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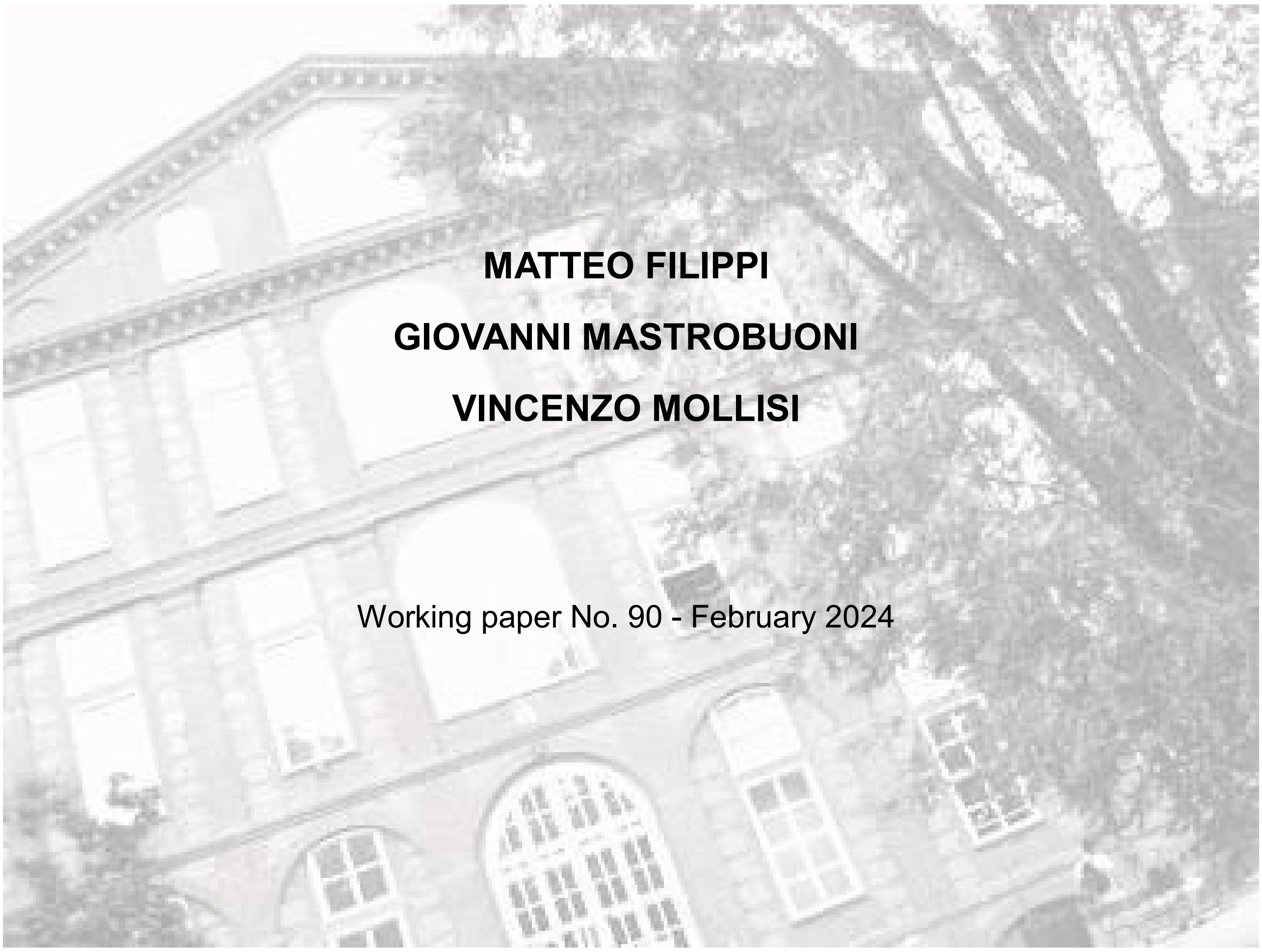
QUASI-EXPERIMENTAL DEMAND ESTIMATION OF MEMBERSHIPS AND OF THEIR USAGE



