Université de Neuchâtel
Institut de recherches économiques

IRENE Working Paper 24-01

Retirement decision and household's gasoline consumption: Evidence from a Regression Discontinuity Design

Nicola Francescutto

Retirement decision and household's gasoline consumption: Evidence from a Regression Discontinuity Design*

Nicola Francescutto[†]

October 5, 2023

Abstract

I employ household-level data over 2006-2017 to quantify the impact of retirement on gasoline consumption. Based on a fuzzy regression discontinuity design, I show that gasoline consumption declines by 32-36 percent on average over my different specifications. The reduction reaches 59-66 percent when I restrict the sample to single-person households. I further find that the probability to use any gasoline decreases by 5-6 percent at retirement (13-16 percent for single-person households). These findings suggest that demographic trends represent an important driver of CO_2 emissions associated with private mobility in developed countries.

Keywords: gasoline consumption; retirement effect; Household expenditure survey; fuzzy regression discontinuity design.

JEL Codes: C21, C23, D12, Q4

*I would like to thank Mehdi Farsi, Daniel Kaufmann, Bruno Lanz, as well as participants of the 2022 IRENE seminar for useful comments and discussions. Any remaining errors are mine.

[†]University of Neuchâtel, Department of Economics and Business, Switzerland. email: nicola.francescutto@unine.ch

1 Introduction

The fast and unprecedented demographic aging of developed economies is going to have numerous impacts through labor market such as reduced labor-force participation (Börsch-Supan and Schnabel, 1998). Studies have shown that households' consumption declines sharply at retirement in many countries (Hamermesh, 1984; Banks et al., 1998; Schwerdt, 2005; Haider and Stephens Jr, 2007) and is often coupled to a decline in work-related expenditures (Battistin et al., 2009; Li et al., 2016).[1] Moreover, households' commuting behavior, mobility choices and energy consumption are also impacted by retirement. Analysing variations in consumer behavior at retirement is therefore a topic of great interest in the economic policy debate.

The main objective of this paper is to provide empirical evidence on the impact of retirement on households' gasoline consumption. I employ several waves of the Swiss Household Budget Survey (SHBS), a cross-sectional household-level survey, from 2006 to 2017. This provides monthly information on households' gasoline consumption and employment status in Switzerland. The Swiss case is of particular interest because of its rapidly aging population, its flexible retirement age at 65 and its very carbon-intensive transport sector.[2] Following Battistin et al. (2009) and Li et al. (2016), my main identification strategy uses a fuzzy regression discontinuity design (RDD). Specifically, I identify a local average treatment effect (LATE) using 2SLS and exploit the Swiss statutory retirement age as an exogenous shock to measure my treatment effect. I fit both parametric and non-parametric fuzzy RDD and instrument retirement with a retirement indicator variable equal to one for households located above the legal retirement age and zero otherwise.

Household composition can pose an important threat to the estimation of the retirement effect. In particular, the treatment effect can be understated by the consumption of other household members that are not retired yet. As single-person households represent approximately 28.5 percent of the households included in my sample, I also estimate a fuzzy RDD separately for single-person households only, using the same identification strategy as before. In addition, I also document whether retirement causes a

[1] This observed decline in consumption after retirement is referred to as the retirement-consumption puzzle and contrasts with the consumption-smoothing hypothesis proposed by Modigliani and Brumberg (1954) and Friedman (1957).

[2] In Switzerland, the share of the population aged 65 or more is expected to increase significantly and linearly in the next decades to reach 25.6 percent of the population in 2050 (SFSO, 2020b). In 2019, the transport sector was the largest source of greenhouse gas emissions in Switzerland. Transport represented over 32 percent of total greenhouse gas emissions as it emitted more than 15 million tons of C02-eq (SFOEN, 2022).

change in households' probability to use any gasoline as I disentangle changes in the decision to participate or not in the market after retirement from changes in the consumption-level decision.

Overall, based on the significant jump in the probability of retiring at retirement age, my empirical results suggest that there is a strong negative impact of retirement on households' gasoline consumption.[3] Quantitatively, I show that retirement decreases households' gasoline consumption on average by 32-36 percent over my main parametric specifications. These results are robust to different bandwidth sizes and to the inclusion of covariates. Moreover, estimates of the local average treatment effect using a non-parametric fuzzy RDD are in line with the results found using the parametric RDD estimation. When I consider single-person households only, I find that the magnitude and the statistical significance of my estimates are both higher than when using all households available in the sample. In this setting, the estimated retirement effect reaches 59-66 percent over my different specifications.

Next, I find different results for the extensive and intensive margin of gasoline consumption. First, I show that retirement decreases the probability that households consume any gasoline on average by 5-6 percent. Again, the estimated effects are larger and more precisely estimated when considering single-person households only, as the decrease in the probability to consume any gasoline reaches 13-16 percent. Second, the estimated retirement effect using only households with a positive amount of gasoline consumed is 12-14 percent (respectively 23-27 percent for single-person households) and is lower than in my baseline results using all households in the sample.

I also test for different threats to internal validity and rule out two possible confounders. First, I find that my retirement effect is not likely to be confounded with an income effect. Besides controlling for the households' disposable income in most specifications, I show that households' disposable income in my sample of households does not drop significantly at the retirement threshold. Evidence of an absence of statistically significant discontinuity at the cutoff is tested both graphically and statistically by applying a fuzzy RDD using the log of the households' disposable income as dependent variable. I find similar results by restricting the sample to single-person households. Second, I exploit data on public transport usage to document that the observed decline in private transport usage by households after retirement is not accompanied by changes in public transport usage. My results indicate that households' public transport usage remains fairly stable after retirement, excluding thus a substitution from private to public

[3] Results from the first stage are all statistically significant and display a partial F-statistic larger than what is recommended by Lee et al. (2022).

transport at retirement.

While no study establishes a clear causal effect of retirement on transport fuel consumption, there is a rather clear consensus in the literature on the relationship between age and energy consumption. On one hand, ageing is usually linked to increased residential energy demand (electricity, heating fuel, natural gas) as older people tend to have a more sedentary lifestyle than younger households (Yamasaki and Tominaga, 1997; Tonn and Eisenberg, 2007; Fan et al., 2021). Indeed, several studies highlight that age-related factors are determinant drivers of energy consumption and greenhouse gas emissions in the residential sector (Zagheni, 2011; Chancel, 2014; Bardazzi and Pazienza, 2020).

