Pay less, consume more? The price elasticity of home care for the disabled elderly in France

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Supplementary material

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A ADDITIONAL INFORMATION ON THE DATA

A.1 Comparison of the department studied with metropolitan France

Table A.I compares the department studied to metropolitan France. We use either administrative sources ([A]: Insee et al. (2013); [B]: Insee (2014); [D]: Drees (2013)) or survey data ([C]: Insee-Drees (2014)).

Column [1] gives descriptive statistics on metropolitan France while Column [2] focuses on the department studied. Column [2] reports intervals around the true department value to preserve its anonymity. Bounds are computed so that 20% of the French departments closest to the department of interest (weighting by the size of the departmental population aged 60 or more) have a value lying in the interval.[1] If the department is located in the bottom quintile, we report as a lower bound the minimum value observed across French departments for the variable; similarly, when the department ranks in the top quintile, the upper bound we report is the maximum value observed in metropolitan France.

The third column tests the significance of the differences between the first two columns. For statistics computed using exhaustive administrative sources ([A], [B] and [D]), we test whether the department *population* can be considered as a random draw from the French metropolitan population. When using survey data ([C]), the tests of difference compare the *sample* of the respondents of the department with the respondents of the rest of France.

Although differences are quasi–systematic in statistical terms, the selected department has socio–demographic characteristics close to that of France overall. Our selected department is however richer than the rest of France: it has a higher share of households subject to the income tax and a lower poverty rate in the 75+ population, although the median taxable income in the department is only slightly higher than in France. Albeit the prevalence of functional limitations in the 60+ population is similar in the department and in the rest of France, the rate of APA beneficiaries is slightly higher in our department. This possibly reflects local variations in the way the APA policy is implemented (Billaud et al., 2012).

[1] Insee et al. (2013) directly provides the deciles of the taxable income distribution in the metropolitan French population aged 75 or more. The department is found to be richer than the 40% least wealthy departments, but poorer than the 40% richest departments. We use the 4^{th} and 6^{th} deciles of the national distribution to bound the median taxable income observed in the department studied.

Table A.I: Descriptive statistics for department studied and metropolitan France

	Metropolitan France	*Department*	*Difference (p. value)*	*Source*
Variable	[1]	[2]	[1] − [2]	-
General population				
Households subject to income tax	58.2%	[61.9%–75.1%]	0.00	[A]
60+ population/total population	24.4%	[23.8%–26.3%]	0.00	[B]
Elderly population (60+)				
Average age	71.8	[71.3–71.7]	0.00	
Health status (functional limitations)				
Level 1 (least severe)	64.9%	[63.9%–66.2%]		
Level 2	21.4%	[20.1%–21.0%]	0.48	[C]
Level 3	7.7%	[7.2%–7.8%]		
Level 4 (most severe)	6.0%	[6.3%–7.0%]		
	100%	*100%*		
Poverty rate in 75+ population	8.9%	[6.9%–7.9%]	0.00	[A]
Median taxable income (75+ households)	€19,536	[€17,380–€22,050]	*n.c.*	
Rate of APA beneficiaries	7.8%	[8.1%–9.1%]	0.00	[D]
At–home recipients/all APA beneficiaries	58.7%	[56.1%–60.6%]	0.00	
At–home APA beneficiaries				
Woman	73.7%	[71.7%–72.8%]	0.00	
Age groups				
Age 60-74	12.7%	[11.2%–12.7%]		
Age 75-79	13.6%	[13.8%–14.6%]		[D]
Age 80-84	23.9%	[23.5%–24.4%]	*n.c.*	
Age 85+	49.7%	[49.2%–51.0%]		
	100%	*100%*		
Living arrangements				
Living alone	55.3%	[54.7%–56.9%]		
Living with her spouse	30.4%	[27.7%–32.7%]	0.88	[C]
Living with a relative other than her spouse	14.3%	[9.5%–12.5%]		
	100%	*100%*		
Disability level				
Disability level 1 (most severe)	2.4%	[1.7%–2.1%]		
Disability level 2	16.8%	[14.1%–15.6%]		
Disability level 3	22.1%	[20.0%–21.7%]	*n.c.*	[D]
Disability level 4 (least severe)	58.8%	[60.5%–64.5%]		
	100%	*100%*		
Amount of effective subsidies	€361.1	[€329.1–€350.5]	*n.c.*	

SOURCES: [A]: Insee et al. (2013); [B]: Insee (2014); [C]: Insee-Drees (2014) – APA benefit is self–declared. Rate of spousal co–residence may be underestimated; [D]: Drees (2013)– Administrative files on APA beneficiaries in 2013, all French departments. Decomposition by sex and age (resp. by disability level) not available in 21 (resp. in 5) departments.
NOTES: Column [2] reports intervals around the true department value to preserve its anonymity. Bounds are computed so that 20% of the French departments closest to the department of interest (weighting by the size of the departmental population aged 60 or more) have a value lying in the interval.
TESTS: *n.c.* stands for "not computable". Test performed is a Student (resp. a Pearson χ^2) test for binary (resp. categorical) variables.

A.2 Sample selection

This Appendix aims at documenting the selection steps the data from October 2014 have gone through. We follow the same steps to construct the samples of October 2012 and 2013. The percentages of individuals selected at each step are very similar to what is found for 2014 and are available upon request.

The initial number of beneficiaries is considered to be 5,486.[2] Table A.II sums up the selection steps.

Table A.II: Sample selection steps

	All	Recipients with an authorized provider *at least*				
		All	Recipients effectively consuming care in the month			
			All	"Stable" recipients		
				All	Recipients consuming *only from one* authorized provider	
					All	Recipients with $0 < c_i < 90\%$
	(1)	(2)	(3)	(4)	(5)	(6)
Number	5,486	4,475	4,199	3,527	3,327	2,862
% of previous step	-	81.6%	93.8%	84.0%	94.3%	86.1 %
% of initial sample	100%	81.6%	76.5%	64.3%	60.6%	52.2%

Notes: "Stable" APA recipients in October 2014 are defined as those for which information is available also for the months of September and November 2014. For additional 63 individuals (not in the numbers here above), the administrative files contain no information on the copayment rate or or the consumption of home care hours, or are inconsistent with national APA legislation.

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 provider. They represent the majority of APA recipients in the department (more than 4/5).

Among them, about 6% have no actual consumption of home care recorded in the files. This might be explained by temporary absences (like hospitalizations) or disruptions (e.g. visits from relatives, who replace temporarily professional home care services by providing informal care). As the outcome of interest is missing, we drop these observations. Another 15% of APA recipients with an authorized provider have missing information on subsidized care consumption for the preceding or the following month. We choose to drop them to avoid potential unobservable shocks likely to bias our estimations. The remaining

[2]For October 2014, administrative records indicate that 5,549 beneficiaries were receiving APA; but for 61 individuals, essential information on subsidized hours, copayment rate or on matrimonial status was missing or inconsistent. These individuals are presumably former APA recipients not yet erased from the files. For 2 additional individuals, the monetary value of the care plan was beyond the national legal ceiling, signaling a probable error in the records. We dropped these 63 observations from our sample.

individuals can be regarded as "stable".

Among beneficiaries actually receiving care from an authorized provider at least, less than 6% receive care from a secondary provider.[3] As we generally do not observe care consumption from the secondary provider nor its price,[4] we drop multiple–provider individuals.

Beneficiaries with income below a certain threshold have a 0% copayment rate: their OOP price is zero. Our log–log specification cannot be estimated on these observations. In addition, so as to make the relationship between the consumer price and the provider price fully linear in disposable income (see Appendix B.1), we retain only those individuals with a copayment rate strictly below 90%. These two income groups represent respectively 12.7% and 1.3% of the remaining 3,327 beneficiaries.

We end up with a sample that represents 52% of total at–home APA recipients of the department.

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 choose 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, as discussed in Section 5.3 of the paper.

[3]The majority of these beneficiaries receive additional care from an over–the–counter worker (see Section E for more details on the different types of home care providers). Over–the–counter workers are generally cheaper and more flexible than home care structures. 7 individuals receive home care from a second authorized provider. Theoretically, there might be a third case: beneficiaries could also complement the care provided by an authorized structure with care provided by a non–authorized structure. Our files do not allow us to identify such cases; we believe they are marginal, as care provision by non–authorized structures is rare (only 6% of beneficiaries with no authorized provider receive home care from a non–authorized structure).

[4]Even if we had all necessary information, dealing with the simultaneity of consumption decisions would have made our empirical strategy considerably more complex.

A.3 Imputation of couples of APA beneficiaries

The data we collected indicate when a beneficiary lives with a partner, but we do not directly 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[5] and residing in the same municipality. If two individuals match, we assume they belong to the same household: our estimations will control for the fact of having a spouse receiving APA.

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 these cases, the Departmental Council simply records the lower or upper income threshold of the APA copayment schedule. In October 2014, only 16 individuals were not matched for this reason. But all our estimations rely on the sample of individuals with a copayment rate strictly between 0 and 90%, for who the matching procedure is systematically successful.

A.4 Descriptive statistics on the pooled sample

Table A.III replicates Columns (3) and (4) of Table I of the paper, by presenting the descriptive statistics on the pooled sample (and not on the 2014 sample only).

The pooled sample we derive our baseline estimates from is an unbalanced panel. In this sample, 26% of beneficiaries are present all three waves; another 26% are present only in two waves; finally, 48% are only present in one wave.[6] Focusing on the sample of beneficiaries in October 2014, we see that the longer the individual has been receiving APA, the older she is; this translates into a higher proportion of women, who have a longer life–expectancy, and a lower proportion of beneficiaries with a spouse alive among the beneficiaries present in two or three waves. Those beneficiaries tend to be more disabled; they have, on average, a higher care plan volume and a higher number of hours subsidized by the APA scheme (consumption relative to the care plan volume being also higher). On the contrary, we do not see any difference in average provider and OOP prices, nor in income.