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Quasi-Experimental Demand Estimation of Memberships and of Their Usage *

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January 11, 2024

Abstract

Memberships are everywhere, and a growing number of superstar and small companies are turning their businesses into a membership-based model. However, the econometric challenges posed by endogenous pricing has caused research to lag behind, resulting in poor knowledge of membership pricing effect on consumers' purchase and usage. We fill this gap by focusing on an Italian museum membership card, an industry where memberships are rapidly gaining momentum. In particular, our Regression Discontinuity (RD) framework leverages several *age-based* price discontinuities to provide the first quasi-experimental estimates of membership cards' price elasticity. Depending on the specific age group, we find (absolute) price elasticities in the range 0.5-2.6, which are larger than the elasticities commonly found for single-ticket visits. Furthermore, we find that higher pricing is associated to a more intense and expensive use of the card; a closer look at the underlying mechanism suggests that a price-induced selection may be more important among the older cohorts, where the larger time availability arguably translates into more systematic price search efforts. Finally, we combine our previously-mentioned RD estimates to provide the first policy recommendation on membership cards' pricing.

Keywords: membership, subscription, demand, elasticity, museum

JEL Codes: key1, key2, key3

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1 Introduction

Memberships are everywhere, and a growing number of companies worldwide are rapidly turning their businesses to new membership models. This applies not only to super-star firms, such as Sky, Netflix, Amazon, Spotify, Google, Microsoft and Adobe, but also to small businesses: in 2014, survey data revealed that over half the annual revenue of 61 percent of small business owners came from repeat customers rather than new customers, and that repeat customer tended to spend 67 percent more (Williams and Campbell (2014))[1]. Despite being initially limited to the publishing industry, the shift to a membership-revenue model is affecting nowadays a variety of sectors, including fashion, airlines, movies and Tv series, music, e-commerce, IT, car sharing and even advocacy[2]. Several membership's advantages contribute to explain this trend, including higher customers' retention, predictable cash flows over time, a market expansion through memberships' renewal or upgrade, the creation of a tighter customers' community, but also lower transaction costs and easier price discrimination (Glazer and Hassin (1982)). For all these reasons, the *ownership economy* is dramatically losing momentum in favor of a *membership economy* (Baxter (2015)). However, despite its growing relevance, the empirical evidence has lagged behind, possibly due to the econometric challenges posed by the endogenous pricing of the membership, and little is known about price effects on consumers' purchase and usage of the membership.

We fill this gap in the literature by looking at the museums industry, a sector which is rapidly growing and increasingly recognizing membership programs as one of the most valuable assets[3]. While limited until the 1970s, the number of museums has dramatically increased in

[1] These results are important, as small businesses provide 55% of all jobs and account for more than half (54%) of all U.S. sales (Williams and Campbell (2014)).

[2] In an influential article looking at how advocacy organizations achieved true scale and predictable revenue, Peter Murray found that organizations like AARP and the National Rifle Association (NRA) have expanded to provide lifestyle benefits, like group insurance, product discounts, and access to special events—going well beyond traditional advocacy (Murray (2013)).

[3] Some relevant initiatives worldwide are the subscriptions offered by the Museums Association, the largest network of museums and galleries in the UK, and by the North American Reciprocal Museum (NARM) Association, one of the largest reciprocal membership programs in the world with members in the United States, Bermuda, Canada, El Salvador and Mexico. Both associations offer free admission during regular museum hours to their members, besides member discounts at museum shops and on concert/lecture tickets.

recent years reaching almost 100k in 2020, a 60% increase with respect to 2012 (UNESCO, 2020)[4]. Unfortunately, even before the outbreak of the COVID-19 pandemic, the costs of running a cultural organization were escalating at a greater pace than the revenues, and museums were struggling with engaging new audiences while first-time visitors were steadily declining (IMPACTS, 2019). On top of this, the unprecedented health, social and economic emergency posed by the pandemic undermined the business model of cultural organizations: international tourist arrivals plunged by 74% in 2020 over the previous year, with an estimated loss of USD 1.3 trillion in export revenues - more than 11 times the loss recorded during the 2009 global economic crisis (UNWTO, 2021).