On the other hand, there seems to be a negative relationship between age and transport energy use. Okada (2012) for instance finds a clear link between CO2 emissions from the road sector and the age structure of the population of developed countries. The author shows that CO2 emissions from the road sector of a country tend to decrease once they reach a share of elderly people of more than 16 percent, confirming thus the positive contribution of aging to curb CO2 emissions in the transport sector. These results are also confirmed by Liddle (2014) who finds that population aging among OECD countries should have a lowering effect on carbon emissions from transport.

The literature in environmental and energy economics on the effect of retirement on energy consumption is rather scarce. Indeed, the bulk of the literature studying the energy consumption patterns of the elderly generally undervalues the effect of retirement on energy consumption and only considers the impact of the elderly population as a whole. I make use of my detailed expenditure and consumption data to provide novel evidence on the impact that retirement has on both gasoline consumption and market participation of elderly households as well. While most household expenditure surveys usually do not provide detailed information on households' consumption, the SHBS used in this paper offers rich information on households' gasoline consumption. Furthermore, the SHBS, through his employment status variable, allows me to identify retired from non-retired units.

To my knowledge, this is the first empirical analysis studying the relation between gasoline consumption and retirement using actual consumption data and a clear identification strategy. Recently, Zhu and Lin (2022) investigated the impact of retirement on residential electricity consumption in urban China using a regression discontinuity design. The authors' findings suggest that retirement increases electricity consumption by 20-32 percent through augmented home time after retirement. Relative to this study, my results show that retirement also impacts elderly households' gasoline consumption.

My study is also closely related to the retirement-consumption puzzle literature, which studies the impact of retirement on consumer behavior. Various studies (Hamermesh, 1984; Banks et al., 1998; Bernheim et al., 2001; Schwerdt, 2005; Haider and Stephens, 2007) found an important decrease in households' consumption in the first post-retirement years. Hamermesh (1984) for instance discusses consumption patterns in the US after retirement and states that the elderly's consumption decreases significantly after retirement. Moreover, many studies show that the drop in post-retirement consumption is primarily related to a decline in work-related expenditures (Battistin et al., 2009; Li et al., 2016). For instance, Battistin et al. (2009) use Italian microdata to evaluate the causal effect of retirement on consumption. Using a regression discontinuity design, the authors find that nondurable consumption drops by 9.8 percent after retirement and is mainly due to a drop in work-related expenses. Similar findings are shown by Li et al. (2016) for China. Their results suggest a significant decrease in work-related expenditures after retirement.

While my work is directly related to the retirement-consumption literature, it contributes to a new literature linking retirement and households' energy consumption as no study explicitly identifies the retirement effect on gasoline consumption. Indeed, the major contribution of this paper is to investigate the effect that retirement has on private households' gasoline consumption, complementing thus the existing work on the effects of retirement on general consumption.

The remainder of this paper is organized as follows: Section 2 displays information on the data and the empirical strategy used in my analysis. Section 3 reports my estimated results followed by sensitivity checks. Finally, Section 4 provides a brief conclusion.

2 Empirical strategy

In this section, I first give a summary of my data, and then present my identification strategy to estimate the impact of retirement on households' gasoline consumption.

2.1 Data overview

This paper uses the Swiss Household Budget Survey (SHBS), a monthly cross-sectional survey conducted by the Swiss Federal Statistical Office as main data source (SFSO, 2020a). The SHBS covers the whole Swiss territory and randomly surveys around 250-300 households each month. All participants provide detailed information on their expenditures and consumption of goods for a whole month. The

SHBS also contains a large variety of socioeconomic and demographic variables of the household. Combining 12 yearly waves of the SHBS from 2006 through 2017 led to a repeated cross-sectional dataset with 38,975 households.

The main dependent variable used for the analysis is the natural logarithm of the households' gasoline consumption (in liters).[4] Figure 1 below presents a histogram of monthly household gasoline consumption across households in the SHBS. It can be seen that a majority of households (more than 30 percent) reported zero consumption of gasoline when surveyed. Several reasons can explain this skewness. First, zero expenditures may arise from individual preferences (households refusing to consume gasoline independently of the price or income level). Second, zero expenditure may also appear in the survey due to the short period of observation. Finally, zero expenditures might also be explained by economic decisions related to price and income. In our sample, an important fraction of zeros correspond to households owning a vehicle (9105 out of 11872 zero observations over the observed period). Therefore, a lot of zeros in our sample are probably related to infrequency of purchase or abstention and less to economic factors.[5]

Table 1 below summarizes the variables used in the analysis. The average amount of gasoline consumed by a household is 73.91 liters. In my sample, around 24 percent of households are retired and the mean age in my sample of households is 52. My sample of households is therefore significantly older than the average Swiss resident who is 42 years old. More than 4 out of 5 households possess at least one car with the proportion of used and new cars being approximately equal. Moreover, the mean disposable income earned is 6981 CHF for my sample of households.[6]

2.2 Fuzzy Regression Discontinuity Design

I identify the effect of retirement on gasoline consumption by using a Fuzzy Regression Discontinuity Design (RDD). I use a fuzzy RDD design because unlike in a sharp RDD design, the probability of treatment in a Fuzzy RDD is not deterministic. In Switzerland, the statutory retirement age is respectively 65 for men and 64 for women. Nonetheless, many persons decide to retire prematurely either through

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[4] I added 1 to the consumption of households reporting zero liters of gasoline consumed before applying the logarithmic transformation to keep these observations in my analysis.

[5] Approximately 25 percent of vehicle owners in our sample did not purchase any gasoline in the surveyed month. This can partially be explained by the short period of observation as households reported their expenditures and consumption during one month only.

[6] On July 28, 2022, 1 CHF was equal to 1.04 USD.

Figure 1: Distribution of monthly household gasoline consumption (liters), 2006-2017.

