms of home care subsidies. The decrease of copayment rates planned by the 2016 APA reform, higher for more–disabled recipients, should reduce beneficiaries' overall OOP expenses on professional home care, while having little volume effect on current APA recipients.

Finally, our study points out the unequal access to home care services over the territory. Individuals living in municipalities with a unique producer cannot choose their producer, on the basis of price or other characteristics such as quality or weekend service. It evidences the need for further development on spatial equity in access to home care services.

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APPENDICES

A CONSTRUCTION OF THE SAMPLE

A.1 Sample selection

This Appendix aims at documenting the selection steps our initial dataset has gone through. For October 2014, administrative records indicate that 5,549 beneficiaries were receiving APA; but for 63 individuals, essential information on subsidized hours, copayment rates or covariates was missing. These individuals are presumably former APA recipients not yet erased from the files, so we dropped them from our sample. The total number of beneficiaries is thus 5,486. Figure A.1 sums up the selection steps.

To observe precisely both the out-of-pocket price and the number of hours that are effectively consumed and subsidized, we retain the beneficiaries receiving care from an authorized producer. They represent the majority of APA recipients in the district (more than 4/5).

We then dropped the observations with missing information for the current month, the preceding month or the following month to avoid potential unobservable shocks likely to bias our estimations. Indeed, missing information could be related to temporary absences (like hospitalizations) or temporary disruptions (e.g. visits from relatives, who replace temporarily professional home care services by providing informal care). The remaining individuals can be regarded as "stable".

8 individuals receive home care from several producers at the same time. If taken into account, the simultaneity of home care consumption decisions for these individuals would make our empirical strategy considerably more complex. We prefer to drop them. In addition, so as to make the relationship between the consumer price and the producer price fully linear in disposable income (see Appendix B), we retain only those individuals with a copayment rate strictly between 0 and 90%.

We end up with a sample that represents 52% of total APA recipients of the district. We follow the same steps to construct the samples of October 2012 and 2013. Percentages of individuals selected at each step are very similar to what is found for 2014 and are available on request.

In order to assess the selection of our sample, we fit a Probit model explaining the probability to choose a authorized producer with the observable characteristics. Results are displayed in Table A.I. Older individuals are less likely to receive care from an authorized producer, while individuals living alone (no spouse or spouse in institution) are more likely to choose that type of provider. Disposable income significantly affects the probability of choosing an authorized producer, but the effect is not linear.

A Heckman-type model would allow to take into account the selection of our sample on both observable and unobservable factors affecting the demand for home care. But we do not have any good instrument at hand to construct an estimator that would not entirely rely on a parametric assumption. We chose to estimate our parameters of interest directly on the selected sample. Such a choice imposes to remain cautious about the external validity of our estimates.

Figure A.1: Sample selection steps

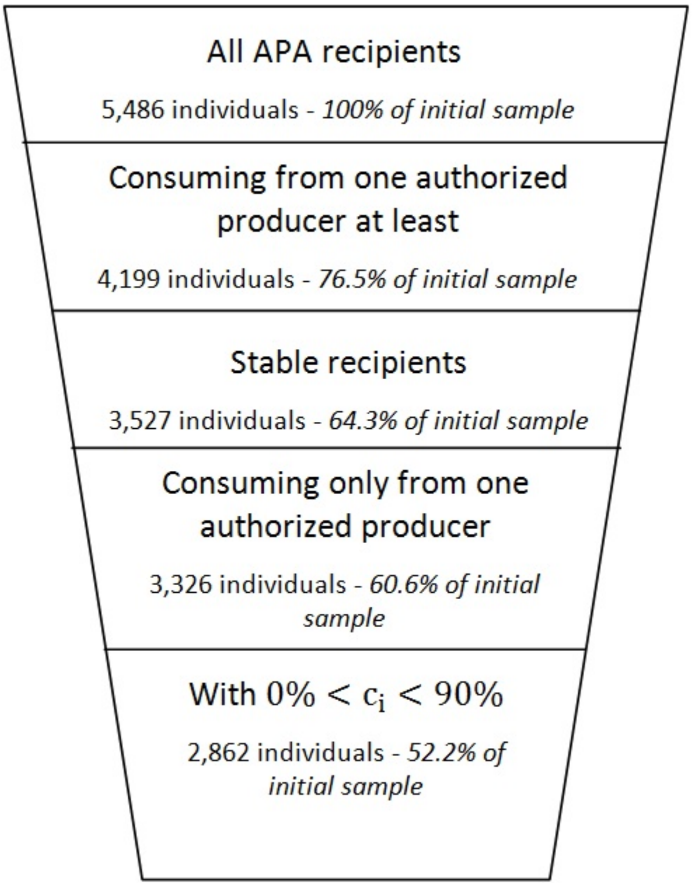


Table A.I: Observable determinants of the choice of a authorized producer (October 2014)

Dependent variable:	Served by an authorized producer
	(1)
Woman	-0.001
	(0.011)
Age: 60-69	0.019
	(0.024)
Age: 70-79	-0.014
	(0.014)
Age: 80-89	*Ref.*
Age: 90 or older	-0.172***
	(0.011)
Disability level: 1	-0.063
	(0.039)
Disability level: 2	-0.014
	(0.017)
Disability level: 3	*Ref.*
Disability level: 4	0.011
	(0.013)
Living with no spouse	0.041***
	(0.012)
Spouse receives APA	0.033
	(0.030)
Spouse in institution	0.202***
	(0.058)
Living with non-APA spouse	*Ref.*
Income quartile: 1	-0.045**
	(0.016)
Income quartile: 2	*Ref.*
Income quartile: 3	-0.038**
	(0.015)
Income quartile: 4	-0.134***
	(0.014)
Observations	5,486
Number of clusters	5,326

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the household level. The sample used correspond to all APA recipients in the District Council in October 2014, except for individuals for which data on the copayment rate, on hours consumed or on sociodemographic characteristics were missing. Estimation is done by a probit model. Average marginal or partial effects (AME – APE) are displayed.

A.2 Imputation of households

Although the data we collected indicate when a beneficiary lives with a partner, we do not know whether the partner also receives APA. Having an APA–recipient spouse may correlate with one's own home care consumption; failing to control for such a characteristic may bias our estimates.

To identify potential couples in our sample, we checked whether each individual could be matched with another recipient of the opposite sex, recorded as living with a spouse, with exactly the same income (as the APA copayment schedule takes into account the household income) and residing in the same municipality. If two individuals match, we assume they belong to the same household. It allows us to construct both a dummy for residing with a spouse receiving APA and a household identification number, which we use when clustering standard errors at the household level (Table A.I).

The matching procedure may fail for individuals whose copayment rate is 0%. The reported disposable income is the same for all such individuals, be they actual spouses or not. The same pitfall applies for individuals whose copayment rate is 90%. In October 2014, only 16 individuals were not matched for this reason; this figure which should be small enough not to affect the results presented in Table A.I. All other estimations rely on the sample of individuals with a copayment rate strictly between 0 and 90%, for who the matching procedure is systematically successful.