[5]The APA copayment schedule takes into account the household income. See Appendix B.1.

[6]This does not mean that the typical APA recipient benefits from the scheme less than one year. For individuals observed only in 2012, for example, we do not know whether they were receiving APA one year or two years before. Average duration of APA benefits is estimated to be around 4 years (Debout, 2010).

Table A.III: Descriptive statistics on the pooled sample (2012–2014)

Variable	Mean [1]	Std-dev. [2]
Care plan volume [a]	20.9	10.7
Care plan monetary value [b]	€456.1	€235.8
Hours effectively subsidized [c]	18.1	10.8
Amount of effective subsidies [d]	€303.1	€199.2
[c] inferior to [a]	60.4%	-
Ratio [c]/[a]	85.6%	19.8pp.
Ratio [d]/[b]	65.5%	21.7pp.
Individualized income	€1,301.5	€415.6
Copayment rate	23.8%	17.2pp.
Provider price	€21.8	€1.3
OOP price	€5.2	€3.8
Total OOP payments on subsidized hours	€91.6	€95.2
Age	84.0	7.3
Woman	73.2%	-
Disability level 1	1.2%	-
Disability level 2	12.8%	-
Disability level 3	20.2%	-
Disability level 4	65.8%	-
	100%	
Lives with a spouse	33.8%	-
Lives alone	65.6%	-
Spouse in institution	0.6%	-
	100%	
Number of individuals	8,190	-

NOTES: "pp." stands for percentage points. 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. Sample from October 2012, 2013 and 2014.

When using the unbalanced sample, we do not select a specific population – the new entrants into the APA scheme –; the shortcoming of such a choice, however, is that the individuals who have been present in several waves weigh more in the estimation than single–observation individuals. The cross–sectional estimates presented in Appendix G.1 show that the magnitude of the price elasticity estimate does not change substantially when replicating our estimations using the sample of beneficiaries present in October of either 2012, 2013 or 2014.

B SPECIFICATIONS

B.1 Addressing income and copayment rate issues in the empirical specifications

In Section 4.2 of the paper, when taking the absolute consumption as the dependent variable, our econometric specification is stated as follows:

$$ln(h^*_{it}) = \gamma_0 + \beta_1.ln(p^j_{it}) + (\beta_1 + \beta_2).ln(I_{it}) + X'_{it}.\theta + \lambda_t + \epsilon_{it} \quad (1)$$

To ensure a clean identification of the parameters, two features of the data must be taken into account. First, the disposable income recorded in the data at time t is not the current value of income but the income when the copayment rate was computed or last revised, denoted I^{obs}_{it}. We express disposable income at time t as: $I_{it} = \rho_{it} I^{obs}_{it}$, with ρ_{it} the rate of increase of individual disposable income between time t and the year i's last copayment rate was computed. As the rate of increase in disposable income ρ_{it} is not directly observable, we include a dummy 1^d_{it} equal to one when i's copayment rate (observed in t) was last revised in year d. Dummy coefficients should capture the rate of increase in income between years d and t.[7] In our data, most copayment rates were last computed between 2010 and 2014; for a few observations though, the latest computation of the copayment rate is older ($d = 2002, ..., 2014$).

Second, the copayment rate is set to be strictly proportional to the disposable income at the time the latest personalized care plan was defined, I^{obs}_{it}, according to the following function:

$$c_{it} = \frac{0.9}{2MTP^D_{it}} I^{obs}_{it}$$

where MTP^D_{it} is the value of a particular disability allowance (*Majoration pour Tierce–Personne*) the year the copayment rate was last computed for individual i observed at time t. For a given observed income, the copayment might differ according to the year d when the copayment rate was last computed. Year dummies 1^d_{it}, $d = 2002, ..., 2014$ thus additionally control for inter–individual and intra–individual variation in this parameter.

For 2% of our sample, the relationship between the income and the copayment rate does not respect the legal formula used to compute the copayment rate. After a careful examination of the data, we hypothesize that most of these errors occurred when the

[7] We implicitly assume the rate of increase in disposable income to be identical for two individuals observed a given year, 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.

copayment rate was computed; conversely, we assume the values of income and copayment rate are well recorded. We add a dummy variable 1^e_{it} signaling whether the observation is affected by such a calculation error. The full equation to be estimated is then:

$$ln(h^*_{it}) = \gamma_0 + \beta_1.ln(p^j_{it}) + (\beta_1 + \beta_2).ln(I^{obs}_{it}) + \sum_{d=2002}^{2014} \xi^d.1^d_{it} + \zeta.1^e_{it} + X'_{it}.\theta + \epsilon_{it} \qquad (2)$$

Finally, note that our econometric specification includes *disposable* income and not income *per se*. In the APA scheme, disposable income is defined as the individualized income[8] minus an amount equal to $0.67 \times MTP^D_{it}$ (€739 per month for an individual whose income and copayment rate was last reassessed in 2014). It roughly equals the old–age minimum income allowance. This amount may be regarded as the minimum income that will ensure the individual can satisfy her basic consumption needs: the individual trades off home care consumption for other consumption goods only when deciding upon the allocation of the part of her income in excess of the minimum income allowance.

B.2 Specification with relative consumption

When using the specification with relative consumption, we consider as the dependent variable the share of the care plan that is effectively consumed by the individual, $h^*_{it}/\bar{h}_{it}$ (this is the ratio we call the "relative consumption").

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

$$\begin{aligned} ln\big(h^*_{it}/\bar{h}_{it}\big) &= \tilde{\gamma}_0 + \tilde{\beta}_1.ln(p^j_{it}) + (\tilde{\beta}_1 + \tilde{\beta}_2)ln(I^{obs}_{it}) + \beta_3.ln(\bar{h}_{it}) \\ &+ \sum_{d=2002}^{2014} \tilde{\xi}^d.1^d_{it} + \tilde{\zeta}.1^e_{it} + X'_{it}.\tilde{\theta} + \tilde{\lambda}_t + \tilde{\epsilon}_{it} \end{aligned} \qquad (3)$$

The dependent variable is still censored when individuals fully consume their care plan volume (exact volume or more), but the censoring point now equals $ln(h^*_{it}/\bar{h}_{it}) = ln(1) = 0$. It is the same for all beneficiaries, whatever the volume of the care plan.

[8]Individualized income equals the individual's monetary income when the beneficiary has no spouse alive; it is equal to the household monetary income divided by 1.7 when the beneficiary has a spouse alive. The consumption unit attributed to the second adult of the household follows the Oxford (or "old OECD") scale (OECD, 2013). Compared to the OECD–modified scale, which is nowadays the most frequently used in France, the use of the Oxford scale to compute APA individualized income implies that the economies of scale in a household with a disabled elderly are lower than in other households.

Equation (3) is equivalent to:

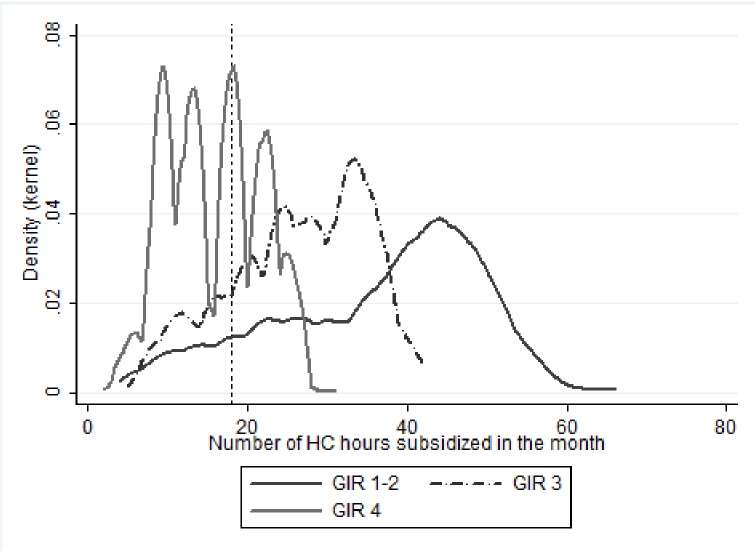
$$\begin{aligned}
ln(h^*_{it}) - ln(\bar{h_{it}}) &= \tilde{\gamma}_0 + \tilde{\beta_1}.ln(p^j_{it}) + (\tilde{\beta_1} + \tilde{\beta_2})ln(I^{obs}_{it}) + \tilde{\beta_3}.ln(\bar{h_{it}}) \\
&+ \sum_{d=2002}^{2014} \tilde{\xi}^d.1^d_{it} + \tilde{\zeta}.1^e_{it} + X'_{it}.\tilde{\theta} + \tilde{\lambda}_t + \tilde{\epsilon}_{it} \\
ln(h^*_i) &= \tilde{\gamma}_0 + \tilde{\beta_1}.ln(p^j_{it}) + (\tilde{\beta_1} + \tilde{\beta_2})ln(I^{obs}_{it}) + (\tilde{\beta_3} + 1).ln(\bar{h_{it}}) \\
&+ \sum_{d=2002}^{2014} \tilde{\xi}^d.1^d_{it} + \tilde{\zeta}.1^e_{it} + X'_{it}.\tilde{\theta} + \tilde{\lambda}_t + \tilde{\epsilon}_{it} \qquad (4)
\end{aligned}$$

In Equation (3), $\tilde{\beta_1}$ can thus be interpreted as the price elasticity of demand. The equation presented in the previous section, Equation (2), is nested in this equation. It would be equivalent to Equation (4) if we imposed the constraint that $\tilde{\beta_3} = -1$.