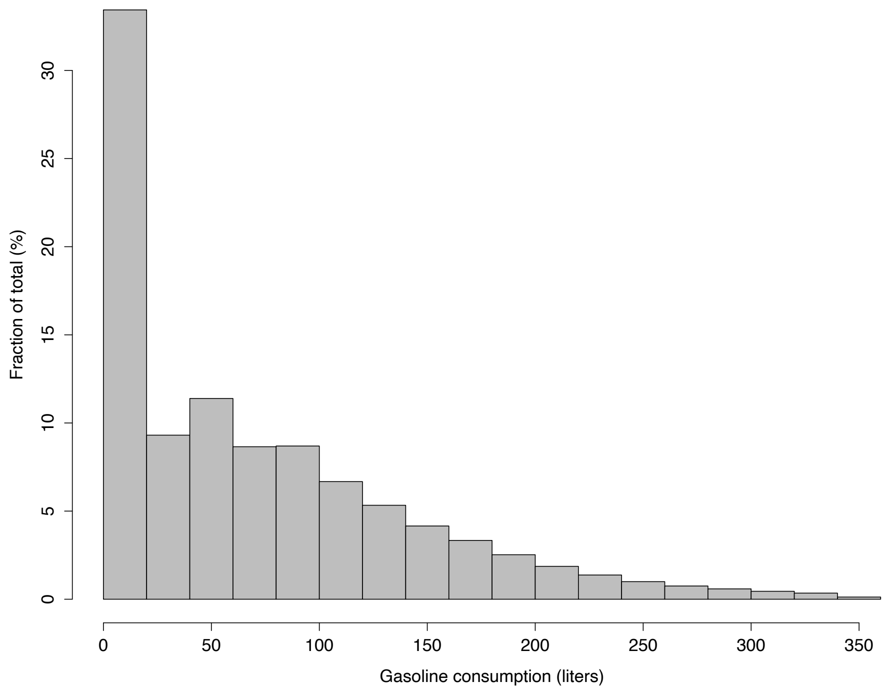


Table 1: Descriptive statistics

Variable	Mean	St. Dev.	Min	Max
Gasoline consumption	73.91	81.42	0	927.21
Gasoline expenditures	120.44	135.08	0	1,581.12
Age	52.63	15.52	18	100
Retired	0.24	0.42	0	1
Disposable income	6,981.64	4,510.90	0.50	163,982.60
Household size	2.32	1.22	1	14
Has at least one car	0.82	0.38	0	1
Number of New cars	0.54	0.64	0	6
Number of used cars	0.56	0.70	0	10

Notes: Data source is the Swiss Household Budget Survey from the Federal Statistical Office (2006-2017). Gasoline consumption is in liters and expenditures are in Swiss CHF.

personal choice or because their professional activity allows them to retire earlier.[7] Some persons also decide to retire after the legal statutory retirement age of 65. Therefore, since the probability of treatment does not jump by one but by less than one at the cutoff, the jump in the relationship between my outcome and my running variable can no longer be interpreted as an average treatment effect (Lee and Lemieux, 2010).[8]

I use the employment status variable of the SHBS to define my treatment variable.[9] Figure 2 displays the average retirement rate (here defined as the ratio of retired households in a particular age group to the total number of households) near the threshold (retirement age).[10] As can be seen in Figure 2, the average retirement rate increases with age with a sharp increase in the retirement rate around the threshold. It can also clearly be seen that the probability of treatment (being retired) does not switch from zero to one at the threshold like in a sharp RDD setup, meaning that not all individuals retire once they reach legal retirement age and that some households are already retired when they reach the threshold.

My main strategy focuses on a parametric estimation of the retirement effect by using a quadratic polynomial function on both sides of the threshold. This model exploits data within a selected range (bandwidth) above or below retirement age to show the local average treatment effect (LATE) of retirement on gasoline consumption. I use a different set of bandwidths to show the robustness of the estimated retirement effect.[11] Moreover, I also control for Swiss canton and year of survey fixed effects as well as for several socioeconomic and demographic characteristics of the household.[12]

To estimate the effect of retirement on gasoline consumption, I use a 2SLS model following Battistin et al. (2009) and Li et al. (2016) by instrumenting retirement with a retirement indicator variable equal to one for households located above the threshold (older than the legal statutory retirement age) and 0

[7] For example, since June 5, 2003, workers from the construction sector are allowed to retire at the age of 60 instead of 65 (Unia, 2022)

[8] Fuzzy RDD exploits discontinuities in the probability of treatment (here being retired) conditional on another variable (Angrist and Pischke, 2009).

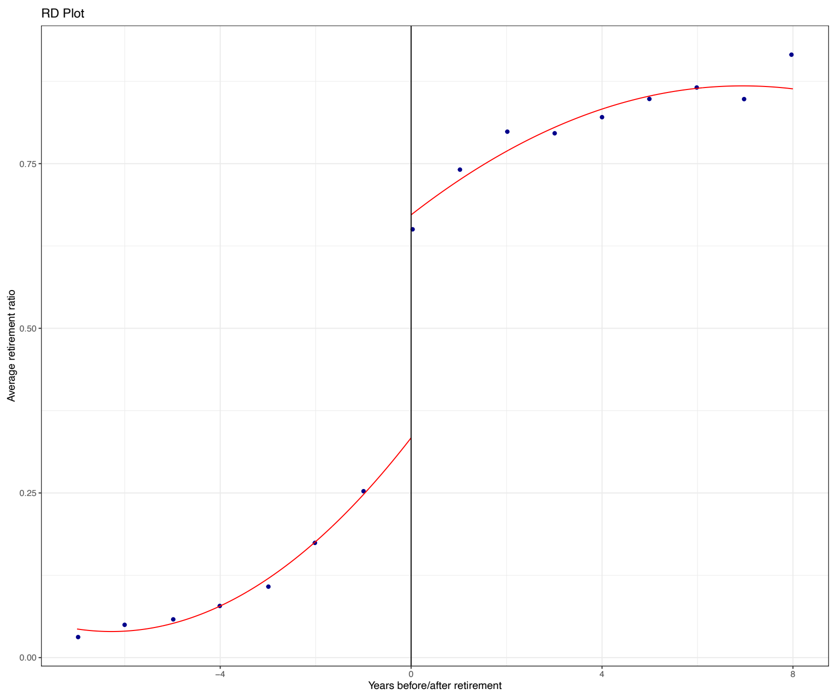
[9] Households' employment status in the SHBS is either employed from an independent working activity, employed from a dependent activity, retired, training, kid younger than 15 years of age, or other status (incl. unemployed).