B IDENTIFICATION

In Section 4.1 of the paper, our baseline equation is stated as follows:

$$ln(h_i^*) = \beta_0 + \beta_1.ln(c_i p_i) + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \lambda^d.1_i^d + X_i'.\theta + \epsilon_i \qquad (5)$$

As the copayment rate is set to be strictly proportional to the disposable income at the time the latest personalized care plan was defined ("observed income"), the consumer price on subsidized hours is a linear function of I_i^{obs}:

$$c_i p_i = \frac{0.9}{2MTP_i^D} I_i^{obs} p_i$$

where MTP_i^D is the value of a particular disability allowance (*Majoration pour Tierce-Personne*) the year individual i's copayment rate was last computed. Equation (5) is thus equivalent to:

$$ln(h_i^*) = \beta_0 + \beta_1.\Big[ln(p_i) + ln(I_i^{obs}) + ln\Big(\frac{0.9}{2MTP_i^D}\Big)\Big] + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \lambda^d.1_i^d + X_i'.\theta + \epsilon_i$$

Given that the disability allowance MTP^D take the same value for two individuals whose copayment rate was last revised in the same year, dummies 1_i^d in Equation (5) control for inter-individual variation in this parameter. Rearranging terms and introducing a new set of parameters $\mu^d_{d=2009,...,2014}$, we obtain[11]:

$$ln(h_i^*) = \beta_0 + \beta_1.ln(p_i) + (\beta_1 + \beta_2).ln(I_i^{obs}) + \sum_{d=2009}^{2014} \mu^d.1_i^d + X_i'.\theta + \epsilon_i \qquad (6)$$

Equation (6) exhibits two interesting features of our econometric specification. First, it shows that inter-individual variations in *producer prices* of home care identify the *consumer price* elasticity of home care, β_1. Second, it indicates that any hypothetical variation in the observed disposable income would have two distinct effects on the *current* volume of home care consumed:

- An income effect, which captures the additional home care consumption induced by a marginal increase in the *current* disposable income (since we assume current disposable income and past disposable income are

[11]Dummies 1_i^d are also meant to capture the unobservable increase in disposable income since the time the observed income was registered in the District Council. Thus, we implicitly assume that MTP and income have evolved at the same rate for a given individual. Provided income of the elderly evolves at the same pace as pension benefits, this assumption is reasonable: both pension benefits and the disability benefit MTP are set to follow the inflation rate.

mechanically related);

- A price effect, as any change in the disposable income induces a change in the *current* individual consumer price when there is a new personalized care plan.

In order to obtain directly the standard errors associated with the estimator of coefficient β_2, (6) can be written alternatively as:

$$ln(h_i^*) = \beta_0 + \beta_1.\left[ln(p_i) + ln(I_i^{obs})\right] + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \mu^d.1_i^d + X_i'.\theta + \epsilon_i \quad (7)$$

Compared to Equation (5), Equations (6) or (7) are less sensitive to the measurement errors on the relationship between income and consumer price. For 2% of our sample, the relationship between the income and the copayment rate does not verify the legal formula used to compute the copayment rate.[12] After a careful examination of the data, we hypothesize that most of these errors occurred when the copayment rate was computed while the values of income and copayment rate are assumed to be the real ones. It is then worthy –in terms of precision gained– to include the corresponding observations in the estimation. We add a dummy variable 1_i^e signaling whether the individual is affected by such a calculation error.

To sum it up, in order to take into account the various subtleties of the APA policy and the measurement errors, the true estimated equation is thus:

$$ln(h_i^*) = \beta_0 + \beta_1.\left[ln(p_i) + ln(I_i^{obs})\right] + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \mu^d.1_i^d + \zeta.1_i^e + X_i'.\theta + \epsilon_i$$

[12]In practical terms, we are not able to retrieve the value of the MTP related to the year in which the copayment rate was officially computed; as a consequence, for those individuals, all dummies 1^d take the value of zero.

C MAXIMUM LIKELIHOOD ESTIMATION

The objective of this appendix is twofold. First, it provides the expression of the likelihood function we maximize to derive our baseline estimates (Tobit estimation). Second, it shows that, within the framework proposed by Moffitt (1986), the censoring of the measure of consumption at the kink and beyond does not prevent the identification of the sample average price elasticity of demand, conditional on some assumptions on the stability of individual preferences.

C.1 General setting

For the sake of simplicity, we consider home care consumption in level, while we include its log in the empirical specification. The demand for home care with the kinked budget constraint generated by APA writes:

$$\begin{cases} h_i^* = g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* < \bar{h}_i \\ g(p_i, \tilde{I}_i; X_i) + \nu_i < \bar{h}_i < g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* = \bar{h}_i \\ h_i^* = g(p_i, \tilde{I}_i; X_i) + \nu_i & \text{if } h_i^* > \bar{h}_i \end{cases} \tag{8}$$

with ν_i an individual preference shifter. We denote:
$f(.|c_i, p_i, I_i, \bar{h}_i, X_i)$ the conditional density function of ν;
$F(.|c_i, p_i, I_i, \bar{h}_i, X_i)$ its conditional cumulative distribution function;
ψ a set of parameters characterizing the function $g(.)$;
κ a set of parameters characterizing the distribution of the error term ν;
S_1 the left-hand side segment of the budget constraint: $i \in S_1 \iff h_i^* < \bar{h}_i$;
S_2 the right-hand side segment of the budget constraint: $i \in S_2 \iff h_i^* > \bar{h}_i$;
K the kink of the budget constraint: $i \in K \iff h_i^* = \bar{h}_i$.

C.2 Observational scheme with censoring

With h_i the consumption in the data and h_i^* the true consumption, our observational scheme is:

$$h_i = \begin{cases} h_i^* & \text{if } h_i^* < \bar{h}_i \\ \bar{h}_i & \text{if } h_i^* \geq \bar{h}_i \end{cases} \tag{9}$$

From Systems 8 and 9, we know that:

1. For all individuals i such that $h_i < \bar{h}_i$, we know that $h_i = h_i^*$; thus we

have $h_i^* < \bar{h}_i$ ($i \in S_1$):

$$h_i = g(c_i p_i, I_i; X_i) + \nu_i < \bar{h}_i$$

2. For individuals i such that $h_i = \bar{h}_i$, we know that $h_i^* \geq \bar{h}_i$; these individuals can be split in two different sub-groups:

   (a) Individuals i such that $h_i^* = \bar{h}_i$ ($i \in K$); then:

   $$\begin{cases} g(c_i p_i, I_i; X_i) + \nu_i > \bar{h}_i \\ g(p_i, \tilde{I}_i; X_i) + \nu_i < \bar{h}_i \end{cases}$$

   (b) Individuals i such that $h_i^* > \bar{h}_i$ ($i \in S_2$); then:

   $$\begin{cases} g(c_i p_i, I_i; X_i) + \nu_i > \bar{h}_i \\ g(p_i, \tilde{I}_i; X_i) + \nu_i > \bar{h}_i \end{cases}$$

Thus, all censored observations ($i \in S_2$ or $i \in K$) have in common the fact that:

$$g(c_i p_i, I_i; X_i) + \nu_i \geq \bar{h}_i$$

We can thus write:

$$h_i = \begin{cases} g(c_i p_i, I_i; X_i) + \nu_i & \text{if } g(c_i p_i, I_i; X_i) + \nu_i < \bar{h}_i \\ \bar{h}_i & \text{if } g(c_i p_i, I_i; X_i) + \nu_i \geq \bar{h}_i \end{cases} \tag{10}$$

which corresponds to the usual censored regression model setting.