In this scenario, *members* and *subscribers* may be especially important for recovery. Indeed, recent research has shown that members tend to have higher retention rates than the average visitor, to spend more annually (90 euros as opposed to around 20), to deliver 4.5x greater value over a 10-years horizon, and to report significantly higher satisfaction rates (IMPACTS, 2019). The last point is important, as satisfaction correlates with the likelihood to endorse an organization, and entities' reopening are likely to benefit from the endorsements of the people who cherish them most (IMPACTS, 2020)[5]. Additionally, intending to renew when they next visit remains the top reason why memberships are *not* renewed, which implies that encouraging membership's renewal and encouraging attendance could go hand in hand. Furthermore, a recent survey in the US revealed that joining an organization by way of membership is considered the best way to support an organization's mission – even more than making a donation (IMPACTS, 2019). As such, a successful recovery strategy may dictate to shift the attention from one-time to repeat customers, not only through appropriate membership's pricing, but also through complementary targeted practices[6].

[4]Cultural tourism has paralleled this trend, with cultural tourists accounting nowadays for 40% of all European tourism and expected to grow further (UNWTO, 2018). Besides for their rising quantitative relevance, cultural tourists are also an appealing market segment in that they tend to spend 38% more per day, and stay 22% longer than other tourists (UNWTO, 2018).

[5]Members and subscribers rate the educational experience higher than regular visitors. They also report better admission value, better perceptions of crowd control, and better parking experiences.

[6]In particular, a recent trend sees art museums switching to digital membership cards faster than ever, with the final aim to streamline membership card fulfillment, save time and money, foster renewals and drive

This paper focuses on the Italian setting, which represents the ideal context to study the museum memberships' pricing implications. As of 2021, Italy was the country with most UNESCO's World Heritage Sites worldwide (58); in 2019 alone, 53 million people visited Italy's 358 museums and archaeological sites, which employed around 120k individuals and generated revenues equivalent to 1.6% of national GDP[7]. As for the tourism sector, one third of the 123 million visitors said they were traveling for cultural reasons, and 57 percent of these declared to be interested in museums. We study a museum membership card, the so-called "Abbonamento Musei" (AM), which covers cultural sites located in Piedmont, Lombardy and the Aosta Valley regions. In particular, we employ a novel administrative dataset on the whole universe of membership cards, and the corresponding museum visits, over the entire period January 2015 - August 2019. Exploiting longitudinal structure of the dataset, we are able to track the individual cultural consumption over time, and to link the consumption behavior to cards' characteristics. We exploit this unique data source to contribute to the literature on several dimensions.

To begin with, this is the first paper (to the best of our knowledge) providing quasi-experimental estimates of membership cards' price elasticity. In particular, our empirical strategy exploits the presence of multiple age-based price discontinuities introduced by the "Associazione Abbonamento Musei" (AAM) after November 2013. Depending on the specific age group, we find (absolute) price elasticities in the range 0.5-2.6, which are larger than the elasticities commonly found in the literature for museum visits. Indeed, econometric estimates for a wide range of museums in a variety of countries indicate that the demand for museum services is price inelastic, with most studies finding an average (absolute) price elasticity ranging between 0.1 and 0.6 (e.g. Goudriaan and Van't Eind (1985), Darnell, Johnson and Thomas (1992), and Luksetich and Partridge (1997), and Frey and

public's engagement. Other options include inviting members exclusively to the early phases of reopening, special hours, or exclusive content to strengthen the relationship prior to reopening.

[7]While already large, the impact of museums on the gross domestic product could potentially reach 35-40 billion euros, after taking indirect effect into account. Source: https://www.bcg.com/it-it/press/07october2019-cultura-musei-statali-valgono-pil-euro-mila-occupati.