[10] Switzerlands' legal statutory retirement age is respectively 65 for men and 64 for women.

[11] More details on the choice of the selected bandwidths are given in section 2.2.

[12] Cantons are administrative subdivisions of Switzerland. There are 26 distinct cantons in the country, 17 are German-speaking, four French-speaking, one Italian-speaking, three bilingual, and one trilingual. Besides the many languages, cultural differences are also very prevalent in the country and can have important effects on revealed environmental preferences for example (Filippini and Wekhof, 2021).

Figure 2: Average retirement ratio near the threshold



otherwise. The first stage of the 2SLS applied to my fuzzy RDD can be written as follows:

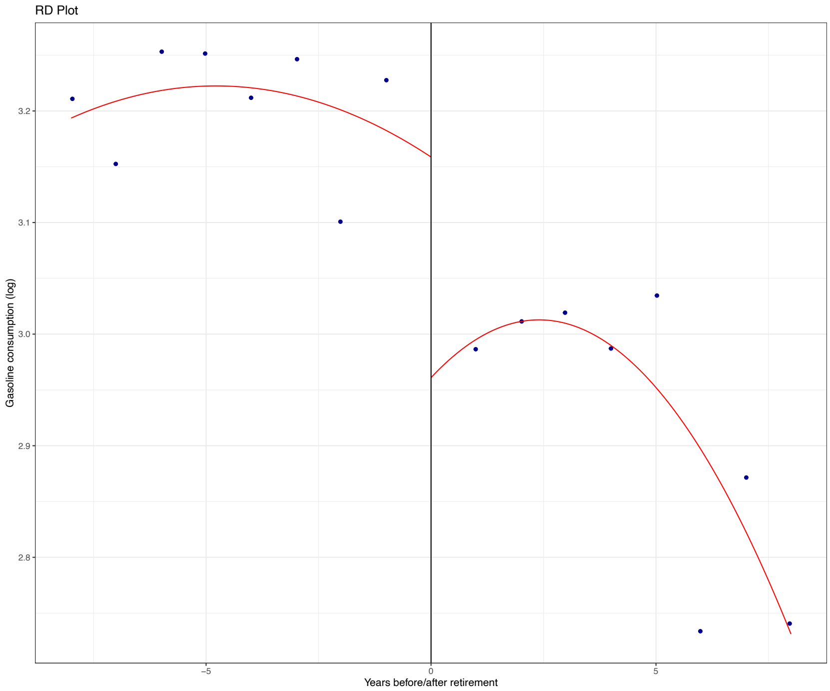
$$R_i = \beta_0 + \beta_1 Z_i + f(age_i) + \gamma X_i + \alpha C + \alpha_t + \mu_{it} \tag{1}$$

While the second stage-equation reads:

$$\ln Y_i = \beta_0 + \beta_1 \hat{R}_i + f(age_i) + \gamma X_i + \alpha C + \alpha_t + \epsilon_{it} \tag{2}$$

Where lnY_i is the natural logarithm of the households' gasoline consumption. Z_i is the assignment variable equal to one for households located above the statutory retirement age and 0 otherwise. R_i is the treatment variable that takes a value of 1 if individual i is retired and a value 0 if the household is not retired. $\hat{R}_i$ is the predicted value of the retirement probability from the first stage. $f(age_i)$ are the interacted multi-order terms of $f(age_i)$ to allow for different polynomial functions for treated and non treated units. I use a quadratic polynomial of the running variable and do not control for higher

Figure 3: Treatment effect near the cutoff



order polynomials of the forcing variable as it leads to noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence interval (Gelman and Imbens, 2019). X_i is a set of control variables. Finally, αC and α_t represent fixed effects for canton and year of survey respectively that control for unobserved heterogeneity across Swiss cantons and years of survey.

As explained above, my setup implies that age functions as the probability of a household to be retired. To estimate the above 2SLS model, there must be a non-zero correlation between my instrument and the treatment status. Evidence of the absence of a weak instrument bias is discussed in section 3.3. Another crucial condition that must hold to have a valid IV strategy is the exclusion restriction (see Lee and Lemieux, 2010), meaning that my instrument (being older than 65) only affects my outcome (gasoline consumption) through the treatment status (being retired). Since age is determined by year of birth, I believe that the exclusion restriction holds as households cannot precisely control it (Lee and Lemieux, 2010).

Next, to deal with the large number of households reporting a null consumption of gasoline, I use a two-step procedure to disentangle changes in the decision of households to participate or not in the market from changes in the consumption-level decision after retirement.[13] In a first step, I estimate how retirement affects households' probability to consume any gasoline. I apply a fuzzy RDD by re-estimating equation (2) using a binary outcome variable equal to one for households with a positive amount of gasoline consumed in the surveyed month and zero otherwise as dependent variable. In a second step, to estimate how retirement affects the consumption-level decision of households, I apply a fuzzy RDD as done in my main identification strategy, but restrict the sample to households having a positive amount of gasoline consumed in the surveyed month.

As a complementary identification strategy, I also estimate the local average treatment effect by applying a non-parametric fuzzy RDD, using a uniform Kernel density estimation with a first-order polynomial local linear regression. This estimation method is primarily used as a robustness test. Furthermore, I also estimate the fuzzy RDD separately using single-person households only to mitigate the influence of other non-retired household members that could understate my treatment effect.

There is a well-known precision-bias trade-off in the literature regarding the choice of the bandwidth. While selecting a larger bandwidth includes more observations and therefore increased precision, choosing a smaller bandwidth will minimize bias by comparing units close to the threshold. I estimate the optimal bandwidth following the method proposed by Calonico et al. (2014) which relies on a non-parametric estimation of a fuzzy RDD. I use a first-order local polynomial as well as a coverage error probability with a uniform kernel and estimate an optimal bandwidth of 7 years. Both larger and narrower bandwidths are also used in the analysis to test the sensitivity of my estimates. Figure 3 above graphically displays the level of discontinuity of the outcome variable (gasoline consumption) at the threshold. As we approach retirement age, gasoline consumption seems to decrease continuously with age, but a clear discontinuity can be observed once retirement age is reached.