C.3 The likelihood function with censoring

Let h be a random variable, from which h_i is a random draw. Conditional on the observable covariates, $h = g(CP_i, \hat{I}_i; X_i) + \nu$, where ν is a normally distributed random variable from which ν_i is a random draw. From System 10, we can derive the individual contributions to the likelihood function:

1. Contribution of an individual i such that $h_i < \bar{h}_i$ ($i \in S_1$):

$$\begin{aligned} \mathbb{P}\big(h_i = h_i^* | c_i, p_i, I_i, X_i\big)_{|h_i^* < \bar{h}_i} &= \mathbb{P}\big(\nu = h_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big) \\ &= f\big(h_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big) \end{aligned}$$

2. Contribution of an individual i such that $h_i \geq \bar{h}_i$ ($i \in S_2$ or $i \in K$):

$$\begin{aligned}\mathbb{P}\big(h_i = \bar{h}_i | c_i, p_i, I_i, X_i\big)_{|h_i^* \geq \bar{h}_i} &= \mathbb{P}\big(h \geq \bar{h}_i | c_i, p_i, I_i, X_i\big) \\ &= \mathbb{P}\big(\nu \geq \bar{h}_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big) \\ &= 1 - F\big(\bar{h}_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big)\end{aligned}$$

Finally, the likelihood function can be written as follows:

$$\begin{aligned}L(\psi, \kappa) = \prod_{i=1}^{n} &\Big[f\big(h_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big)\Big]^{\mathbb{I}_{[h_i < \bar{h}_i]}} \\ &\times \Big[\Big(1 - F\big(\bar{h}_i - g(c_i p_i, I_i; X_i) | c_i, p_i, I_i, X_i\big)\Big)\Big]^{\mathbb{I}_{[h_i = \bar{h}_i]}}\end{aligned}$$

In our setting, the censoring of the dependent variable exactly at the kink prevents us from distinguishing between the individuals who consume exactly at the kink and those who actually locate on the right-hand side segment of the budget constraint. Interestingly, it does not prevent the identification of our parameters of interest (which relate to the function $g(.)$), although it comes at a cost in terms of precision. Assuming some stability of individual preferences,[13] we can interpret the price elasticity estimated using information relating to the left-hand side of the kink as the price sensitivity of demand along the entire budget constraint.

Weaker assumptions on individual preferences would not undermine the identification of the price sensitivity for the selected sample of APA beneficiaries consuming less than their care plan volume. However, if the underlying data generating process actually changes at the kink, censored regression methods would not adequately correct for the bias induced by the non-observability of all individuals consuming at the kink or beyond.

C.4 Likelihood function of our sample

Using the previous section, we can derive the conditional likelihood function for our sample, i.e the probability we observe the sample values of hours consumed, h_i, given the consumer price $c_i p_i$, the disposable income at the time the personalized care plan was set I_i^{obs} and other individual characteristics X_i.

Remember we assume the following specification for the demand for home

[13] Moffitt (1986) assumes the functional form of $g(.)$ is invariant to changes in consumer price and income.

care:

$$ln(h_i^*) = \beta_0 + \beta_1.ln(c_i p_i) + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \lambda^d.1_i^d + X_i'.\theta + \epsilon_i$$

In addition, we assume a normal distribution for the idiosyncratic shock ϵ:

$$\epsilon \sim \mathcal{N}(0, \sigma^2)$$

Finally, our likelihood function writes:

$$L(\beta, \lambda, \theta, \sigma) = \prod_{i=1}^{n} \Big[\frac{1}{\sigma}\phi\big(\frac{ln(h_i) - \beta_1.ln(c_i p_i) - \beta_2.ln(I_i^{obs}) - \big(\sum_{d=2009}^{2014} \lambda^d.1_i^d\big) - X_i'.\theta}{\sigma}\big)\Big]^{\mathbb{I}_{[h_i < \bar{h}_i]}}$$
$$\times \Big[\Big(1 - \Phi\big(\frac{ln(\bar{h}_i) - \beta_1.ln(c_i p_i) - \beta_2.ln(I_i^{obs}) - \big(\sum_{d=2009}^{2014} \lambda^d.1_i^d\big) - X_i'.\theta}{\sigma}\big)\Big)\Big]^{\mathbb{I}_{[h_i = \bar{h}_i]}}$$

where $\phi(.)$ (resp. $\Phi(.)$) the conditional density (resp. cumulative distribution) function of a standardized normal variable.

Consistent estimators of β_1, β_2 and θ can be derived as the arguments of the maximization of the log-likelihood function, provided it is concave.

In order to derive the expression here–above, we must assume the censoring point $\bar{h}_i$ does not depend on the error term, ϵ_i. In other words, the individual censoring point is assumed to be exogenous, conditional on the observable variables. This assumption is discussed in Appendix E.2.

D SUPPLY BY AUTHORIZED PROVIDERS

D.1 Components of home care prices

In this section, we explain why customers may exogenously face different producer prices: to do so, we detail the components of prices.

Authorized producers are priced by the County Countil (CC). The hourly price of each producer is computed as the overall average hourly production cost of the producer. The various components of production costs are described in qualitative studies, either in academic works (Gramain and Xing, 2012) or in public reports.[14] By order of importance (top–down), production costs can be decomposed as follows:

[parsep=0.05cm,itemsep=0.05cm,topsep=0.05cm]Employee costs (80% of total charges): wages paid to professional caregivers and, for a small part (around 10% of total charges), to the supervising staff. The wage of a caregiver depends on her qualification, according to collective labour agreements. We expect that the larger the proportion of skilled caregivers, the higher the production cost and the price. Wages are also augmented if employees work on Sunday or on public holidays, in accordance with general labour legislation. Operating costs (10–15% of total charges): those include rents for the service's offices and other running expenses. Transportation costs (5–10% of total charges) correspond to the compensation for the costs borne by employees to go to the consumer's home. This item is likely to vary largely across services according to their geographic area of intervention. Contrary to the health care sector, technological progress and capital costs are negligible in the home care industry.

We represent the relationship between the producer price and several providers' characteristics graphically. We distinguish between non–public (mainly non–profit) producers and public producers. The latest are likely to receive grants or advantages (e.g., a free office) from local municipalities that reduce operating costs. Such advantages are taken into account in the pricing process done by the CC and lower down the regulated price of public producers. In the graphical representation, we exclude the largest producer of the district, a nationwide non–profit organization, which has systematically the highest values for the variables we are here interested in.