Meier (2006)). Second, we exploit the same RD design to explore possible implications of pricing in terms of card's usage, and find that higher prices are usually associated with a more intense and expensive use of the card. In order to disentangle a mechanism of pure price-induced selection of members from a behavioral response to the price shift, we employ a diff-in-diff strategy exploiting i) the age-based price discontinuities and ii) the presence of repeat memberships of the one-year subscriptions. Our results indicate that a mechanism of pure selection may be more important among the older cohorts, where the larger time availability arguably translates into more systematic price search's efforts. Third, taking into account that any museum visit represents a cost for the AAM, we combine our above-mentioned RD estimates to provide the first policy recommendation on membership cards' pricing, which could inform in particular those initiatives where the membership's usage entails additional costs on behalf of the issuing entity.

In terms of theoretical underpinnings, our study is closely related to the literature on bundled pricing strategies and, in particular, to the literature that discusses bundling in the context of information and cultural goods. Most bundling studies show that mixed or pure bundling strategies can benefit monopolists (e.g., Burstein (1960), Stigler (1963), Adams and Yellen (1976), McAfee, McMillan and Whinston (1989), and Armstrong (1996)) and are particularly appropriate when products have low or no marginal costs (Stigler (1963)), and when the bundle's components are hard to discern on consumer's end (Fang and Norman (2003)). On the contrary, when consumers' value to subsequent goods decrease quickly, bundling is usually sub-optimal (Geng, Stinchcombe and Whinston (2005)). While early research on bundling focused on the competitive effect of bundling in monopolistic, and duopolistic markets (Armstrong and Vickers (2010)), more recent research indicates that bundling can either prevent competitors from entering markets (Nalebuff, 2004) or be anti-competitive in the presence of more firms (Zhou, 2017). Furthermore, marketing research on pricing bundles has indicated that bundling is particularly appropriate for information and cultural goods provided through subscriptions (Danaher et al., 2014; Kübler, Seifert and Kandziora, 2021). Broadening on this literature, there are a number of analytic models that analyze pricing and bundling strategies in the context of information goods — goods with high fixed cost and low marginal costs (e.g., Bakos and Brynjolfsson (1999), Geng, Stinchcombe and Whinston (2005), and Hitt and Chen (2005)). For information goods, the majority of these models show that some form of bundling is preferable to pure unbundling. However, we are aware of only a few empirical papers that deal with product bundle pricing using real-world price and sales data. For instance, Crawford (2008) estimates demand for TV bundles and finds that bundling an average top-15 special-interest cable network significantly increases the estimated elasticity of cable demand through reduced consumer heterogeneity. Crawford and Yurukoglu (2012) investigates the effect of television channel bundling on short-run welfare using a structural model, showing that unbundling TV channels enhances consumer surplus but lessens producer surplus. While the majority of bundling research focuses on whether to offer products separately or in the form of a bundle, we are not aware of studies specifically investigating the impact of bundle's pricing on consumer behavior and their level of membership utilization.

The paper is organized as follows. Section 2 introduces the institutional background, while Section 2.1 reviews the age-based price schedule(s). Section 3 presents the data, and Section 3.4 details the dataset construction and samples definitions. Some summary statistics are presented in Section 3.5. Section 4 describes our main econometric specification, and Section 4.2 details how we compute price elasticities. Section 5 describes the main results. Section 6 is devoted to highlight the mechanism behind the results on museum visits. A number of robustness checks is presented in section 7. Section 8 details how we (locally) identify the demand curves for museums' cards. Section 10 discusses the results's implications in term of policy guidance. Section 11 concludes.

2 Institutional background

The “Associazione Abbonamento Musei” (AAM) is a non-profit organization, whose aim is to broaden the usage of museums and promoting the cultural heritage of Turin, Piedmont and Italy more in general[8]. At the heart of the AAM’s activities is the ”Abbonamento Musei” (AM for short), a 1-year subscription card to museums, whose first introduction dates back to 1998. In particular, the card entitles the individual members to enter the affiliated museums, exhibitions, royal residences, villas and gardens *for free*[9]. Importantly, any visit to an affiliated museum represents a cost to AAM, in the form of a museum’s compensation for the free entrance granted by the AM subscription. In particular, as the AAM’s statute prevents it from re-distributing profits to its members, the yearly revenues from the card sales (after deduction of the operating expenditures) are re-allocated to the affiliated museums[10].