I conduct an extensive robustness analysis of the 2SLS estimates that I obtain. First, I present results using both smaller and larger bandwidths (respectively 5 and 10 years) than the ones used in the baseline results. Second, I also investigate both graphically and statistically possible discontinuities in my covariates to make sure that my treatment effect is not confounded with a drop in another variable

[13] This procedure is similar to the double-hurdle model developed by Cragg (1971), where null values of consumption can arise at both stages of the consumers' decision process. The major differences with regard to Cragg (1971) are that I apply a fuzzy RDD at both stages of the decision process and I do not allow for null values in the consumption-level decision as I restrict my sample to households having a positive amount of gasoline consumed.

used in the model. Specifically, I test for a possible discontinuity in households' disposable income at retirement, which could be confounded with the measured retirement effect. Third, I also conduct a placebo-treatment test, where I move the threshold point for the fuzzy RDD by 3 years on both sides of the cutoff. I do so by moving the point with distance zero to either direction of the cutoff by 3 years. This allows me to assign a new placebo retirement treatment and conduct a placebo-fuzzy RDD.

3 Empirical results

This section reports my empirical results. First, I quantify the impact of retirement on households' gasoline consumption. Second, I estimate the implied change in the probability that a household consumes any gasoline after retirement. Third, I estimate the impact of retirement on households' consumption-level decision. All the previous steps are estimated both using a sample containing all the households and separately for single-person households to avoid the influence of other household members' consumption. Finally, I test the robustness of my results by providing various sensitivity checks.

3.1 Main results

Table 2 displays results from a fuzzy RDD, using several waves of the SHBS from 2006 to 2017. All model specifications include both canton and year Fixed effects to control for unobserved heterogeneity across different Swiss cantons available and year of survey. In columns (1) and (2), I report 2SLS regression estimates without and with control variables, respectively. I use a quadratic polynomial of the running variable and the optimal bandwidth that I obtained following the method proposed by Calonico et al. (2014).[14] Columns (3) and (4) are estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Columns (5) to (8) are similar to columns (1) to (4) but with a sample restricted to single-person households only. Only the results of the second stage are presented, but results from the first stage can be found in the appendix.

Starting in columns (1) and (2), the estimated retirement effect on gasoline consumption is negative and lies between 32 and 36 percent under the optimal bandwidth of 7 years and is statistically significant

[14] 2SLS regression estimates using larger and smaller bandwidths respectively 10 and 5 years to test the robustness of my estimates can be found in section 3.3. Larger bandwidths contain more observations and are thus more precise, but they also potentially understate the treatment effect as many confounding variables are present (Filippini and Wekhof, 2021).

Table 2: Fuzzy RDD - Second stage results on gasoline consumption (log)

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.360^{***}	-0.320^{***}	-0.301^{*}	-0.321^{*}	-0.623^{***}	-0.587^{***}	-0.639^{**}	-0.659^{**}
	(0.120)	(0.119)	(0.176)	(0.174)	(0.213)	(0.210)	(0.312)	(0.311)
Observations	10,028	10,028	10,028	10,028	3,302	3,302	3,302	3,302
Adjusted R^2	0.020	0.042	-	-	0.027	0.050	-	-
Polynomial	Quadratic	Quadratic	-	-	Quadratic	Quadratic	-	-
Kernel	-	-	Uniform	Uniform	-	-	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is the log of gasoline consumption. In columns (1), (2), I estimate the retirement effect parametrically (2SLS) using a quadratic polynomial function on both sides of the cutoff. In columns (3), (4), (7) and (8), I present estimates of the retirement effect from a non-parametric fuzzy RDD, using an uniform Kernel density estimation with a first-order polynomial local linear regression. Columns (1) to (4) use all households available in the sample while columns (5) to (8) only use single-person households. All specifications use the optimal bandwidth of 7 years. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

at the one percent level of significance. Non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression results in columns (3) and (4) confirm my previous results. Estimates under these specifications also indicate a negative and statistically significant effect of retirement of -30 to -32 percent on households' gasoline consumption. Therefore, retirement seems to have a strong negative impact on households' gasoline consumption.

Next, I provide further evidence of the retirement effect by restricting the analysis to single-person households only. This allows me to avoid the mixture of the household heads' gasoline consumption with the consumption of other household members that are not retired. Similarly than in columns (1) to (4), columns (5) and (6) are estimated using a 2SLS with a quadratic polynomial of the running variable under the optimal bandwidth, without and with control variables, respectively. In columns (7) and (8) the retirement effect is estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Again, all columns include both canton and year Fixed effects.

Starting in columns (5) and (6), the estimated retirement effect on gasoline consumption is both larger and more precisely estimated than the effect measured previously using all households. The estimated retirement effect under these specifications lies between -58.7 and -62.3 percent and is statistically significant at the one percent level of significance. By contrast, this effect was only of -36 and -32 percent, respectively, in columns (1) and (2). In columns (7) and (8), results from the non-parametric fuzzy

RDD using a local linear regression also confirm a significantly larger retirement effect for single-person households, as it is more than twice larger than under columns (3) and (4). Results under columns (5) to (8) therefore show that estimates are broadly consistent and of a significantly larger magnitude than the results from columns (1) to (4). Overall, the estimated retirement effects are also more precisely estimated even though the number of observations is much lower when considering exclusively single-person households.

3.2 Extensive and intensive margin of gasoline consumption

In this section, I disentangle the decision of households to participate or not in the market after retirement from their consumption-level decision.

3.2.1 Extensive margin

Table 3 displays results from a fuzzy RDD. In all columns, I use a binary variable equal to one for households with a positive amount of gasoline consumed in the surveyed month and zero otherwise as dependent variable. Again, all model specifications include both canton and year fixed effects and use the optimal bandwidth of 7 years. Similarly to Table 2, columns (1), (2), (5) and (6) are estimated using a 2SLS with a quadratic polynomial of the running variable. Only the results of the second stage are presented. Columns (3), (4), (7) and (8) are estimated with a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order local linear regression. Columns (1) to (4) use all households available while columns (5) to (8) restrict the analysis to single-person households.