The specification with relative consumption comes with several advantages. First, it includes the care plan volume as a control, which might be a proxy of the unobserved determinants of consumption. Second, relative consumption is a better–behaved outcome than absolute consumption: its distribution is closer to a normal (Figures B.1 and B.2) and the consistency of Tobit estimates requires the normality of the error term. Finally, it enables us to overcome the limitation of having an individual–specific censoring point: it eases the implementation of the estimations.

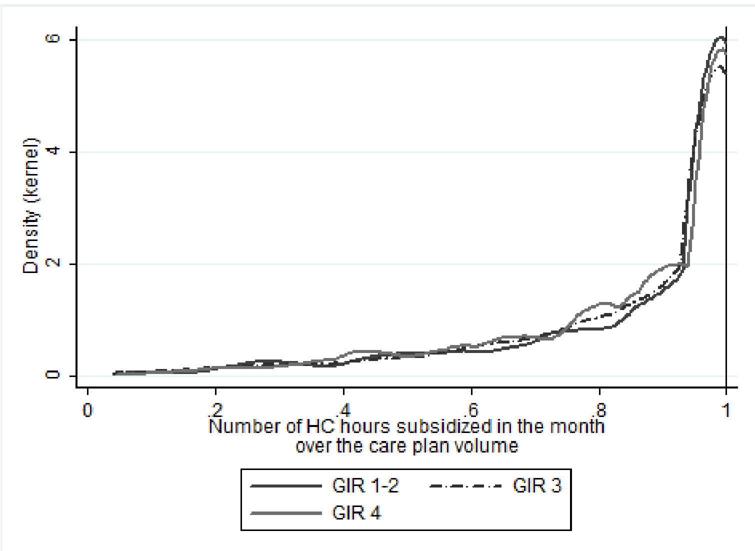
[Figures B.1 and B.2 to be found on the following page]

Figure B.1: Distribution of absolute home care consumption, by disability level



SAMPLE: Estimation sample (data from October 2012, 2013 and 2014; 8,190 individuals). Sub–sample size: N=1,145 in GIR 1 or 2 (most severe disability levels); N=1,655 in GIR 3; N=5,390 in GIR 4 (least severe disability level).
NOTES: The "GIR" corresponds to the official disability level of APA beneficiaries. The dashed vertical line indicates the pooled sample median value of home care consumption.

Figure B.2: Distribution of relative home care consumption, by disability level



SAMPLE: Estimation sample (data from October 2012, 2013 and 2014; 8,190 individuals). Sub–sample size: N=1,145 in GIR 1 or 2 (most severe disability levels); N=1,655 in GIR 3; N=5,390 in GIR 4 (least severe disability level).
NOTES: Relative home care consumption designates the ratio $h_i/\bar{h}_i$. The "GIR" corresponds to the official disability level of APA beneficiaries. The solid vertical line at 1 indicates the censoring point of relative consumption.

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.

To keep notations simple and concise, we ignore the time dimension (subscript t and year dummies are not included) and consider home care consumption in level when deriving the likelihood function (while we include its log in the empirical specification).

C.1 General setting

The demand for home care with the kinked budget constraint generated by APA writes:

$$\begin{cases} h_i^* = g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* < \bar{h}_i \\ g(p_i, \tilde{I}_i; X_i) + \nu_i \leq \bar{h}_i \leq g(c_i p_i, I_i; X_i) + \nu_i & \text{if } h_i^* = \bar{h}_i \\ h_i^* = g(p_i, \tilde{I}_i; X_i) + \nu_i & \text{if } h_i^* > \bar{h}_i \end{cases} \tag{5}$$

with ν_i an individual preference shifter. We denote:
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:

$$h_i = \begin{cases} h_i^* & \text{if } h_i^* < \bar{h}_i \\ \bar{h}_i & \text{if } h_i^* \geq \bar{h}_i \end{cases} \tag{6}$$

From Systems 5 and 6, 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:

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

   (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:

$$h_i = \begin{cases} g(c_i p_i, I_i; X_i) + \nu_i & \text{if } g(c_i p_i, I_i; X_i) + \nu_i < \bar{h}_i \\ \bar{h}_i & \text{if } g(c_i p_i, I_i; X_i) + \nu_i \geq \bar{h}_i \end{cases} \tag{7}$$

which corresponds to the usual censored regression model setting.

The individual contributions to the likelihood function are derived from this setting. Denote $f(.|c_i, p_i, I_i, \bar{h}_i, X_i)$ the conditional density function of ν and $F(.|c_i, p_i, I_i, \bar{h}_i, X_i)$ its conditional cumulative distribution function. Then the likelihood function writes:

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

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 function $g(.)$), although it comes at a cost in terms of precision. Assuming some stability of individual preferences,[9] 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

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

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 the individuals consuming at the kink or beyond.

C.3 Likelihood of our sample

As explained in Section 4.2 of the paper, we assumed the following specification for the demand for home care:[10]

$$ln(h_i^*) = \gamma_0 + \beta_1.ln(p_i^j) + (\beta_1 + \beta_2).ln(I_i) + X_i'.\theta + \epsilon_i$$

We assume a normal distribution for the idiosyncratic shock ϵ:

$$\epsilon \mid p, I, X \sim \mathcal{N}(0, \sigma^2)$$

Our likelihood function thus writes:

$$L(\beta,\gamma,\theta,\sigma) = \prod_{i=1}^{n} \Big[\frac{1}{\sigma}\phi\big(\frac{ln(h_i) - \gamma_0 - \beta_1.ln(p_i^j) - (\beta_1+\beta_2).ln(I_i) - X_i'.\theta}{\sigma}\big)\Big]^{\mathbb{I}_{[h_i<\bar{h}_i]}}$$
$$\times \Big[\Big(1 - \Phi\big(\frac{ln(\bar{h}_i) - \gamma_0 - \beta_1.ln(p_i^j) - (\beta_1+\beta_2).ln(I_i) - X_i'.\theta}{\sigma}\big)\Big)\Big]^{\mathbb{I}_{[h_i=\bar{h}_i]}}$$

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

When using the specification with the relative consumption, we have:

$$ln\big(h_i^*/\bar{h}_i\big) = \tilde{\gamma}_0 + \tilde{\beta}_1.ln(p_i^j) + (\tilde{\beta}_1 + \tilde{\beta}_2).ln(I_i) + \tilde{\beta}_3.ln(\bar{h}_i) + X_i'.\tilde{\theta} + \tilde{\epsilon}_i$$

Similarly, we assume a normal distribution for the idiosyncratic shock $\tilde{\epsilon}$:

$$\tilde{\epsilon} \mid p, I, X, \bar{h} \sim \mathcal{N}(0, \tilde{\sigma}^2)$$

[10] Again, for the sake simplicity, we do not include in the expressions provided in this Appendix the full set of dummies we actually include in our specifications to control for both the unobserved increase in income and the legal relationship between the copayment rate and disposable income (see Appendix B.1).

The likelihood function writes:

$$\tilde{L}(\tilde{\beta},\tilde{\gamma},\tilde{\theta},\tilde{\sigma}) = \prod_{i=1}^{n} \Big[\frac{1}{\tilde{\sigma}}\phi\big(\frac{ln(h_i^*/\bar{h_i}) - \tilde{\gamma}_0 - \tilde{\beta}_1.ln(p_i^j) - (\tilde{\beta}_1 + \tilde{\beta}_2).ln(I_i) - \tilde{\beta}_3.ln(\bar{h}_i) - X_i'.\tilde{\theta}}{\tilde{\sigma}}\big)\Big]^{\mathbb{I}[h_i/\bar{h_i}<1]}$$
$$\times \Big[\Big(1 - \Phi\big(\frac{ln(h_i^*/\bar{h_i}) - \tilde{\gamma}_0 - \tilde{\beta}_1.ln(p_i^j) - (\tilde{\beta}_1 + \tilde{\beta}_2).ln(I_i) - \tilde{\beta}_3.ln(\bar{h}_i) - X_i'.\tilde{\theta}}{\tilde{\sigma}}\big)\Big)\Big]^{\mathbb{I}[h_i/\bar{h_i}=1]}$$

Consistent estimators of β_1, β_2 and θ (respectively of $\tilde{\beta}_1$, $\tilde{\beta}_2$, $\tilde{\beta}_3$ and $\tilde{\theta}$) can be derived as the arguments of the maximization of the log–likelihood function, provided it is concave.[11]

In order to derive the likelihood function when taking the log–absolute consumption as the dependent variable, 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 the next Section and is not needed when we take the log–relative consumption as the dependent variable.

[11]Similarly, though with a little more work, we could derive the likelihood function of the IV–Tobit model. In the version we estimate (using Stata command `ivtobit`), the error terms of the first–stage and second–stage equations are assumed to be jointly normally distributed.

D DETERMINANTS OF THE CARE PLAN VOLUME AND CENSORING

When taking the log–*absolute* consumption as the dependent variable, the Maximum Likelihood function (Appendix C) is derived assuming the individual censoring point, defined by $\bar{h}_i$, is exogenous conditional on explanatory variables. In addition, consistency of estimates relies on the additional assumption that the provider price p_i^j is exogenous. When estimating Equation (1) (Appendix B.1), one particular concern is that the provider price and the care plan volume are correlated even conditional on the control variables.

These two assumptions – exogeneity of the censoring point and no systematic conditional relationship between the care plan volume and the provider price – are relaxed when we take the log–*relative* consumption as the dependent variable. This Appendix nonetheless discusses the plausibility of these assumptions, by presenting elements on the establishing of the care plan volume and additional empirical material.

When setting the care plan volume $\bar{h}_i$, the evaluation team supposedly takes into account the needs of the beneficiary in terms of assistance with the activities of daily living. By law, the care plan volume should depend on the administrative disability group. Gender and age (which we control for) may influence the care plan volume, as they correlate with unobserved health problems and housekeeping skills. Additionally, even tough matrimonial status and family structure are not supposed to influence the care plan volume, anecdotal evidence suggests that the evaluation team takes into account the possible assistance regularly provided by relatives when establishing the care plan.