In Figure D.1, producer prices are plot against the number of APA benefi-

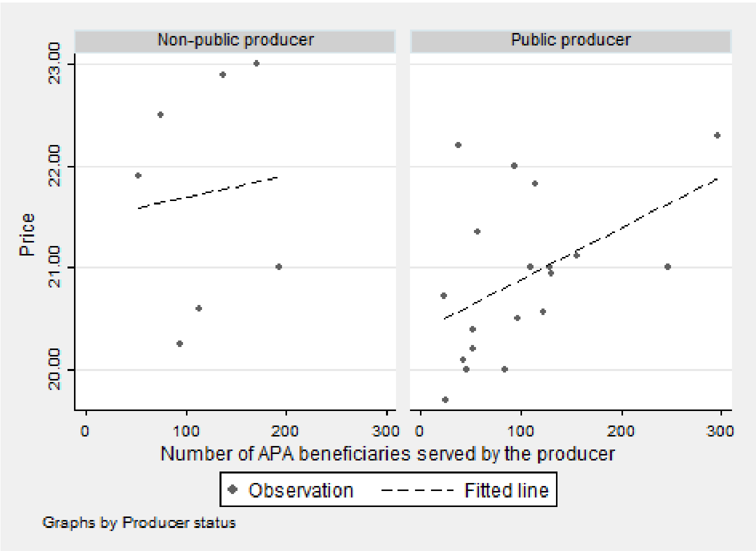
[14] There is, though, no national, comprehensive benchmark study on the costs of home care services. Public reports regularly deplore the lack of information on costs as a major shortcoming preventing from understanding the functioning of the sector (Vanlerenberghe and Watrin, 2014; Poletti, 2012).

ciaries served by the corresponding services. Graphically, the more customers the producer has, the higher its price. Having more customers might be associated with more municipalities to serve (see Figure D.3) or more unproductive hours.[15] This graph should be interpreted cautiously though: we only know the number of APA recipients served by each home care producer, instead of the total number of customers (including non–APA beneficiaries) served in the district.

Figure D.2 shows the relationship between the producer price and the share of hours they serve on Sundays or on public holidays. Public producers have a very low share of such hours, as most public services do not operate on weekends and holidays. A higher share of hours made on holidays is associated with a higher price among public structures, which is consistent with the financial compensation of employees for working on public holidays.

Finally, Figure D.3 shows that the relationship between the price and the number of municipalities served by the producer is actually increasing. Taking into account the spatial distribution of municipalities could be a way to refine the analysis, as it would reflect transportation costs more accurately.

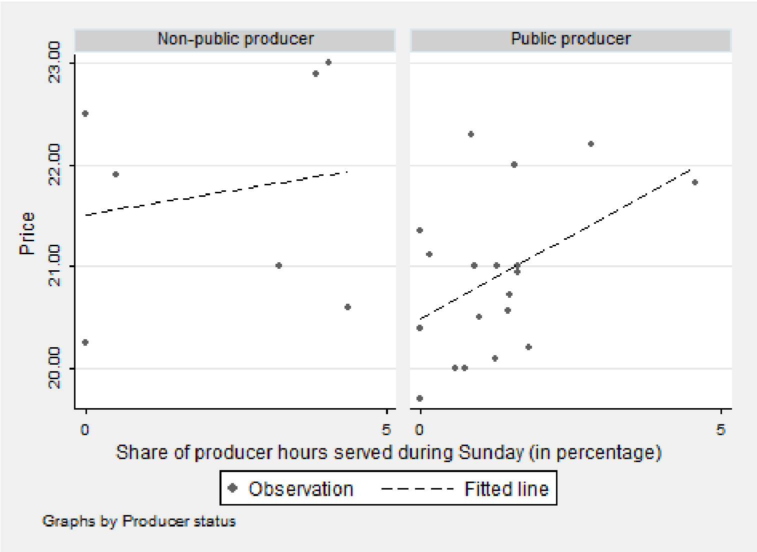
Figure D.1: Producer price according to the number of APA beneficiaries served by the producer, by status



Sample: Authorized home care producers of the district serving at least one APA beneficiary in October 2014.
Notes: The largest producer, which serves 43% of the APA beneficiaries who receive care from an authorized producer in the district, is not included.

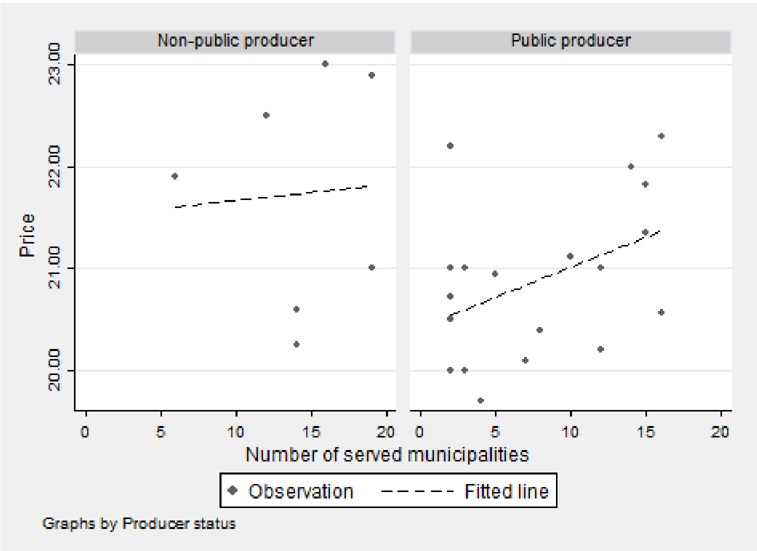
[15]Unproductive hours (meetings, training) may become relatively more numerous when a service gets relatively large.

Figure D.2: Producer price according to the share of the producer's hours served on Sundays and public holidays, by status



SAMPLE: Authorized home care producers of the district serving at least one APA beneficiary in October 2014.
NOTES: The largest producer, which does 1.80% of the home care hours it provides on Sundays and holidays, is not included.

Figure D.3: Producer price according to the number of served municipalities, by status



SAMPLE: Authorized home care producers of the district serving at least one APA beneficiary in October 2014.
NOTES: The largest producer, which serves 199 municipalities, is not included.

D.2 Unequal spatial coverage

Single–producer and multiple–producer areas

According to their geographic location in the district, beneficiaries can not systematically choose among several producers of the district. In some municipalities, a single producer is found to operate (single-producer areas, "SPA areas"). As displayed in D.I, it is the case for 79% of the municipalities represented in our sample, in which live 35% of beneficiaries included in the baseline sample. Other beneficiaries are living in a municipality where two or more authorized producers have customers (multiple-producer areas, "non–SPA areas"). Table D.I interestingly reflects spatial concentration: 65% of the beneficiaries in our sample live in 21% of the represented municipalities.

Table D.I: Single–producer areas and multiple–producer areas

	Municipalities		Beneficiaries		Average price
	Number	*Frequencies*	*Number*	*Frequencies*	
SPA	221	79.2%	997	34.8%	€21.2
Non–SPA	58	20.8%	1,865	65.2%	€21.2
Total	279	100%	2,862	100%	-

NOTES: Baseline sample from October 2014. Average provider price per type of area is not weighted by the number of customers of the producers.