Starting in columns (1) and (2), estimates under the optimal bandwidth are respectively -0.062 and -0.054 and are both statistically significant at the 5 percent level of significance. These estimates suggest a decrease in the probability of households to consume any gasoline at retirement by 5.4 to 6.2 percent. Non-parametric fuzzy RDD results in columns (3) and (4) are of a similar magnitude than the parametric estimates but are not statistically significant.

In columns (5) and (6), results suggest a strong negative impact of retirement on households' probability to consume any gasoline. Specifically, estimates are statistically significant at the one percent level of significance and indicate a decrease in the probability to consume any gasoline by 13.4 to 14.8 percent at retirement. Results from the non-parametric fuzzy RDD under columns (7) and (8) also suggest a statistically significant decrease in market participation after retirement of 16.1 to 16.5 percent.

Table 3: Fuzzy RDD - Second stage results on gasoline consumption (log) - Extensive margin

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.062^{**}	-0.054^{**}	-0.061	-0.060	-0.148^{***}	-0.134^{***}	-0.161^{**}	-0.165^{**}
	(0.026)	(0.026)	(0.041)	(0.041)	(0.048)	(0.048)	(0.069)	(0.069)
Observations	10,028	10,028	10,028	10,028	3,302	3,302	3,302	3,302
Adjusted R^2	0.015	0.033	-	-	0.021	0.041	-	-
Polynomial	Quadratic	Quadratic	-	-	Quadratic	Quadratic	-	-
Kernel	-	-	Uniform	Uniform	-	-	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is a dummy variable equal to one if the household reported a positive consumption of gasoline and zero otherwise. In columns (1), (2), I estimate the retirement effect parametrically (2SLS) using a quadratic polynomial function on both sides of the cutoff. In columns (3), (4), (7) and (8), I present estimates of the retirement effect from a non-parametric fuzzy RDD, using an uniform Kernel density estimation with a first-order polynomial local linear regression. Columns (1) to (4) use all households available in the sample while columns (5) to (8) only use single-person households. All specifications use the optimal bandwidth of 7 years. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

The suggested decrease in market participation using solely single-person households is therefore much larger than what I observed in columns (1) to (4) using all types of households.

3.2.2 Intensive margin

In Table 5, I estimate the intensive margin of gasoline consumption. To estimate how retirement affects households' consumption-level decision, I restrict the sample to households having a positive amount of gasoline consumed in the surveyed month and apply a fuzzy RDD as done in my main identification strategy. Similarly to before, columns (1), (2), (5) and (6) are estimated applying a 2SLS with a quadratic polynomial of the running variable while columns (3), (4), (7) and (8) show the results of a non-parametric fuzzy RDD using a uniform Kernel density estimation with a first-order polynomial local linear regression. Again, columns (1) to (4) use all households available while columns (5) to (8) restrict the analysis to single-person households.

Overall, estimates are broadly consistent across columns (1) to (4), and confirm a significant effect of retirement on households' gasoline consumption-level decision. Both parametric and non-parametric results suggest a statistically significant decrease between -12.2 and -13.9 percent. The fact that the treatment effect is larger and more precisely estimated for single-person households is also confirmed in the subsequent columns. In columns (5) and (6), estimates are statistically significant at the one percent

Table 4: Fuzzy RDD - Second stage results on gasoline consumption (log) - Intensive margin

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.128^{**}	-0.122^{**}	-0.124^{*}	-0.139^{*}	-0.249^{***}	-0.231^{***}	-0.274^{**}	-0.275^{**}
	(0.050)	(0.050)	(0.071)	(0.070)	(0.087)	(0.087)	(0.124)	(0.124)
Observations	7,187	7,187	7,187	7,187	1,872	1,872	1,872	1,872
Adjusted R^2	0.011	0.020	-	-	0.006	0.015	-	-
Polynomial	Quadratic	Quadratic	-	-	Quadratic	Quadratic	-	-
Kernel	-	-	Uniform	Uniform	-	-	Uniform	Uniform
Bandwidth	7 years	7 years	7 years	7 years	7 years	7 years	7 years	7 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is the log of gasoline consumption. Only households with a positive amount of gasoline consumed are used. In columns (1), (2), I estimate the retirement effect parametrically (2SLS) using a quadratic polynomial function on both sides of the cutoff. In columns (3), (4), (7) and (8), I present estimates of the retirement effect from a non-parametric fuzzy RDD, using an uniform Kernel density estimation with a first-order polynomial local linear regression. Columns (1) to (4) use all households available in the sample while columns (5) to (8) only use single-person households. All specifications use the optimal bandwidth of 7 years. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

level of significance and indicate a decrease in gasoline consumption by 23.1 to 24.9 percent after retirement. Finally, non-parametric estimates under columns (7) and (8) further confirm my previous findings. Estimates show there is also a significant negative impact of retirement on single-person households' gasoline consumption of -27.5 percent.

In sum, retirement seems to have a significant negative impact on households' gasoline consumption. Results suggest that both their consumption-level decision as well as their market participation decision are affected by retirement. Moreover, including other household members seems to have a significant impact on the measured treatment effect as estimates using single-person households are systematically larger and more precisely estimated in magnitude than estimates that use all types of households.

3.3 Sensitivity checks

In this section, I present different robustness checks that were conducted. First, I present results using both smaller and larger bandwidths than the ones used in my baseline results. Second, I pursue with a placebo test for non-discontinuities points. Finally, I test for discontinuities in my covariates both graphically and statistically.

Table 5: Fuzzy RDD - Second stage results on gasoline consumption (log) - Different BW size

	All households				Single-person households			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement	-0.248^{***}	-0.207^{**}	-0.281^{*}	-0.246^{*}	-0.614^{***}	-0.556^{***}	-0.615^{**}	-0.576^{**}
	(0.095)	(0.095)	(0.147)	(0.146)	(0.216)	(0.214)	(0.264)	(0.261)
Observations	13,703	13,703	7,477	7,477	4,839	4,839	2,475	2,475
Adjusted R^2	0.025	0.047	0.020	0.042	0.019	0.046	0.030	0.059
Bandwidth	10 years	10 years	5 years	5 years	10 years	10 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is the log of gasoline consumption. In all columns, I estimate the retirement effect parametrically (2SLS) using a quadratic polynomial function on both sides of the cutoff. In columns (1), (2), (5) and (6), I use a bandwidth of 10 years while a bandwidth of 5 years is used in columns (3), (4), (7) and (8). Columns (1) to (4) use all households available in the sample while columns (5) to (8) only use single-person households Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

3.3.1 Larger and smaller bandwidths

In Table 5, I re-estimate my fuzzy RDD applying the same 2SLS model as before but use both larger and smaller bandwidths with respect to my baseline results to test the sensitivity of my estimates. Columns (1) to (4) use all households available while columns (5) to (8) only include single-person households. Starting in columns (1) and (2), results under a 10-year bandwidth suggest a retirement effect of -20.7 to -24.8 percent, which is similar to the estimated treatment effect from my baseline results. The same conclusion can be drawn from columns (3) and (4) as it can be seen that the retirement effect under the 5-year bandwidth is still negative and statistically significant. As expected, further decreasing the bandwidth increases the standard error and thus decreases statistical significance since the number of observations is substantially smaller.