Additionally, $\bar{h}_i$ could directly relate to the price of the chosen provider in a specific case: 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 of the beneficiary. In the case care is provided by an authorized provider, the monetary equivalent of the care plan equals the number of hours granted by the evaluation team times the provider price. If the monetary equivalent of the care plan volume is higher than the legal ceiling, the adjustment will go through a reduction in $\bar{h}_i$ or the choice of a cheaper provider. This may be a source of price endogeneity in both (absolute and relative consumption) specifications.[12]

Empirically, once controlling for income, gender, age, disability group, matrimonial status and professional care received on weekends, we find a small positive correlation between the (OOP or provider) price and the volume of the care plan, but the effect is

[12]Yet it should remain limited: 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 provider operating in their municipality.

not statistically significant.[13] Then, a probit estimation of the probability to be censored, $\mathbb{P}(h_i = \bar{h}_i)$, shows that the probability to be censored slightly correlates with the price. A €1 increase in the provider price is predicted to increase the probability to be censored by 2 pp. (as a reminder, the sample censoring rate is around 40% and the standard–deviation in provider prices is of €1.3).

Although they are statistically significant, these effects are small in practical terms. In addition, they fade out when we restrict our attention to beneficiaries living in a municipality where only one provider is operating. This suggests that the strategic choice of a provider (price) to comply with the legal ceiling is empirically negligible in this sub–sample (see Appendix G.3.1).

The probability to be censored 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[14] and from informal help provided by their spouse. Consuming the care plan volume totally is also more likely for individuals who are entitled to subsidies on formal care served during the weekends.

Individual observable characteristics explain about 50% of the variations observed in the care plan volume. This leaves a large share of the variations unexplained. Ethnographic work suggests that unobserved informal care or health status can influence the evaluation team in the set up of the care plan volume (Billaud et al., 2012).

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 when estimating the specification with log–absolute consumption as the dependent variable. This is one of the reasons why we favour the specification with the relative consumption (Equation (3), Appendix B.2).

[13]In the panel analysis, we include fixed effects and cluster at the individual level. Table of results is not included but is available upon request.

[14]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.

E THE HOME CARE SECTOR IN FRANCE

E.1 Three main types of home care providers

Home care to the disabled elderly can be provided by three types of providers:

(1) Authorized structures (*services autorisés*), which must receive a special authorization granted by the Departmental Council to enter the market; their price is fixed by the Departmental Council.

(2) Non–authorized structures (*services agréés non autorisés*) are allowed to provide home care services to APA beneficiaries under lighter conditions than authorized structures; they are free to set their price (with some restrictions on yearly price evolution being set at the departmental level).

(3) Over–the–counter workers (*gré–à–gré* ou *mandataire*): the beneficiary directly contracts with a home care worker. The beneficiary is free to set her employee's hourly wage provided she complies with general labor law.

There is no regulation for over–the–counter workers. Both authorized and non–authorized structures have to meet quality standards, though requirements are higher for authorized structures. The existence of differences in quality between *authorized* providers is less clear–cut. From a theoretical prospective though, the uncertainties regarding the quality of services in the home care sector lead to rule out vertical differentiation through prices (Messaoudi, 2012).

In our empirical analysis, we focus on authorized providers: technically, we are able to compute the exact OOP price of their customers receiving APA as these services are priced by the Departmental Council. More broadly, APA subsidized professional care is mainly provided by this type of structure: using a survey conducted on the French departments (LEDa-LEGOS and CES, 2012), Hege et al. (2014) document that in over 45% of (responding) departments, more than two thirds of APA home care hours are provided by authorized services. Care provided by authorized structures represent less than one third of APA hours in only 15% of departments.[15]

E.2 The different status for authorized providers

Authorized providers can be either public, for–profit or non–profit. Historically, in France, non–profit organizations were important providers of home care and they remain predominant in most rural areas. In our department, 5 authorized providers are

[15]Using our data, we study the determinants of the choice of a provider. We find that individuals receiving care from an authorized provider are on average less rich than the overall population of APA beneficiaries; they tend to be younger, less disabled and live more often alone (results available upon request).

non–profit, providing care to about 54% of our estimation sample in October 2014. 20 municipal services are providing care to APA recipients (about 43% of the 2014 sample). For–profit structures represent a small share of the authorized home care providers (3 in the department), as they provide home care only to 3% of our 2014 sample.[16]

Theoretically, an APA beneficiary is free to choose her provider. In practice, the spatial coverage by the different types of authorized services is unequal over the territory. In some municipalities, several providers are found to operate, while there is only one provider in others (see Section G.3). In our department, among the beneficiaries living in a municipality where several authorized providers serve APA recipients, more than 50% can choose between the three types of authorized providers. These beneficiaries live in relatively large municipalities: the supply mix is more diversified when there is an important market for home care services, while small municipalities are generally *de facto* served by a unique, non–profit structure. Conversely, the typical supply mix in medium–size municipalities is the combination of non–profit and public authorized providers. Finally, a for–profit provider is never found to be the only authorized service operating in a given municipality.

[16]Proportions are similar in the pooled sample. The small market share of for–profit services among authorized providers is not a specific feature of the department studied.

F EXPLAINING VARIATIONS IN PROVIDER PRICES

F.1 Components of costs in the home care sector

In this section, we explain why customers may exogenously face different provider prices, by detailing the components of prices in the home care sector.

Authorized providers are priced by the Departmental Council. The hourly price of each provider, for one given year, should be set on the basis of the overall average hourly production cost of the provider, of two years before. The various components of production costs are described in qualitative studies, either in academic works (Gramain and Xing, 2012) or in public reports.[17] By order of importance (top–down), production costs can be decomposed as follows:

- Workforce 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)[18] 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 geographical area of intervention.
- Contrary to the health care sector, technological progress and capital costs are negligible in the home care sector.

We represent the relationship between the provider price and several providers' characteristics graphically.[19] We distinguish between non–public (mainly non–profit) providers and public providers. 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 Departmental Council and lower down the regulated price of public providers. In the graphical representation, we exclude the

[17] 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).

[18] This item only includes the compensation of employees for the monetary costs associated with transport. The ongoing study mentioned in the paper additionally takes into account the unproductive hours spent on transports by the employees that are paid by the provider.

[19] We explore here other characteristics than the number of served municipalities, that we use as an instrument for the price. The empirical relationship between the two variables is documented by Figure 2 in the paper.

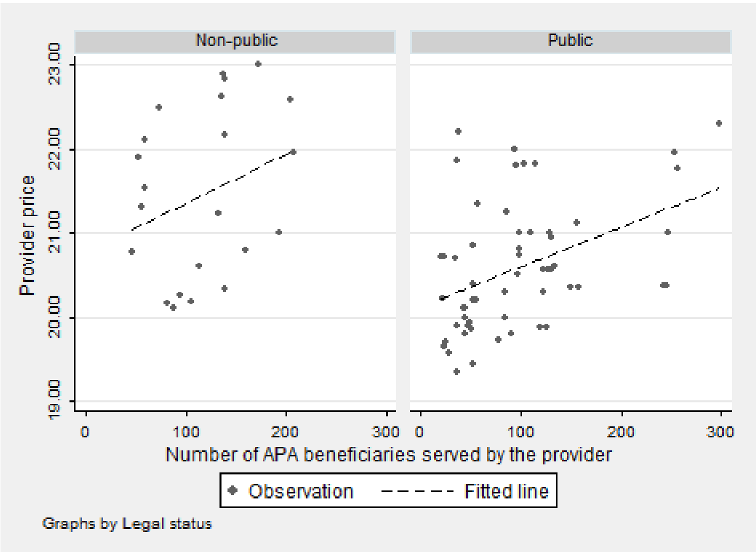
largest provider of the department, a nationwide non–profit organization, which has systematically the highest values for the variables we are here interested in (see Appendix G.2).

In Figure F.1, provider prices are plotted against the number of APA beneficiaries served by the service. Graphically, the more customers the provider has, the higher its price. Having more customers might be associated with more municipalities to serve (see discussion in Section 4.4 of the paper) or more unproductive hours.[20] This graph should be interpreted cautiously though: we only know the number of APA recipients served by each home care provider, instead of the total number of customers (including non–APA beneficiaries, like other elderly or disabled individuals) served in the department.

Figure F.2 shows the relationship between the provider price and the share of hours they serve on Sundays or on public holidays. Public providers 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.

[Table F.2 to be found on the following page]

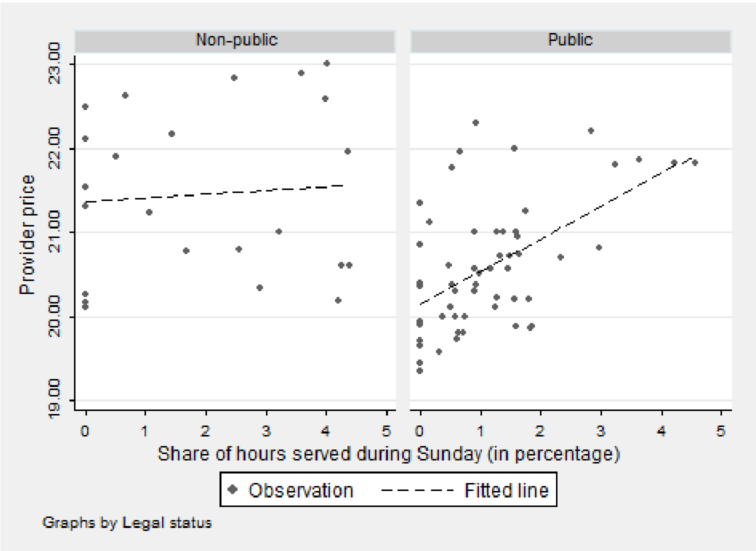
Figure F.1: Provider price according to the number of APA beneficiaries served by the provider, by legal status



Sample: Authorized providers of the department serving at least one APA beneficiary in October 2012, 2013 or 2014.
Notes: The largest provider, which serves 43% of the APA beneficiaries receiving care from an authorized provider in the department in 2014, is not included.