Table D.II presents the descriptive statistics computed on the two subsamples. They are similar regarding average sociodemographic characteristics. Although they slightly differ in terms of average care plan volume, the average home care consumption is similar in both subsamples. Once the relative sizes of providers are taken into account, producer prices appear to be higher on average in SPA municipalities. The effect on the OOP price though is counterbalanced by the lower average income of their residents and thus lower copayment rates. Price endogeneity of home care due to residential mobility should be negligible: the residential mobility of the elderly is generally low (Laferrère and Angelini, 2010) and when moves occur, they are mainly explained by family motives or the need for adapted residences.

Overall, the two subsamples do not differ substantially in terms of the outcome and of explaining variables. Without systematic differences in the unobservable characteristics associated with home care consumption, the estimate of the price and income elasticities we obtain on the subsample of individuals with no choice of producer price can be reasonably extrapolated to our entire baseline sample of APA recipients.

Such an extrapolation would be undermined if profit–maximizing home care producers willing to act as monopolies were targeting the municipalities with no competitors and where residents are the least price–elastic. As explained further below, the home care providers are highly regulated: their intervention area is defined by the CC. Moreover, they mostly come from the non–profit organizations or from public municipal structures. It makes the assumption that providers would choose their commercial area so as to extract more profit quite unlikely.

Table D.II: Descriptive statistics on two subsamples (SPA and non SPA, October 2014)

Variable	SPA (1)	Non–SPA (2)	P-value (diff. in means) (3)
Care plan volume	20.1	20.8	0.06
Care plan monetary value	€456.8	€454.8	0.83
Hours effectively subsidized	17.5	17.8	0.37
Amount of effective subsidies	€311.7	€294.9	0.03
Underconsumption of care plan volume	57.2%	61.2%	0.03
Individualized income	€1,272	€1,339	0.00
Copayment rate	21.9%	24.6%	0.00
Producer price	€22.8	€21.8	0.00
Hourly out-of-pocket price	€5.0	€5.4	0.01
Total out-of-pocket payments on subsidized hours	€86.0	€94.2	0.03
Age	84.4	84.0	0.19
Women	72.5%	74.7%	0.19
Disability level 1 (most severe)	1.5%	1.0 %	0.25
Disability level 2	12.2%	12.6%	0.78
Disability level 3	20.7%	19.1%	0.31
Disability level 4 (least severe)	65.6%	67.3%	0.36
	100%	-	
Living with a spouse	34.7%	33.3%	0.45
Living alone	64.7%	66.1%	0.45
Spouse in institution	0.6%	0.6%	0.96
	100%	-	-
Number of individuals	997	1,865	-
Number of households	965	1,820	-

NOTES: Baseline sample from October 2014. Descriptive statistics are computed on the subsample of APA beneficiaries living in single–producer municipalities in Column (1) and those living in multiple–producer municipalities in Column (2). Column (3) presents the p–values associated with the bilateral tests of comparison of the means.

We additionally tested the effect of including in our baseline regression a dummy associated with the fact of living in an area with one single producer operating (Table D.III). Once controlling for observable characteristics, living in a SPA does not affect significantly home care consumption nor its estimated price elasticity.

Table D.III: Consumer price elasticity estimations, controlling for the type of area of residence (October 2014)

Dependent variable: hours consumed during the week h^* (log)		
	(1)	(2)
Consumer price (log)	-0.709**	-0.823**
	(0.290)	(0.333)
Disposable income (log)	0.660**	0.776**
	(0.291)	(0.329)
Lives in a SPA		0.041
		(0.046)
Observations	2,862	2,862
Number of clusters	27	27
AIC	5,355	5,355
BIC	5,468	5,474

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the producer level. Baseline sample from October 2014. Estimation of a Tobit model by Maximum Likelihood. Estimations include as controls sociodemographic variables, dummies for the year the latest plan was decided upon as well as dummies for the year in which the copayment rate was computed. SPA stands for "single-producer area".

Producer types in multiple–producer areas

Beneficiaries living in non–SPA areas can choose their home care provider, which can be either public, for–profit or non–profit. This section first documents the "supply mix" available in the municipalities of the district and the profiles of consumer resorting to each type of authorized providers. Second, it highlights the correlation between APA recipients' characteristics and the fact of resorting to a "low–price" service.

Historically, in France, non–profit organizations were important providers of home care and they remain predominant in many rural areas. In our district of interest, there are 5 non-profit services, providing care to exactly 50% of our baseline sample. In addition, 20 municipal services are providing home care services to APA recipients. As displayed in Table D.IV, more than 3/4 of SPA beneficiaries are served by a non–profit organization while public services provide care to the remaining 23%. Finally, private structures can be found in the home care sector, but they still represent a small share of the authorized home care providers. Private services, which happen to operate only in municipalities where at least a public service can be found, provide home care to 3.4% of our baseline sample.

More than 50% of non–SPA beneficiaries can choose between the three types of authorized providers.[16] Conversely, the typical supply mix in medium–size municipalities is the combination of non-profit and public providers.

Table D.IV: Types of authorized producers in the municipality of residence

	SPA municipalities		Non–SPA municipalities	
Types of producers operating in the municipality	*Share of municipalities*	*Share of beneficiaries*	*Share of municipalities*	*Share of beneficiaries*
Public only	27.5%	22.8%	3.3%	0.7%
For–profit only	0.0%	0.0%	0.0%	0.0%
Non–profit only	72.5%	77.2%	8.2%	1.9%
Public & for–profit only	-	-	0.0%	0.0%
Public & non–profit only	-	-	59.0%	41.8%
For-profit & non–profit only	-	-	4.9%	2.2%
Public, for–profit & non–profit	-	-	24.6%	53.4%
Total	100%	100%	100%	100%
Number	218	967	61	1,895

NOTES: Baseline sample from October 2014. In order to determine which types of authorized producers operate in a given municipality, the sample of APA beneficiaries being served by an authorized producer at least (before any selection) was used.

In order to see whether each type of authorized producer has a specific profile of customers, we regress the type of provider chosen by each non–

[16] It concerns 25% of the municipalities with several producers. The supply mix is then more diversified in the largest municipalities

SPA recipient on her individual characteristics. Columns (1), (2) and (3) of Table D.V present the average impact of each observable characteristic on the probability to be provided care by, respectively, a public, a for–profit or a non–profit provider. The estimated coefficients should be regarded as the distinctive characteristics of the subpopulation of customers of each producer type. Indeed, 4 individuals out of 10 in the sample used for the estimation can actually choose only between two different types of producers and we do not control for any systematic difference in prices between producer types.

In our sample, the probability of choosing a public producer decreases with high income, high disability level and week–end interventions. It might be due to the fact that the operating hours and days of public services are more restricted than the intervention schedules of private structures. The probability of choosing a for–profit producer increases when the individual belongs to the top income quartile income. Non–profit producers are more likely to be chosen by highly–disabled individuals. The evaluation team may tend to recommend them for the most severely disabled APA recipients who will be likely to need interventions in the evening and during the weekend.