After the expansions in 2016 and 2019, the AAM offers nowadays 3 broad categories of museum cards: AM Piedmont - Aosta valley (with over 230 affiliated museums and 120k current members), the AM Lombardy - Aosta valley (with over 200 affiliated museums and 25k current members), and the AM Extra (covering Piedmont, Lombardy and Aosta valley). Although we have data on both the first and third category of cards, we focus on the AM Piedmont - Aosta valley card only, due to the relatively little number of subscriptions and the different pricing schedule associated to the AM Extra.

[8]The project was originally launched in 1995 under the joint initiative of the Turin municipality, Turin district and Piedmont region to manage the municipal cultural events. In 2016, the AAM was formalized as an association and the project was extended to cover Lombardy, while Aosta Valley joined AAM in 2019.

[9]The AM is conceived as an instrument of cultural welfare, aiming at sustaining the local demand for culture and at increasing the engagement of the local audience. For this reason, the card holders are also eligible for special discounts on theater shows, concerts, festivals, events and theme parks.

[10]The AAM makes use of a rather complicated system for determining the exact allocation if its revenues among the affiliated museums. However, informal meetings with the AAM officers revealed that for the years of interest here (2015-2019), the AAM tended to pay back to museums *half* the price of the individual ticket, which is also recorded in their administrative dataset (see section 3

2.1 Price schedule

Our main empirical strategy exploits the presence of multiple discontinuities in the card's age-based price schedule (see Section 4). The current section briefly summarizes how this price schedule has evolved over time.

Until 2013, the AM was sold at a flat price of 49 euro, the only exceptions being a discounted card for special categories of customers, and a 4-euros discount in case of repurchase. Since 2013, the AAM has introduced age-based discounts to further broaden the customer base of the association: the Junior card (people aged 6-14, sold for 20 euros), the Young card (people aged 15-26, sold for 28 euros), the Senior card (people aged above 65, sold for 35 euros)[11]. In November 2014, the price of the Young and Senior card was increased to 32 and 37 euros, respectively; while the standard and the discounted fares went up to 52 and 48 euros[12]. Finally, in November 2017, due to the rising prices charged by museums on elderly customers and the consequent need to adequate fares to maintain a balanced budget, the price of the Senior card increased further to 45 euros. In 2013 the Piedmont local administration introduced, free of charge, a new Youth Card, called *Pyou* card, which entitles young people aged between 15 and 30 to special discounts for cultural, sport and music events. The card targets anyone who is resident or lives in the Piedmont region, lasts 4 years and automatically expires when the subscriber turns 30. Importantly, the Pyou card holders qualify for a special discount to the AM, equivalent in magnitude to the Young card[13]. This implies that there is no incentive to buy a full-price AM between the age 27 and 30 (when the Standard's card price of 52 euros applies), and anyone interested in purchasing the card should choose the Pyou card instead. Figure 1 summarizes the price schedule evolution over the years by card type, and the resulting age-based fare system by time period.

[11] At the same time, the special discounted price for standard cards (30 euros) was evened out to the fidelity fare (45 euros).

[12] With repurchase no longer entitling to a discount.

[13] In addition, the Pyou card can be loaded with the individual public transport or bike sharing subscription, and used as a public transport card. Furthermore, a special reward system is active, with participation to some events granting points which can be redeemed against language courses or special discounts to theater events.