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

Figure F.2: Provider price according to the share of hours served on Sundays and public holidays, by legal status



Sample: Authorized providers of the department serving at least one APA beneficiary in October 2012, 2013 or 2014.
Notes: The largest provider, which has 1.80% of its home care hours provided on Sundays and holidays in 2014, is not included.

F.2 Correlations between individual characteristics and provider price

We also investigate the importance of the observable characteristics on the choice of a given level of provider price. Table F.I presents the individual characteristics associated with the choice of a "low–price" authorized provider, defined as a provider charging a price strictly below the average price charged by the authorized providers operating in the beneficiary's municipality (in a given month). We estimate the probability of choosing a "low–price" provider by a Probit on the sub–sample of individuals who live in a municipality where several authorized providers serve APA recipients. 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" provider, possibly reflecting that they perceive home care as less necessary and are thus *ex ante* more sensitive to its price. Income is not found to have any impact on this choice, nor is matrimonial status (Fisher tests reject the joint significance of both the set of income quartile dummies and the set of matrimonial status dummies).[21]

[Table F.I to be found on the following page]

[21] Although we do not find any evidence that beneficiaries who are able to choose between different authorized providers choose a price level according to their income, it might still be the case that there is systematic correlation between income and provider price in the sample, as about 30% of beneficiaries are suspected not to be able to choose between different providers (Appendix G.3). When we take our estimation sample and regress the provider price on income and all the socio–demographic variables we include in our estimations as well as year dummies, we find a negative partial correlation between income and provider price. Although it is statistically significant, it is fairly small: a one standard–deviation increase in disposable income is predicted to decrease provider price by 0.01 standard–deviation. This is small enough not to undermine the separate identification of the price and empirical income elasticities.

Table F.I: Individual characteristics associated with the choice of a low provider price

	Dependent variable: chooses a "low–price" provider
	(1)
Income quartile: 1	-0.010
	(0.025)
Income quartile: 2	*Ref.*
Income quartile: 3	-0.003
	(0.028)
Income quartile: 4	-0.006
	(0.029)
Woman	-0.030
	(0.019)
Age: 60–69	-0.050
	(0.054)
Age: 70–79	-0.040*
	(0.021)
Age: 80–89	*Ref.*
Age: 90 or more	-0.029
	(0.021)
Disability level: 1 (most severe)	-0.102
	(0.113)
Disability level: 2	-0.024
	(0.036)
Disability level: 3	*Ref.*
Disability level: 4 (least severe)	0.068***
	(0.022)
Lives with no spouse	-0.000
	(0.021)
Spouse receives APA	0.004
	(0.051)
Lives with non–APA spouse	*Ref.*
Spouse in institution	-0.098
	(0.110)
Observations	5701
Number of clusters	82

NOTES: Standard errors in parentheses, clustered at the municipality level; $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimation of a Probit model by Maximum Likelihood. Average partial effects (APE) are displayed. "Low-price" providers are charging a price below the average price of authorized providers within a given municipality (in one given month: October 2012, 2013 or 2014); the estimation uses the sample of beneficiaries served by only an authorized provider living in a municipality where at least two different prices are offered by authorized providers. Data pooled from October 2012, October 2013 and October 2014. Specifications include year fixed effects.

G ROBUSTNESS CHECKS

G.1 Additional results: absolute or relative consumption

In this section, we present the results obtained on the pooled sample and by year, fitting several specifications. Table G.I presents the estimates of the first specification, when the dependent variable is the absolute consumption (Equation (1), Appendix B.1). Tables G.II and Table G.III present the results obtained with the second specification, when the dependent variable is the relative consumption, either assuming the provider price is exogenous (Table G.II) or instrumenting it (Table G.III). In all three tables, Column (1) gives the estimate obtained on the pooled sample, while Columns (2) to (4) display the estimates obtained on October 2012, 2013 or 2014.

Whatever the specification, estimates on 2014 are of a lower precision, essentially because there is one provider less (one provider closed down in 2014). The point estimates are also systematically lower (in absolute value) in 2014 than in the other two years, although the difference from one year to the other is never statistically significant.

When the dependent variable is the absolute consumption, the coefficients associated with the price lie between -0.7 and -1.0: they are higher than those obtained with the relative consumption (between -0.3 and -0.7 with no instrumentation, -0.1 and -0.5 when the IV strategy is implemented). It might be explained by the fact that the care plan volume, which may be a proxy for some unobserved determinants of professional care consumption, is not taken into account in the specification with absolute consumption as the dependent variable.

With the absolute consumption, the income effect within the APA scheme is suggested to be negative. When taking the relative consumption as the dependent variable, and including the care plan volume as a control, point estimates are lower in absolute value (presumably because the omitted variable bias is reduced); the effect of income within the APA scheme is no longer significant. The IV–strategy only little affects point estimates. Except for 2014, we can systematically reject that the price elasticity is zero.

Overall, these results confirm that the price elasticity is significantly different from zero and inferior to one in absolute value. The -0.4 point estimate we finally retain is the one that is the most likely to be unbiased (care plan volume as a control & IV strategy) and the most precise (pooled data with both intra– and inter– individual price variations). Yet we must acknowledge the relatively low precision of our results: the 95%-level confidence interval derived from our favoured specification indicates a price elasticity between -0.01 and -0.76.

[Tables G.I and G.II to be found on the following page;
Table G.III to be found on page 28]

Table G.I: Censored regression estimates of demand for home care hours (absolute consumption)

Dependent variable: absolute consumption h^* (log)				
	(1) 2012–14	(2) 2012	(3) 2013	(4) 2014
Price (log)	-0.793***	-0.977***	-0.721**	-0.709**
	(0.248)	(0.260)	(0.297)	(0.290)
Disposable income (log)	-0.039***	-0.033***	-0.039***	-0.048***
	(0.010)	(0.012)	(0.015)	(0.019)
Other controls	Yes	Yes	Yes	Yes
Yes				
Observations	8190	2571	2757	2862
Censored observations	36.6%	40.4%	38.2%	40.2%
Number of clusters	28	28	28	27

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$. Data from October 2012, 2013 and 2014. Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls socio–demographic variables, dummies for the year the latest plan was decided upon and dummies for the year in which the copayment rate was computed. Column (1) additionally includes year fixed effects.

Table G.II: Censored regression estimates of demand for home care hours (relative consumption)

Dependent variable: relative consumption $h^*/\bar{h}$ (log)				
	(1) 2012–14	(2) 2012	(3) 2013	(4) 2014
Price (log)	-0.450**	-0.670***	-0.376	-0.300
	(0.181)	(0.180)	(0.236)	(0.238)
Disposable income (log)	-0.010	-0.003	-0.014	-0.014
	(0.008)	(0.009)	(0.009)	(0.016)
Care plan volume (log)	0.040*	0.054*	0.019	0.041
	(0.023)	(0.030)	(0.027)	(0.033)
Other controls	Yes	Yes	Yes	Yes
Observations	8190	2571	2757	2862
Censored observations	36.6%	40.4%	38.2%	40.2%
Number of clusters	28	28	28	27

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from October 2012, 2013 and 2014. Estimation of a Tobit model by Maximum Likelihood. All specifications include as controls socio–demographic variables, dummies for the year the latest plan was decided upon and dummies for the year in which the copayment rate was computed. Column (1) additionally includes year fixed effects.

Table G.III: Censored regression estimates of demand for home care hours (relative consumption, IV)

	(1) 2012-14	(2) 2012	(3) 2013	(4) 2014
Panel A: Second Stage	Dependent variable: relative consumption h^*/h (log)			
Price (log)	-0.387**	-0.537**	-0.460**	-0.134
	(0.192)	(0.209)	(0.214)	(0.245)
Disposable income (log)	-0.010	-0.003	-0.014	-0.014
	(0.008)	(0.009)	(0.008)	(0.016)
Care plan volume (log)	0.040*	0.054*	0.019	0.042
	(0.023)	(0.030)	(0.028)	(0.033)
Panel B: First Stage	Dependent variable: provider price p (log)			
Number of municipalities (std.)	0.049***	0.050***	0.046***	0.050***
	(0.004)	(0.004)	(0.004)	(0.004)
Other controls	Yes	Yes	Yes	Yes
Observations	8190	2571	2757	2862
Censored observations	36.6%	40.4%	38.2%	40.2%
Number of clusters	28	28	28	27

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from October 2012, 2013 and 2014. Estimation of an IV–Tobit model by Maximum Likelihood. Price is instrumented by the number of municipalities served by the provider. In the first stage (Panel B), the log–provider price is regressed on the standardized number of municipalities served by the provider. All specifications, for both Panel A and Panel B, include as controls socio–demographic variables, dummies for the year the latest plan was decided upon and dummies for the year in which the copayment rate was computed. Column (1) additionally includes year fixed effects.

G.2 Clustering and Bootstrap inference

G.2.1 Level of clustering

In the paper, we denote $\tilde{\epsilon}_{it}$ the error term in our favoured specification (Equation (5)). As we cluster at the provider level j, we actually implicitly assume the following structure for the error term $\tilde{\epsilon}$:

$$\tilde{\epsilon}_{ijt} = \tilde{\xi}_i + \tilde{\nu}_j + \tilde{\zeta}_{ijt}$$

with $\tilde{\xi}_i$ capturing the unobserved individual heterogeneity, and $\tilde{\nu}_j$ the provider level time–invariant unobserved heterogeneity. For two individuals i and i' that are served by the same provider j (assume for the sake of simplicity that t is not varying), $corr(\tilde{\epsilon}_{ijt}, \tilde{\epsilon}_{i'jt}) \neq 0$ as long as there are unobserved shocks taking place at the provider level.