In columns (5) to (8), estimates for single-person households under a 10-year and 5-year bandwidth draw identical results than in the previous columns. Estimates under all four columns are statistically significant and of a similar magnitude to my baseline results. Overall, results derived using both larger and smaller bandwidths also imply retirement effect estimates that are very similar to my baseline results. Moreover, all estimates are still statistically significant although as expected standard errors are larger for the specifications using a smaller bandwidth of 5 years due to a loss of observations.[15]

[15] Similar results are found for the extensive and intensive margin. Results are available on demand.

Table 6: Fuzzy RDD - Second stage results - Disposable income (log)

	All households		Single-person households	
	(1)	(2)	(3)	(4)
Retirement	-0.070	-0.090	-0.011	-0.053
	(0.061)	(0.080)	(0.112)	(0.140)
Observations	10,028	7,477	3,302	2,475
Adjusted R^2	0.097	0.024	0.014	0.009
Bandwidth	7 years	5 years	7 years	5 years
Covariates	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes

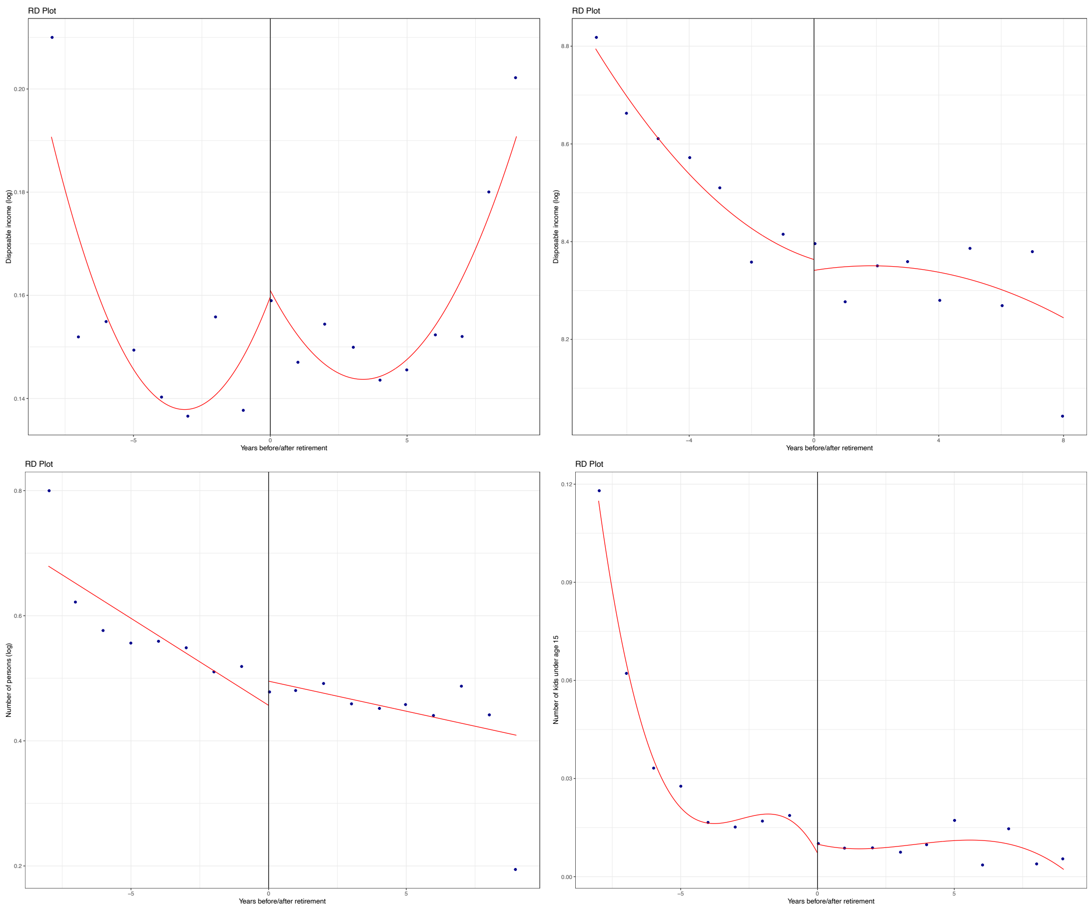
Notes: In all columns, the dependent variable is the log of disposable income and a quadratic polynomial function is used on both sides of the cutoff. In columns (1) and (3), a 7 year bandwidth is used to estimate the regressions while a 5 year bandwidth is used for columns (2) and (4). Columns (1) and (2) include all types of households in their sample while columns (3) and (4) only include single person households. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects as well as a set of covariates. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

3.3.2 Testing for discontinuities in covariates

One important condition for the validity of my results is the absence of discontinuity in my covariates. Indeed, they should display no discontinuous change at the threshold to exclude any correlation of my covariates with the treatment effect. Figure 4 graphically shows that there is no apparent discontinuity in the main socioeconomic and demographic covariates that I used in my models. Moreover, I also apply a fuzzy RDD and use a 2SLS by replacing gasoline consumption with the log of disposable income as dependent variable to test if disposable income shows a jump at the threshold as my retirement effect could be confounded with an income effect.

Table 9 shows the second stage results from the 2SLS model that I estimate using both a 7 and a 5-year bandwidth. I also estimate the model separately for single-person households only in columns (3) and (4). Results shown in all specifications of Table 9 confirm my previous conclusion. Indeed, elderly households' disposable income does not seem to display a significant discontinuity at the threshold as the estimated retirement effect is not statistically significant in all columns. These findings are thus in line with the intuition given in Figure 4 and further support my baseline results.