3 Data

3.1 Abbonamento Musei (AM) dataset

We have access to a novel administrative dataset on museum cards purchases and their usage, covering the whole universe of subscribers to the AAM between January 2013 and August 2019. In total, we observe roughly 750k individual subscriptions and have data on the date of purchase, start and expiration date, nominal card price, possible discounts and the resulting net card price. We also have some personal information about the subscriber, including the date of birth, gender, city, zip code and province of residence. In addition, we observe a total of over 5 millions individual visits and have information on the museum where the visit took place, the museum's municipality and zip code, the specific date and time of the visit, and the price of the visit through a normal ticket (as opposed to the free entry granted by the AM)[14]. Importantly, each individual is identified by a time-invariant unique identification code, allowing us to track visits over time and to build a panel of individual-level visits to museums. Exploiting this identifier, as well as the information on the visits' time and on cards' start and expiration date, we consistently match card-level information about the individual subscriptions to individual-level information about the specific visits to museums. This process results in about 30k invalid visits, which are thus discarded[15]; furthermore, slightly less than 30k cards (or less than 1 percent) could not be matched to any available visit, resulting in zero visits for these subscriptions.

Given that the AM explicitly targets resident customers, and that a proof of domicile or residency is needed to be eligible for a Pyou card (see Section 2.1), we limit the sample to subscribers listing one of the municipalities in the Turin district as their residence; the resulting sample still accounts for more than 84% of the original sample size. Additionally,

[14]Specifically, this is (half) the price the individual visitor would had paid, had they entered the museum through a normal ticket. This figure proxies for the museum's compensation for the free entrance granted by the AM subscription.

[15]Specifically, a subscriber's visit is considered to be valid if the visit time falls within the start and expiration date of any of the individual museum cards purchased by that subscriber.

the Young and Senior cards were first introduced in November 2013, which makes earlier subscription data useless for our purposes; in addition, until 2014 the card's expiration date was automatically set at the end of the year, implying that most of the purchases took place in January, and that very few people purchased a card in the following months. Given the relatively short time span between the launch of the age-based cards (November 2013) and the first price change (November 2014), and the different rules related to the card's validity period until 2014, our main sample is restricted to the years between 2015 and 2019.

3.2 ISTAT Population data

In order to study the endogenous response to the age-based discounts, we also need information about people who never subscribed to the AAM. As such, we complement our dataset with the *National Bureau of Statistics* (ISTAT)'s official data on the municipality-level population stock. The figures are disaggregated by year, gender and age, and refer to the number and age of males and females resident in each municipality at the beginning of the year[16]. As we only need population data around the relevant cutoff ages (15 for the Junior card, 27 for the Young card, 30 for the Pyou card, 65 for the Senior card), we limit our attention to the age ranges 11 - 19 for the teenagers, 23 - 33 for the youth and 61 - 69 for the elderly, with a 4 years margin below and above the cutoffs 15, 27 and 65, and a 3 year margin above the cutoff 30 to match the distance from the lower cutoff 27. Figure 2 summarizes the evolution of the population stock over time (2015-2019) for the 3 age groups of interest. As can be noticed, the Turin municipality accounts for the lion's share of the total district's population stock, while very few people live in the mountain villages far from the district's capital.

[16]We only know the figure by *integer* age, meaning that someone aged 25 at the beginning of 2015 may be both very close or very far from the next birthday. This implies that this person may turn 26 either in 2016 (if she was born exactly at the beginning of the year) or in 2015 (if she was born later in the year).

3.3 Additional datasets

Finally, we collect a number of additional datasets to perform some of the robustness checks in Section 7. First, we employ yearly data on gross income and tax revenue provided by the Italian *Ministry of Finance* (MEF). These data are available at the municipality level for the entire period 2015-2019, and at the zip-code (CAP) level for 2015 and 2019 only; they contain detailed information on gross income, both as a whole and broken down by source type [17]. Additionally, we use ISTAT municipality-level data on the per-capita number of people enrolled at university, broken down by field of study, and on the per-capita number of vehicles (cars, motorbikes and buses), as a proxy for the ease of movement across the Turin district.