We also investigate the importance of the producer's relative price in the choice of a given home care provider. Column (4) of Table D.V presents the individual characteristics associated with the choice of a "low–price" producer, defined as a provider charging a price strictly below the average price charged by the producers operating in the beneficiary's municipality. We estimate the probability of choosing a "low–price" producer by a Probit, on the sample of individuals who live in a non–SPA municipality. Beyond a slight age effect, only the disability level is found to have a significant impact. The least severely disabled are more likely to choose a "low–price" producer, possibly reflecting that they perceive home care as less necessary and are thus *ex ante* more sensitive to its price.

Table D.V: Determinants of producer type for non–SPA beneficiaries (2012–2014)

	Probability of choosing a:			
	Public producer	For–profit producer	Non–profit producer	"Low–price" producer
	———	*Multinomial logit*	———	— *Probit* —
	(1)	(2)	(3)	(4)
Woman	0.023	-0.001	-0.022	-0.033
	(0.018)	(0.005)	(0.017)	(0.020)
Age: 60-69	-0.141***	0.078**	0.063*	-0.053
	(0.040)	(0.035)	(0.036)	(0.053)
Age: 70-79	-0.089***	0.018*	0.071***	-0.040*
	(0.019)	(0.010)	(0.020)	(0.021)
Age: 80-89	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Age: 90 or older	-0.008	-0.008	0.017	-0.031
	(0.025)	(0.006)	(0.021)	(0.023)
Disability group: 1	-0.230**	0.051	0.179**	-0.120
	(0.091)	(0.063)	(0.075)	(0.096)
Disability group: 2	-0.004	-0.015*	0.018	-0.033
	(0.039)	(0.009)	(0.035)	(0.033)
Disability group: 3	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Disability group: 4	0.065**	0.024	-0.089***	0.085***
	(0.023)	(0.018)	(0.022)	(0.021)
Living with no spouse	-0.010	-0.014	0.024	-0.006
	(0.025)	(0.009)	(0.026)	(0.025)
Spouse receives APA	-0.047	0.049	-0.001	0.009
	(0.059)	(0.033)	(0.057)	(0.051)
Spouse in institution	-0.033	0.053	-0.020	-0.105
	(0.095)	(0.043)	(0.095)	(0.108)
Living with non–APA spouse	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Income quartile: 1	-0.049**	0.025	0.025	-0.011
	(0.024)	(0.022)	(0.036)	(0.025)
Income quartile: 2	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Income quartile: 3	-0.061	0.037*	0.024	-0.009
	(0.039)	(0.022)	(0.030)	(0.026)
Income quartile: 4	-0.130**	0.090**	0.039	-0.004
	(0.042)	(0.038)	(0.026)	(0.029)
Care plan volume	0.001	0.002*	-0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Receives care on weekends	-0.113**	0.027	0.086*	-0.079
	(0.051)	(0.020)	(0.047)	(0.050)
Sample		Municipalities with at least 2 types of authorized producers		Non–SPA municipalities
Observations		5,516		5,699
Number of clusters		72		82

NOTES: Standard errors in parentheses, clustered at the municipality level; $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. Average marginal or partial effects (AME – APE) are displayed. Columns (1) to (3) were obtained by estimating a multinomial logit on three mutually exclusive outcomes on the sample of non–SPA beneficiaries with several types of authorized providers. In Column (4), "low-price" providers are charging a price below the average price of authorized producers within a given municipality; the estimation uses the sample of beneficiaries living in a municipality with at least two different prices. Data pooled from October 2012, October 2013 and October 2014 (population–average model). Specifications include year fixed effects.

E ADDITIONAL RESULTS AND ROBUSTNESS CHECKS

E.1 Additional results

Table E.I: Price elasticity by income quartile (SPA, October 2012-2014)

Dependent variable: hours consumed during the week h^* (log)		
	(1)	(2)
Consumer price (log)	-0.452***	-0.472***
	(0.001)	(0.001)
Consumer price × 1st income quartile		0.002**
		(0.001)
Consumer price × 2nd income quartile		*Ref.*
Consumer price × 3rd income quartile		-0.007***
		(0.001)
Consumer price × 4th income quartile		-0.005***
		(0.001)
Disposable income (log)	0.428***	0.468***
	(0.002)	(0.002)
Observations	2,491	2,491
Censored observations	40.6%	40.6%
Number of clusters	37	37
AIC	4,454	4,457
BIC	4,600	4,620

NOTES: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the price level. Data pooled from October 2012, 2013 and 2014 (population–average model). Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls sociodemographic variables, dummies for the year the latest plan was decided upon, dummies for the year in which the copayment rate was computed and year fixed effects.

E.2 Determinants of the care plan volume and censoring

With our baseline specification, the Maximum Likelihood function (Appendix C) is derived assuming the individual censoring point, $ln(\bar{h}_i)$, is exogenous conditional on explanatory variables. In addition, as explained in the paper, consistency of estimates relies on the additional assumption that the producer price, p_i, is exogenous.

This assumption is discussed in this section. When setting the care plan volume $\bar{h}_i$, the CC evaluation team supposedly takes into account the precise needs of the beneficiary in terms of assistance with the activities of daily living.

Besides the administrative disability group, matrimonial status, gender and age (as correlating with unobserved health problems and housekeeping skills) can be expected to influence the care plan volume. Additionally, there is a situation in which $\bar{h}_i$ would directly relate to the price of the chosen producer: when the evaluation team sets the personalized care plan, it has to check that the monetary equivalent of the care plan volume is below the legal ceiling associated with the disability level (GIR) of the beneficiary. The monetary equivalent equals the number of hours granted by the evaluation team times the producer price. If the monetary equivalent of the care plan volume is higher than the legal ceiling, the adjustment will go through a reduction in $\bar{h}_i$ for SPA beneficiaries. But non–SPA individuals might choose a cheaper producer in order to be entitled to a higher amount of subsidized hours $\bar{h}_i$. This may be a source of price endogeneity in our specification.[17]

Empirically,[18] once for controlling for income, gender, age, disability group, matrimonial status, hours received on weekends and whether a beneficiary was already receiving APA 1 or 2 years earlier, we find no empirical correlation between the OOP price and the volume of the care plan on the 2014 sample of SPA beneficiaries. Similarly, a probit estimation of the probability to be censored, $\mathbb{P}(h_i = \bar{h}_i)$, shows that the probability to be censored is not correlated with the price.This suggests that the strategic choice of a producer (price) to comply with the legal ceiling is empirically negligible. The probability to reach one's ceiling is higher for individuals with no partner at home, possibly because individuals living with a partner benefit from economies of scale in home care utilization[19] and from some informal help provided by their spouse. Consuming totally the care plan volume is also more likely for individuals living in a SPA, but less likely on average for individuals who are entitled to subsidies on formal care served during the weekends.

Individual observable characteristics explain about 55% of the variations observed in the volume of the care plan. This leaves more than 40% of the variations unexplained. If they correlate with unobservable determinants of the care plan volume, this may undermine our empirical strategy. Ethnographic work (Billaud et al., 2012) indeed suggests that unobserved informal care or health status can influence the evaluation team in the set up of the care plan volume.

[17] For 7% of our sample at most, the monetary equivalent of their care plan volume would exceed their legal ceiling if they choose the most expensive producer operating in their municipality.