Figure 4: Treatment effect near the cutoff in GA travelcard (upper left), disposable income (upper right), number of persons in the HH (lower left) and number of kids under 15 in HH (lower right)



3.3.3 Placebo test for non-discontinuities points

In Table 10, I conduct a placebo-treatment test, where I move the threshold point for the fuzzy RDD by 3 years on both sides of the cutoff. I do so by moving the point with distance zero to either direction of the cutoff by 3 years. This allows me to assign a new placebo retirement treatment and conduct a placebo-fuzzy RDD. I conduct the placebo treatment using a 2SLS with a quadratic polynomial of the running variable. I use both the optimal bandwidth of 7 years as well as a 5-year bandwidth.

As can be seen in columns (1), (2), (5), and (6), moving the threshold 3 years prior does not produce any statistically significant effect of retirement on gasoline consumption and does not display any consis-

Table 7: Fuzzy RDD - second stage on gasoline consumption (log) - placebo cutoff

	-3 years placebo				+3 years placebo			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Placebo treatment	-0.049	0.128	-0.257	-0.054	-0.078	-0.115	0.252	0.274
	(0.349)	(0.351)	(0.583)	(0.587)	(0.347)	(0.343)	(0.672)	(0.670)
Observations	10,496	10,496	7,735	7,735	9,322	9,322	7,047	7,047
Adjusted R^2	0.019	0.037	0.019	0.037	0.023	0.051	0.013	0.043
Bandwidth	7 years	7 years	5 years	5 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is the log of gasoline consumption. In all columns, I estimate the retirement effect parametrically (2SLS) using a quadratic polynomial function on both sides of the cutoff. In columns (1)-(4) and (5)-(8), I move the cutoff point for the RDD respectively 3 years to the left and to the right of the cutoff. In columns (1), (2), (5) and (6), I use the optimal bandwidth of 7 years to estimate the regressions while columns (3), (4), (7) and (8) use a 5 year bandwidth. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

tency in terms of sign or magnitude. The same conclusions are drawn from columns (3), (4), (7), and (8), which show that moving the cutoff 3 years later to the real threshold does not produce any statistically significant treatment effect as well.

4 Conclusion

In this paper, I use Swiss household-level microdata to provide novel evidence on the impact of retirement on households' gasoline consumption. My data includes information on households' monthly gasoline consumption as well as a rich amount of socio-economic and demographic characteristics of the households. I exploit the Swiss statutory retirement age as an exogenous shock and apply a fuzzy regression discontinuity design as identification strategy to estimate how retirement affects gasoline consumption.

My results show that retirement decreases households' gasoline consumption significantly by 32-36 percent on average. Both the magnitude and the precision of my results are larger when considering only single-person households as the consumption of other household members is not mixed up with the household heads' gasoline consumption. The reduction reaches 59-66 percent when I restrict the sample to single-person households. In addition, I also find that retirement not only affects the consumption-level decision but also impacts households' decision to participate or not in the market. Specifically, retirement causes an average decrease in the probability of consuming any gasoline by 5-6 percent (13-16 percent for single-person households).

My results can be interpreted as an illustration of the potential effects that population aging could have on both gasoline demand as well as on the CO_2 emissions associated with it. With back of the envelope calculations, I estimate that the increase in the share of retired people in Switzerland could save 0.47 millions of tons of CO_2 by 2050.

I close by emphasizing that the estimated retirement effect is by definition a local treatment effect, applying to compliers in the selected bandwidth. Given the lack of studies linking the effects of retirement on households' energy consumption, further work on this matter seems indicated. Investigating other changes in households' energy consumption patterns after retirement, such as heating fuel demand, represent important future research areas. In the present context, future studies should also consider potential welfare losses of the elderly caused by soaring energy prices.

5 Appendix

5.1 First stage results

My last sensitivity check derives results for the first stage of my 2SLS estimation for a set of different bandwidths to test for a possible weak instrument bias that would be a threat to the validity of my results. As can be seen in Table 11 and Table 12 below, all specifications display a highly statistically significant estimate as well as a very large partial F-statistic. Therefore, the presence of a weak instrument bias seems very unlikely and confirm the validity of my instrument.

Table 8: First stage results - All households

	Retirement					
	(1)	(2)	(3)	(4)	(5)	(6)
Above age 65	0.758***	0.756***	0.695***	0.693***	0.653***	0.651***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.014)	(0.014)
Observations	13,703	13,703	10,028	10,028	7,477	7,477
Adjusted R^2	0.702	0.704	0.680	0.682	0.662	0.665
Partial F-stat	5745.6	5715.3	3354.3	3335.1	2175.5	2162.2
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Bandwidth	10 years	10 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is a dummy variable equal to one if the household's head is retired and zero otherwise and a quadratic polynomial function is used on both sides of the cutoff. In columns (1) and (2), a 10 year bandwidth is used. Columns (3) and (4) use the optimal bandwidth of 7 years, while columns (5) and (6) consider a 5 year bandwidth. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Table 9: First stage results - Single person households only

	Retirement					
	(1)	(2)	(3)	(4)	(5)	(6)
Above age 65	0.801***	0.801***	0.742***	0.741***	0.707***	0.704***
	(0.023)	(0.023)	(0.026)	(0.026)	(0.031)	(0.031)
Observations	2,475	2,475	1,872	1,872	1,438	1,438
Adjusted R^2	0.705	0.706	0.693	0.693	0.682	0.683
Partial F-stat	1212.8	1212.8	814.4	812.3	520.1	515.7
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Bandwidth	10 years	10 years	7 years	7 years	5 years	5 years
Covariates	no	yes	no	yes	no	yes
Fixed effects	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is a dummy variable equal to one if the household's head is retired and zero otherwise and a quadratic polynomial function is used on both sides of the cutoff. In columns (1) and (2), a 10 year bandwidth is used. Columns (3) and (4) use the optimal bandwidth of 7 years, while columns (5) and (6) consider a 5 year bandwidth. Heteroskedasticity robust standard errors in parentheses. All specifications include canton and year fixed effects. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

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