For a given individual observed at t and t', error terms will be necessarily correlated if there is some individual time–invariant unobserved heterogeneity.[22] As standard with panel data, we would need to cluster at the individual level. Yet, as almost all APA beneficiaries keep the same provider j over time, the latter way of clustering (at the individual level) is essentially nested in the former clustering option (at the provider level). We believe that within–individual correlation of errors is more important than within–provider shock correlation; we nonetheless choose to cluster at the most aggregate level. In our specific setting, in which our main explanatory variable varies at the provider–year level, clustering at the provider level is of due caution as the provider price does not change within one cluster cross–sectionally (Moulton, 1990; Cameron and Miller, 2015).

G.2.2 Inference with few clusters

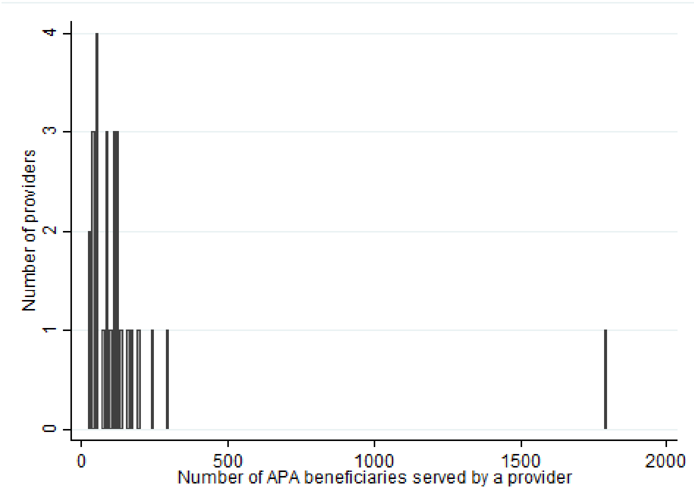
With clustered standard errors, inference relies on asymptotic properties that kick in as the number of clusters tends to infinity. The "few–cluster issue" was documented notably by Cameron et al. (2008): in an OLS setting, Wald hypothesis tests based on the standard cluster–robust estimate of the variance matrix tend to over–reject the null. Rejection rates increase when clusters are of unequal sizes (Imbens and Kolesár, 2015).

In our department, there are relatively few authorized providers (28 in 2012 and 2013, 27 in 2014 as one provider closed down).[23] and there is one very large authorized provider (Figure G.1). This service is a local branch of a long–standing nationwide non–profit home care service; it serves 37% of the APA beneficiaries in our sample. With only 28 clusters, including one being considerably larger than the others, we face the risk that standard cluster–robust inference is biased.

[22]Note that we are not able to include individual fixed–effects in the type 1–Tobit model, as there is no parametric solution to the incidental parameter problem (Lancaster, 2000).

[23]This is not a feature specific to our department though (LEDa-LEGOS and CES, 2012).

Figure G.1: Distribution of the size of authorized providers (October 2014)



NOTES: Size of a provider is measured by the number of APA beneficiaries it serves. Data from October 2014, 27 authorized providers (one authorized provider closed down in 2014).

In order to assess the robustness of the inference on the estimates presented in the paper, we use a bootstrap procedure. By bootstrapping the Wald t–statistic associated with the price elasticity estimate $\hat{\hat{\beta}}_1$, we may improve small–sample inference by attaining asymptotic refinement (Cameron and Miller, 2015).

We start by estimating our equation on the original sample (by Tobit or IV–Tobit).[24] We retrieve the point estimate of the price elasticity, $\hat{\beta}_1$ and its standard error, $se(\hat{\hat{\beta}}_1)$, and we compute the original sample Wald t–statistic $t = \hat{\hat{\beta}}_1 / se(\hat{\hat{\beta}}_1)$. We then implement a percentile pair cluster bootstrap, by repeating 1,000 times the following steps:

1. We form 28 "pair" clusters of observations by re–sampling with replacement 28 times from the original clustered sample.
2. For each bootstrap sample $b = 1, ..., 1000$, we estimate $\hat{\hat{\beta}}_1^b$ (by Tobit or IV–Tobit), and the associated cluster–robust standard error $se(\hat{\hat{\beta}}_1^b)$.
3. For each bootstrap sample b, we compute the Wald t–statistic centered in $\hat{\hat{\beta}}_1$:

$$t_b = \frac{\hat{\hat{\beta}}_1^b - \hat{\hat{\beta}}_1}{se(\hat{\hat{\beta}}_1^b)}, \quad b = 1, ..., 1000$$

[24]Here, as well as in the subsequent bootstrap replications, we do not use Stata's `ivtobit` command, through which standard errors are derived using the observed information matrix (oim). Instead, we first regress the (log) provider price on the instrument and the other exogenous controls (clustering at the provider level) and derive a prediction of the log of the provider price. We run the second step by regressing the (log) relative consumption on the *predicted* log–provider price and the other controls, again clustering at the provider level. It gives the inputs we use in the bootstrap procedure.

We then use the empirical distribution of the bootstrap t–statistics t_b to derive the critical values to be used in lieu of the critical values derived from a standard normal or T distribution. We compare the t–statistic associated with the price elasticity coefficient obtained in the observed sample to the symmetrical critical values derived from the bootstrapped t–statistic distribution. The percentile–t p–value for the symmetric two–sided Wald test of H0: "$\tilde{\beta}_1 = 0$" is computed as the proportion of times the absolute value of the boostrapped t–statistic is greater than the absolute value of the observed sample t–statistic; that is to say, the proportion of times that $|t_b| > |t|, \quad b = 1, ..., 1000$

Issues may arise when using pair cluster resampling with dummy control variables: some of the bootstrap samples may have little or even no variation in the control variables. The computation of t_b in those samples is not possible; using the bootstrap t–statistics that were actually computed is not an option either, as completed replications cannot be assumed to be random.[25] In order to avoid failure to complete the target number of cluster bootstrap replications, we drop from our original sample the 8 individuals whose copayment rate was last reassessed prior to 2011.[26]

Table G.IV displays the price elasticity estimates and compares standard inference with bootstrap inference. Columns (1) to (3) display the estimates obtained using a Tobit model to estimate our specification with relative consumption, while Columns (4) to (6) are derived from an IV–Tobit estimation. Columns (1) and (3) display the original consumer price elasticity estimates obtained by either Tobit or IV–Tobit estimations, while Columns (2) and (5) display the same estimates obtained on the sample on which the pair cluster bootstrap can be completed. Comparing (1) and (2) first, then (4) and (5), we see that dropping the 8 aforementioned individuals has virtually no effect on the point estimate.

[Table G.IV to be found on the following page]

The Tobit estimation of the specification with the relative consumption produces a t–stat equal to -2.50. The 25$^{\text{th}}$ lowest value of the bootstrap t–statistics is -1.87, while its 975$^{\text{th}}$ is equal to 1.90. Using a symmetric Wald test, we find that the absolute value of the original t–stat is larger than $|t_b|$ a little less than 99% of times (p–value of 0.018, Column (3) of Table G.IV). Bootstrap inference thus indicates that we can reject the hypothesis that the price elasticity is zero at the 5% level.

Similarly, the IV–Tobit estimation of the specification with relative consumption produces a t–stat equal to -1.93. The 25$^{\text{th}}$ lowest value of the bootstrap t–statistics is -1.73,

[25] Wild cluster bootstrap has been documented as leading to more robust inference in the case of few clusters, as well as helping in the case that right–hand side dummy variables induce incomplete replications (Cameron and Miller, 2015). To our knowledge though, wild cluster bootstrap has not been extended to nonlinear models.

[26] Our specifications with absolute and relative consumptions include a dummy for the year in which the copayment rate was assessed, as justified in Appendix B.1.

Table G.IV: Bootstrap inference

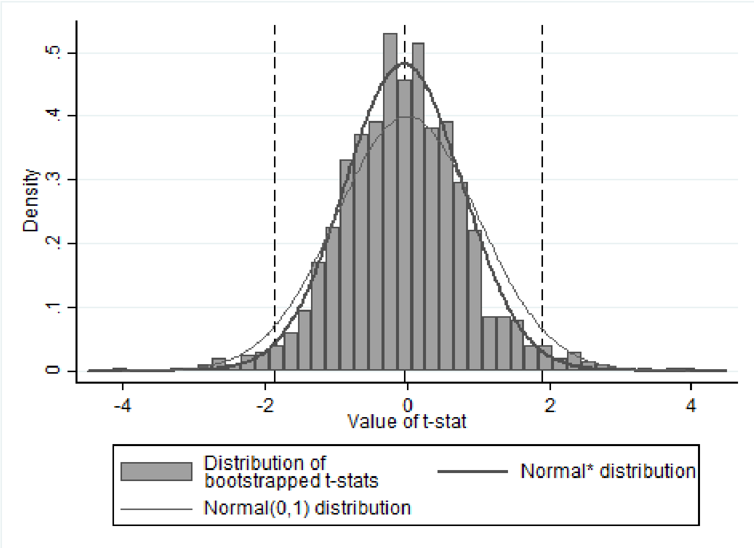
	Dependent variable: relative consumption $h^*/\bar{h}$ (log)					
	——— *Tobit* ———			——— *IV–Tobit* ———		
	(1)	(2)	(3)	(4)	(5)	(6)
Price (log)	-0.450**	-0.451**	-0.451**	-0.387**	-0.388**	-0.386**
(se)	(0.181)	(0.180)	-	(0.192)	(0.192)	-
p-value	*0.013*	*0.012*	*0.018*	*0.044*	*0.044*	*0.014*
Disposable income (log)	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
(se)	(0.007)	(0.007)	-	(0.007)	(0.007)	-
p-value	*0.184*	*0.184*	*0.163*	*0.186*	*0.186*	*0.165*
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Copayment reassessed no earlier than 2011		All	Copayment reassessed no earlier than 2011	
Observations	8190	8182	8182	8190	8182	8182
Censored observations	39.6%	39.6%	39.6%	39.6%	39.6%	39.6%
Inference	Default	Default	Bootstrap	Default	Default	Bootstrap
Number of clusters	28	28	28	28	28	28