[18] Tables of results are not included but are available upon request.

[19] These economies of scale are not factored in by the evaluation team when setting the care plan volume. This is consistent with the fact that APA is meant to be a personal subsidy: legal ceilings do not depend on whether a beneficiary has a partner also receiving APA.

As we do not have any good instrument to test the endogenity of the care plan volume in our dataset, we have to rely on the assumption that it is reasonably exogenous. Still, we can go round the limitations raised by having an individual–specific censoring point with an alternative specification we present in the following section. Its second advantage is that it is arguably more robust to potential price endogeneity.

E.3 Specification in ratio

As presented in Section 4.1 of the paper, our baseline specification is the following:

$$ln(h_i^*) = \beta_0 + \beta_1.\big[ln(p_i) + ln(I_i^{obs})\big] + \beta_2.ln(I_i^{obs}) + \sum_{d=2009}^{2014} \mu^d.1_i^d + \zeta.1_i^e + X_i'.\theta + \epsilon_i$$

Alternatively, we consider as the dependent variable the share of the care plan volume that is effectively consumed by the individual, $h_i^*/\bar{h}_i$, that we call the "relative consumption". The dependent variable is still censored when individuals fully consume their care plan volume (exact volume or more), but the censoring point is unique now.

Empirically, we take the log of the ratio and estimate the following specification:

$$\begin{aligned} ln\Big(\frac{h_i^*}{\bar{h}_i}\Big) = {} & \alpha_0 + \alpha_1.\big[ln(p_i) + ln(I_i^{obs})\big] + \alpha_2.ln(I_i^{obs}) + \alpha_3.ln(\bar{h}_i) \\ & + \sum_{d=2009}^{2014} \tilde{\mu}^d.1_i^d + \tilde{\zeta}.1_i^e + X_i'.\tilde{\theta} + \tilde{\epsilon}_i \end{aligned} \tag{11}$$

The censoring point is thus equal to $log(1) = 0$ whatever the volume of the care plan. Equation (11) is equivalent to:

$$\begin{aligned} ln(h_i^*) - ln(\bar{h}_i) = {} & \alpha_0 + \alpha_1.\big[ln(p_i) + ln(I_i^{obs})\big] + \alpha_2.ln(I_i^{obs}) + \alpha_3.ln(\bar{h}_i) \\ & + \sum_{d=2009}^{2014} \tilde{\mu}^d.1_i^d + \tilde{\zeta}.1_i^e + X_i'.\tilde{\theta} + \tilde{\epsilon}_i \\ ln(h_i^*) = {} & \alpha_0 + \alpha_1.\big[ln(p_i) + ln(I_i^{obs})\big] + \alpha_2.ln(I_i^{obs}) + (\alpha_3 + 1).ln(\bar{h}_i) \\ & + \sum_{d=2009}^{2014} \tilde{\mu}^d.1_i^d + \tilde{\zeta}.1_i^e + X_i'.\tilde{\theta} + \tilde{\epsilon}_i \end{aligned} \tag{12}$$

In Equation (11), α_1 can thus be interpreted as the price elasticity of demand.

This specification comes with two advantages. First, it enables us to overcome the limitation of having an individual–specific censoring point. Specification tests that usually come with Tobit models with a fix censoring point have not been extended to the case of individual–specific censoring. Recent theoretical developments in semi–parametric estimation methods have proposed ways to deal with individual–varying censoring, but, to our knowledge, they have not been implemented so far in empirical works.

The specification in ratio additionally permits to address partly the potential endogeneity of price. In our main results, taking into account the potential non-random selection into a producer highlights a negative bias of the baseline estimate. We suspect an omitted variable is negatively correlated with the price and positively correlated with consumption. Our hypothesis is that individuals may *ex ante* choose their producer price according to their individual "expected level of consumption". For instance, holding income constant, beneficiaries with a high expected level of consumption could choose a lower price to contain their total expenses on home care.

If the consumption of home care h_i^* depends on the expected consumption h_i^{exp}, we should estimate the following specification:

$$ln(h_i^*) = \beta_0 + \beta_1.\left[ln(p_i) + ln(I_i^{obs})\right] + \beta_2.ln(I_i^{obs}) + \beta_3.ln(h_i^{exp}) \sum_{d=2009}^{2014} \mu^d.1_i^d + \zeta.1_i^e + X_i'.\theta + \epsilon_i \tag{13}$$

Schematically, assuming a negative correlation between h_i^{exp} and p_i ($Corr_{h_i^{exp},p_i} < 0$: the more individuals intend to consume, the lower their price) and a positive effect of h_i^{exp} on h_i^* ($\beta_3 > 0$: the higher the expected consumption, the higher the effective level of consumption), then the omission of h_i^{exp} in the baseline specification can be expected to downward bias coefficient β_1.

Using the specification in ratio could partly neutralize this omitted variable bias in our baseline sample. Indeed, we expect the care plan volume $\bar{h_i}$ to be a proxy for the expected consumption h_i^{exp}. Including $\bar{h_i}$ directly as a control in our original specification yields interesting results, but raises multi–colinearity issues, as the care plan volume is highly correlated with the disability level. Moreover, it does not allow us to go beyond the individual-specific censoring point problem.

In the following subsections, we present the results obtained with the specification in ratio using both parametric and semi–parametric regression techniques.

Parametric estimations

Table E.II displays the price elasticity estimate obtained by Maximum Likelihood estimation of the specification in ratio (Equation (11)), assuming $\tilde{\epsilon} \mid p, I^{obs}, X, 1 \sim \mathcal{N}(0, \tilde{\sigma}^2)$. We depart from a structural approach by not constraining α_3 to be equal to -1 in the estimation. Column (1) uses the entire sample of October 2014, while Column (2) and (3) present the results of estimations run respectively on the subsample of non–SPA and SPA beneficiaries. Contrary to the quite large difference obtained in the baseline specification, the estimate obtained on non–SPA sample do not to differ from the estimate obtained on the SPA sample (-0.55 *versus* -0.39, precision being low). This suggests that the issue of price endogeneity due to non-random producer selection, which was argued to be more of a concern in the non–SPA sample, is attenuated in the specification in ratio.

In Column (4), the estimation is run on the pooled data from October 2012, 2013 and 2014. With the gain in precision, the price elasticity of -0.5 is significantly different from zero at the 1% level.

Table E.II: Consumer price elasticity estimations with the specification in ratio

	Dependent variable: ratio $h^*/\bar{h}$ (log)			
	CS			PA
	(1)	(2)	(3)	(4)
Consumer price (log)	-0.300	-0.552*	-0.394	-0.522***
	(0.238)	(0.290)	(0.398)	(0.001)
Disposable income (log)	0.286	0.545*	0.376	0.524***
	(0.241)	(0.287)	(0.395)	(0.001)
Care plan volume (log)	0.041	0.055	0.040***	0.039***
	(0.033)	(0.043)	(0.013)	(0.002)
Sample	All	Non–SPA	SPA	SPA
Year	2014	2014	2014	2012-2014
Observations	2,862	1,865	997	2,491
Number of clusters	27	23	14	37
AIC	4,290	2,859	1,424	3,294
BIC	4,409	2,969	1,488	3,445

NOTES: Standard errors in parentheses. Standard errors are clustered at the producer level in Specification (1), at the price level in Specifications (2) to (4). Columns (1) to (3) are cross-sectional (CS) estimations. They use data from October 2014, Column (1) using the entire sample, Column (2) the sub–sample of multiple–producer area (non–SPA) beneficiaries and Column (3) the SPA sub–sample. Specification (4) estimates a population–average (PA) model on the sub–sample of SPA beneficiaries in pooled data from October 2012, 2013 and 2014. All specifications include as controls sociodemographic variables, dummies for the year the latest plan was decided upon, dummies for the year in which the copayment rate was computed and year fixed effects.

The parametric estimation of the specification in ratio produces an estimate of the price elasticity statistically similar to our baseline results. However, the consistency of Tobit estimates relies heavily on the assumption of normality and homoscedasticity of the error term. The specification with a fix censoring point makes it possible to implement semi–parametric techniques such as quantile regressions, which rely on much weaker assumptions.

Semi–parametric estimations

We first use the censored least-absolute-deviation (CLAD) estimator proposed by Powell (1984). CLAD consists in a generalization of the least absolute deviations estimation of the linear model. CLAD estimator is consistent and asymptotically normal for a wide class of distributions of the error term. In addition, it is robust to heteroskedasticity. As CLAD relies on the conditional median of the (log) latent relative home care consumption $\frac{h_i^*}{\bar{h}_i}$, it proves more robust to censoring than estimators based on the conditional mean, like the Tobit. Given the high censoring rate in our sample (reaching 55% for the GIR–1 individuals), this makes the CLAD estimator attractive.

With a CLAD estimation (Table E.III), the price elasticity at the median point of the distribution of relative consumption is inferior to one, with a magnitude of -0.181. The coefficient here has to be estimated on the entire sample of SPA and non-SPA beneficiaries to achieve convergence. The bias-corrected confidence interval shows that this estimate is significantly different from zero at the 95% level.

Further developments of quantile regressions have been extended to the case of censored data (Powell, 1986; Chernozhukov and Hong, 2002; Chernozhukov et al., 2015): we also estimate our ratio–specification by a censored quantile regression. Estimates were produced for 12 quantiles (quantile 5 to quantile 60). Given that the censoring rate is around 39%, quantiles 65 and higher cannot be estimated. Estimates for quantiles 5 to 55 are represented on Figure E.1. As the estimate for quantile 60 is very imprecise (the boostrapped confidence interval is $[-1.6; -0.3]$), we exclude it from the graphical representation. Except for quantiles 5 and 60, the price elasticity estimate is significantly different from 0 at the 5% level. Although confidence intervals are relatively large, especially for the upper quartiles, the results suggest that there is some heterogeneity in the degree of price sensitiveness among APA beneficiaries. Individuals whose consumption is relatively closer to the care plan volume seem more price–elastic, with an estimate reaching 0.5 in absolute value. The price elasticity of the 30% smallest consumers (relatively to their care plan volume) is stable around -0.15.

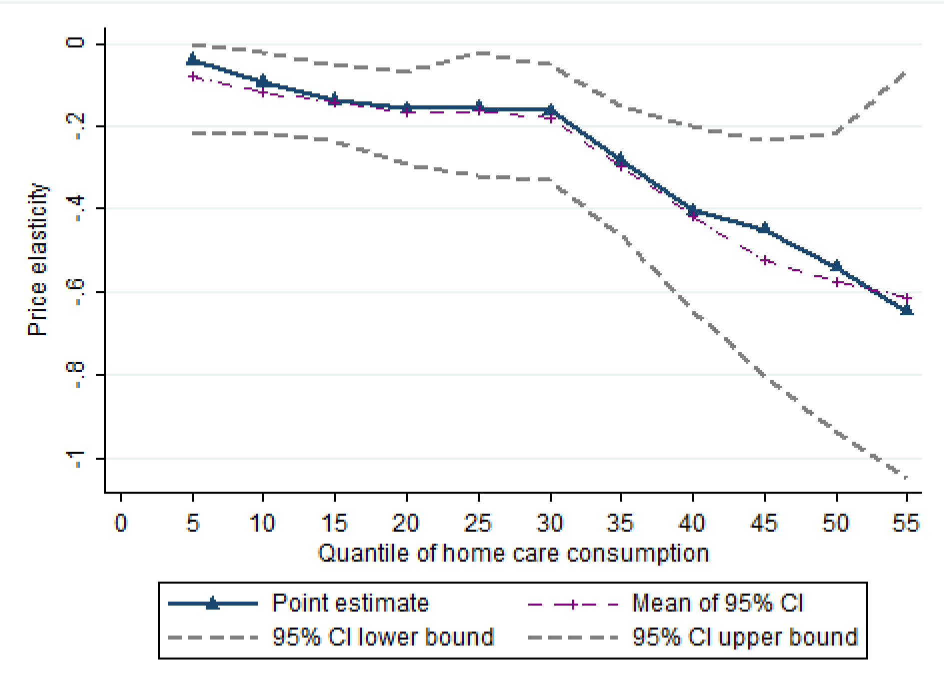
Table E.III: CLAD estimation of consumer price elasticity (October 2012–2014)

	Dependent variable: ratio h^*/h (log)
	(1)
Consumer price (log)	
Observed	-0.181
Bias	-0.002
Standard error	0.054
95% Confidence Interval (BC)	[-0.311 ; -0.091]
Replications (Bootstrap)	100
Initial sample size	8,190
Final sample size	7,502
Pseudo R-squared	0.021

NOTES: Confidence interval is a bias–corrected (BC) interval. Pooled data from October 2012, 2013 and 2014. Convergence could not be achieved on the subsample of single–producer areas beneficiaries. The dependent variable is the log of relative consumption. Censored least-absolute-deviation estimation (using Stata user command `clad`). The specification includes as controls sociodemographic variables, dummies for the year the latest plan was decided upon, dummies for the year in which the copayment rate was computed and year fixed effects. We were not able to include some dummies indicating very rare situations (spouse living in institution, dummy for the computation of copayment rate in 2010): bootstrapped samples picked up unique values for these variables.

One word of caution is warranted: as with the CLAD estimation, convergence could not be achieved on the subsample of SPA beneficiaries. Although we argue that the specification in ratio should decrease the issue of price endogeneity, the quantile estimates presented here may still suffer from a potential upward bias. Our main conclusions though would remain unchanged: quantile estimates provide further evidence that the price elasticity of the demand for home care is, on average, substantially inferior to one.

Figure E.1: Censored quantile regression estimates



Notes: Bootrstrapped confidence interval (100 replications). Pooled data from October 2012, 2013 and 2014 (8,190 observations). The dependent variable is the log of relative consumption $h^*/\bar{h}$. Censored quantile regression estimation (using Stata user command `cqiv`). Controls include disposable income, sociodemographic variables, dummies for the year the latest plan was decided upon as well as dummies for the year in which the copayment rate was computed.