NOTES: Standard errors in parentheses, the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data pooled from October 2012, 2013 and 2014. Estimation of a Tobit or IV–Tobit model by Maximum Likelihood (Stata commands `tobit` for Columns (1) to (3), and `ivtobit` for Columns (4) and (5)). In Columns (3) and (6), inference is obtained using a bootstrap procedure. Difference in the point estimates between Columns (5) and (6) is due to the fact that in Column (6) we implement manually the IV strategy in two separate steps, rather than using the `ivtobit` command, to make the Bootstrap procedure consistent.
SAMPLES: In Columns (2), (3), (5) and (6), individuals whose copayment rate was reassessed prior to 2011 are not included in the sample (8 individuals).
BOOTSTRAP INFERENCE: We implement a pair cluster percentile bootstrap of the t–statistics (1,000 replications). The percentile–t p–value for the symmetric two–sided Wald test of H0: $\tilde{\beta}_1 = 0$, is computed as the proportion of times the absolute value of the boostrap t–statistic is greater than the absolute value of the observed sample t–statistic.

while its 975$^{\text{th}}$ is equal to 1.38. Using a symmetric Wald test, we reject the hypothesis that the relative consumption of home care is price inelastic, again at the 5% level.

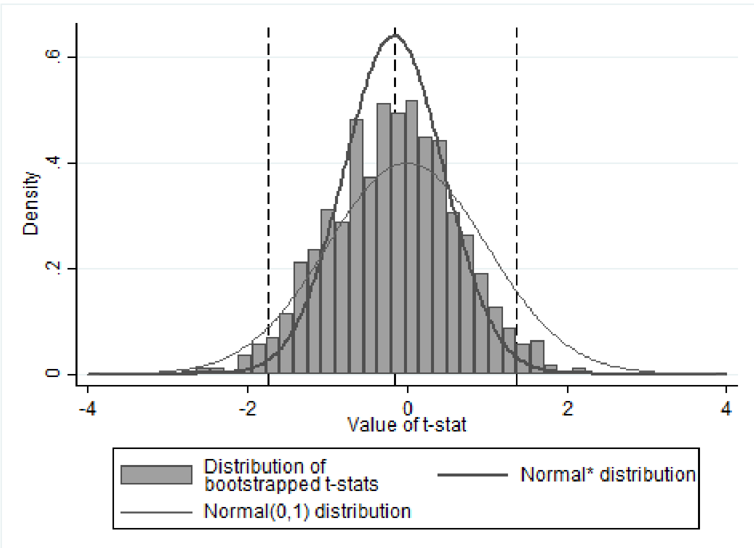
Figures G.2 and G.3 display the empirical distribution of the bootstrap t–statistics obtained following either the Tobit or the IV–Tobit estimation of the consumer price elasticity. We display a normal distribution with mean and variance equal to the mean and variance of the empirical distribution of the bootstrap t–statistics, and the normal distribution with mean 0 and variance 1 as a benchmark. Despite the sample containing one very large cluster, we observe a quite smooth distribution of t–statistics in both Figures. All replications are complete and the tails of the distribution do not seem excessively fat, making us confident in the quality of our bootstrap and in the statistical power of the deriving Wald test on the price elasticity estimate.

Figure G.2: Percentile-t bootstrap quality: distribution of bootstrap t–statistics (Tobit estimation)



NOTES: t-stats from percentile bootstrap–t (1,000 replications). Output from Tobit estimation on relative consumption (Column (3) of Table G.IV) on sample of 8,182 individuals. *The first normal distribution displayed has a mean and variance equal to the mean and variance of the distribution of bootstrap t-stats. Dashed vertical lines represent the 25^{th} and 975^{th} ordered elements and the mean of the bootstrap t–stat distribution.

Figure G.3: Percentile-t bootstrap quality: distribution of bootstrap t–statistics (IV–Tobit estimation)



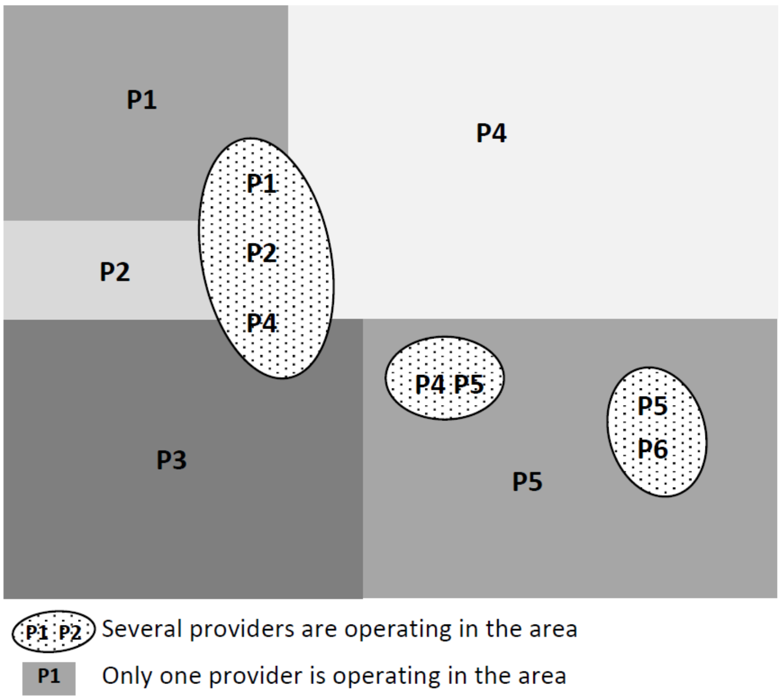
NOTES: t-stats from percentile bootstrap–t (1,000 replications). Output from manual IV–Tobit estimation on relative consumption (Column (6) of Table G.IV) on sample of 8,182 individuals. *The first normal distribution displayed has a mean and variance equal to the mean and variance of the distribution of bootstrap t-stats. Dashed vertical lines represent the 25^{th} and 975^{th} ordered elements and the mean of the bootstrap t–stat distribution.

G.3 Alternative identification strategy: using single–provider areas

G.3.1 Single–provider and multiple–provider areas

According to their geographical location in the department, beneficiaries may not be systematically able to choose between several providers of the department. We divide our sample into two sub–populations (Figure G.4): on the one side, beneficiaries living in a municipality where a single provider is found to operate, or single–provider area (denoted "SPA"; areas in plain color). On the other side, individuals living in a municipality where two or more authorized providers have customers, or multiple–provider area (denoted "non–SPA"; dotted areas).[27]

Figure G.4: Distribution of providers in the department – Schematic representation



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

As displayed in Table G.V, 79% of the municipalities represented in our sample belong to an SPA; 35% of beneficiaries included in the estimation sample live in this type of areas. The remaining beneficiaries live in a municipality where two or more authorized

[27]To identify the two types of areas, we use the full population of APA beneficiaries in the department, not only the APA beneficiaries of our estimation sample.

providers have customers. This partition interestingly reflects the spatial concentration of the APA population: 65% of the beneficiaries in our sample live in 21% of the department municipalities. Consistently, non–SPA municipalities are more often urban centers than SPA municipalities.

Table G.V: Single–provider areas and multiple–provider areas (October 2014)

	Municipalities		Beneficiaries		Average price
	Number	*Frequencies*	*Number*	*Frequencies*	
SPA	220	78.9%	995	34.8%	€22.7
Non–SPA	59	21.1%	1,867	65.2%	€22.0
Total	279	100%	2,862	100%	-

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

The spatial distribution of professional care provision is consistent with the fact that transportation costs are an important factor in the provision decision of home care services (cf. Section 4.4 of the paper). Providing services all over the department would be costly for a relatively small service. Typically, municipalities where only one provider is found to operate are served by non–profit home care services. In urban centers, the supply proposed by non–profit services may be complemented with municipal home care services, or even, in the largest municipalities, with one of the few for–profit authorized services found in the department (cf. Appendix E.2).

Table G.VI presents the descriptive statistics computed on the two sub–samples of APA beneficiaries, depending on the type of area in which they live. The two sub–samples are similar in terms of their socio–demographic characteristics albeit non–SPA residents are richer on average. This is consistent with the fact that non–SPA residents tend to locate in urban centers. The under–consumption rate is higher among non–SPA beneficiaries, but the average number of hours effectively subsidized is similar in both types of areas. This goes against the concern that SPA beneficiaries may experience rationing in the provision of professional care. Although subsidized consumption *relative* to the care plan volume is slightly higher for SPA beneficiaries on average (86% *versus* 84%), the overall distribution of relative consumption is fairly similar in the two sub–samples. Overall, except for the income level, the two populations little differ in terms of outcome and explaining variables.

[Table G.VI to be found on the following page]

Table G.VI: Descriptive statistics on the two sub–samples (SPA/non–SPA, October 2014)

Variable	*SPA* [1]	*Non–SPA* [2]	*Difference (p-value)* [1] - [2]
Care plan volume [a]	20.1	20.8	0.06
Care plan monetary value [b]	€456.8	€454.8	0.83
Hours effectively subsidized [c]	17.5	17.8	0.38
Amount of effective subsidies [d]	€311.7	€294.9	0.03
[c] inferior to [a]	57.2%	61.2%	0.03
Individualized income	€1,272	€1,339	0.00
Copayment rate	21.9%	24.6%	0.00
Provider price	€22.8	€21.8	0.00
Hourly out-of-pocket price	€5.0	€5.4	0.01
Total OOP payments on subsidized hours	€86.0	€94.2	0.03
Age	84.4	84.0	0.18
Women	72.5%	74.7%	0.18
Disability level 1 (most severe)	1.5%	1.0 %	
Disability level 2	12.2%	12.6%	0.54
Disability level 3	20.7%	19.1%	
Disability level 4 (least severe)	65.6%	67.3%	
	100%	*100%*	
Living with a spouse	34.7%	33.3%	
Living alone	64.7%	66.1%	0.81
Spouse in institution	0.6%	0.6%	
	100%	*100%*	
Number of individuals	995	1867	-
Number of households	965	1820	-

Notes: Estimation sample from October 2014. Descriptive statistics are computed on the sub–sample of APA beneficiaries living in single–provider municipalities (SPA) in Column (1) and those living in multiple–provider municipalities (non–SPA) in Column (2). Compared to Table G.V, average provider price in each sub–sample is weighted by the number of beneficiaries in the sample.

Tests: Last column presents the p–values associated with the tests of difference between SPA and non–SPA beneficiaries. Test performed is a Student (resp. a Pearson χ^2) for binary or continuous (resp. categorical) variables.

G.3.2 Price elasticity estimates using SPA and non–SPA beneficiaries

Arguably, SPA beneficiaries have limited choice if they resort to an authorized provider. As a consequence, they are not able to choose their price p_i^j. Note that home care price endogeneity due to residential mobility is suggested to be negligible: the overall residential mobility of the elderly is very low (Laferrère, 2008) and when moves occur, they are mainly explained by family motives or the need for adapted residences. Price endogeneity should thus be limited in the SPA sub–sample; on the contrary, we suspect it may arise in the non–SPA sample. Comparing the price elasticity estimates obtained on the two sub–samples may thus provide a test of price endogeneity in the estimation sample.

The estimation is run using the specification with the relative consumption, the outcome being $h^*_{it}/\bar{h}_{it}$. Results are displayed in Table G.VII.[28] As presented in the paper, the price elasticity is of -0.45 when estimated on the whole sample, significantly different from zero at the 5% level. Restricting the sample to individuals who are assumed to have no provider choice, the point estimate slightly changes to -0.52. Because of reduced sample size and price variations, precision is lower but the estimate is still significantly different from zero at the 10% level.

The point estimate is higher when we run the estimation on the sub–population of individuals who can choose between different providers, with a point value of -0.63. The difference between the two sub–sample estimates might potentially be explained by both an omitted variable bias affecting the choice of the provider price and some differences in the characteristics of the individuals of the two samples. However, the difference is not statistically significant even at the 10% level. Overall, this alternative estimation strategy (relying on SPA beneficiaries only) confirms our main results: the consumption of home care by the disabled elderly is price–elastic, with a point estimate inferior to one in absolute value and a magnitude seemingly around -0.5 or -0.4.

Table G.VII: Censored regression estimates of demand for home care hours (SPA/non-SPA)

	Dependent variable: relative consumption $h^*/\bar{h}$ (log)		
Sample:	*All* (1)	*SPA* (2)	*Non–SPA* (3)
Price (log)	-0.450**	-0.522*	-0.626**
	(0.181)	(0.305)	(0.258)
Disposable income (log)	-0.010	0.001	-0.013
	(0.008)	(0.010)	(0.009)
Care plan volume (log)	0.040*	0.039***	0.049*
	(0.023)	(0.014)	(0.029)
Other controls	Yes	Yes	Yes
Observations	8190	2489	5701
Censored observations	39.6%	40.7%	39.1%
Number of clusters	28	18	28
AIC	11454	3277.318	8144
BIC	11643	3376.252	8324

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Pooled data from October 2012, 2013, 2014. 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. SPA stands for "single–provider area" beneficiaries, non–SPA for "multiple–provider area" beneficiaries.

[28] We only display the price and income coefficients as the effects of controls are similar to the estimates obtained with the full estimation sample (displayed in Table II of the paper).

This alternative identification strategy has several drawbacks. First, focusing on SPA beneficiaries induces additional intra–departmental selection. We find the non–SPA to be richer than SPA beneficiaries. If richer individuals are more price–elastic, as suggested by Table III in the main text, the price elasticity obtained on the SPA sub–sample would then be a lower bound (in absolute value) for the average price elasticity of our estimation sample. But we may additionally suspect that the two sub–samples differ in terms of unobservable determinants of professional care consumption. Using the specification with relative consumption, we tested the effect of including a dummy equal to one for SPA beneficiaries (Table G.VIII): living in a SPA is found to positively affect home care relative consumption, *ceteris paribus*. The inclusion of the SPA dummy affects the price elasticity estimate (although not statistically significantly). This might suggest that SPA beneficiaries behave differently than non–SPA in terms of care consumption decisions.

[Table G.VIII to be found on the following page]

One might fear that authorized providers operating as monopolies may set their price in accordance with the price elasticity of demand. In SPA municipalities, provider prices could be higher where the price sensitivity of APA beneficiaries is lower, inducing a potential downward bias (in absolute value) in our point elasticity estimate. Given that the authorized providers operating in an SPA are systematically non–profit structures and that they are priced by the Departmental Council, there is limited scope for consumer surplus extraction by monopolist providers.

A more serious issue *a priori* is that SPA and non–SPA sub–samples are constructed using the available information of our sample. We construct the non-SPA sample by observing the municipalities in which there are beneficiaries served by at least two different authorized providers.[29] It might be the case, especially in very small municipalities, that there are few beneficiaries living in a municipalities and they happen to all choose the same provider. In this case, we will infer that there is only one provider operating; we do not have any other way to infer from the data whether the individuals were able to choose between different providers. Although such cases are scarce,[30] we should remain cautious when interpreting the price elasticity estimated on the SPA sample.

Finally, when focusing on SPA beneficiaries, we loose 10 clusters (corresponding to authorized providers who are only found to operate jointly with other providers in the municipalities where they are present). This may undermine the validity of inference in the SPA sub–sample.

[29] We do not have direct information on the supply and geographical coverage by the different providers.

[30] 8% municipalities turn out to have a unique APA beneficiary, hosting 1% of the department's beneficiaries. More largely, beneficiaries living in municipalities with 5 or less APA recipients represent around 10% of total beneficiaries.

Table G.VIII: Censored regression estimates of demand for home care hours, controlling for the type of area of residence

	Dependent variable: relative consumption h^*/h (log)	
	(1)	(2)
Price (log)	-0.450**	-0.613***
	(0.181)	(0.202)
Disposable income (log)	-0.010	-0.008
	(0.008)	(0.007)
Lives in a SPA		0.064***
		(0.023)
Other controls	Yes	Yes
Observations	8190	8190
Censored observations	36.9%	36.9%
Number of clusters	28	28
AIC	11454	11431
BIC	11644	11621

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Pooled data from October 2012, 2013 and 2014. Estimation of a Tobit model by Maximum Likelihood. 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. SPA stands for "single-provider area", non–SPA for "multiple–provider area" beneficiaries.

G.4 Additional results: sensitivity to the inclusion of care received on weekends

As we do not directly observe the informal care received by the individuals, we include as a control in our estimation the formal home care the individual possibly receives during the weekend and public holidays (Table G.IX).

As in our baseline estimations, the latent dependent variable is the number of hours consumed between Monday and Saturday, except for public holidays, divided by the care plan volume open for business days. Consistently, the care plan volume taken into account to compute relative consumption only includes the hours that were prescribed to be consumed over the week. APA beneficiaries may also be entitled to subsidies for a few hours of care to be received during weekends and public holidays, which are set separately in the personalized care plan. Although weekend hours are charged the same price, they are not fungible with week hours. Only 7.5% of our estimation sample has weekend hours included in her personalized care plan, for a median volume of about 5 hours a month.[31] We did not include the home care hours received on weekends as a control in our baseline specifications because of a simultaneity concern.

We hypothesize that, for given disability and socio–demographic characteristics, individuals not receiving professional home care over the weekend are more likely to receive assistance from their relatives. We find that receiving formal care during the weekend is associated with more hours consumed during working days; reassuringly though, it does not significantly affect the price elasticity estimate.

[Table G.IX to be found on the following page]

[31] As beneficiaries with weekend care plan volume tend to be more severely disabled, their week care plan volume, $\bar{h}_{it}$, is on average higher than the week care plan volume of the rest of beneficiaries. Among these beneficiaries, APA hours prescribed on weekends amount only to 15% of the week care plan volume on average.

Table G.IX: Inclusion of home care received on weekends

Dependent variable: relative consumption during the week $h_i^*/\bar{h}_i$ (log)			
	(1)	(2)	(3)
Price (log)	-0.392**	-0.452**	-0.392**
	(0.193)	(0.195)	(0.196)
Consumes care on weekends		0.227***	-0.054
		(0.020)	(0.054)
Number of hours received on weekends			0.080***
			(0.017)
Observations	8,190	8,190	8,190
Censored observations	39.6%	39.6%	39.6%
Number of clusters	28	28	28
AIC	-22073.724	-22168.783	-22215.301
BIC	-21884.435	-21979.495	-22026.013

NOTES: Standard errors in parentheses, clustered at the provider level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Pooled data from October 2012, 2013 and 2014 (population–average model). Estimation of an IV–Tobit model by Maximum Likelihood. Provider price is instrumented by the number of municipalities served by the provider. All specifications, in both the first and second stages, include as controls the care plan volume, 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.

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