3.4 Further details

This paper studies how prices change i) the probability of purchase (Section 5.1) and ii) the number of visits and their implied cost (Section 5.2). While the latter only requires matching card-level and visit-level data (see Section 3), studying the membership purchase's response to price changes requires information on *potential* buyers. Section 3.4.1 outlines how we build this sample. Section 3.4.2 details the categories of membership we consider at each age cutoff, and presents the corresponding price discontinuities. Section 3.4.3 reviews our treatment definition (read, the price shift).

3.4.1 Sample construction

Estimating the price effect on the probability of purchase requires kwowing not only the age profile of actual buyers, but also the total stock of people who i) turned the same age, and ii) *could have* potentially bought a card. In this section, we review how we complement our AAM data on card purchases with information on potential buyers from ISTAT. The dataset

[17] In particular, the income categories include properties, employment, self-employment, pension and shareholding. We also consider the total taxable income and the resulting net tax.

construction proceeds in 3 steps.

First, we build a municipality-level dataset consisting of the total stock of population turning any (tenth of) age in any given year between 2015 and 2019, by gender and municipality (henceforth *raw* population stock). As we do not observe the actual individual birth dates from the ISTAT data, we are forced to work under the assumption of a *uniform distribution* of birth dates within each 1-year age group. In particular, the stock of population from ISTAT is binned in age groups of a tenth of year, and the age at purchase of actual subscribers (from AAM) is rounded down to a tenth of year as well.[18]. However, this dataset does not take into account that a fraction of these individuals is actually not eligible to buy a card, simply because they already have a valid card which is not expired yet. For this reason, as a second step we consider the card-level data from AAM, and collapse it to an aggregated dataset recording the number of valid cards, by gender, municipality, year and (tenth of) age (henceforth *ineligible* population stock). Third, we drop the *ineligible* population from the *raw* population stock, and turn it into an individual-level dataset only recording people who could have bought a card (*eligible* population). The final dataset is then obtained by superimposing the latter with the card-level dataset from AAM, thereby brokening down the total population stock in the Turin district by a binary condition for having a valid card or not.

3.4.2 Samples definition and price discontinuities

We now present the categories of membership included in the samples around each relevant cutoffs (15, 27, 30 and 65) and show how the theoretical price schedule overlaps the actual price trajectory, as obtained from a local polynomial approximation (see Figure 3).

The sample around the cutoff 15 (henceforth, "Sample around 15") includes the Junior cards (20 euros) to the left of the cutoff (83% of the subscriptions), and the Young and Pyou cards

[18] For instance, the total number of females turning 25.5 in Turin during 2015 will be given by: females aged 25.5 at the beginning of 2015; females aged 25.4 at the beginning of 2015 (turning 25.5 0.1 years after the beginning of the year); ... ; females aged 24.6 at the beginning of 2015 (turning 25.5 0.9 years after the beginning of the year).

(32 euros) to the right of the cutoff (60% of the subscriptions, the main excluded categories being special categories of free tickets[19]), in addition to the non-subscribers. The sample size is above 7 million observations, equivalent to 99.93% of the total population stock. Figure 3 shows that the sample almost perfectly matches the theoretical price schedule.

The sample around the cutoff 27 (henceforth, "Sample around 27") includes, besides the non-subscribers, the Young and Pyou cards (32 euros) to the left of the cutoff (67% of the subscriptions[20]) and the Pyou and Standard cards to the right (81% of the subscriptions), the latter either at full (52 euros) or discounted (48 euros) price. The total sample size is almost 8 million observations, representing roughly 99.9% of the total population stock. Instead, the sample around the cutoff 30 (henceforth, the "Sample around 30") is conceptually different. Indeed, if the eligibility to treatment (read, the price change) around the cutoffs 15, 27 and 65 is based only on the individual age, the eligibility to treatment around the cutoff 30 requires an additional condition, namely being *informed* about the existence of the Pyou card[21] For this reason, among the subscribers we limit our attention to those individuals whose last card before age 30 is a Pyou card, and also include in the sample a number of non-subscribers equivalent to the proportion of Pyou cards before age 27. The idea is that, as before age 27 both the Pyou and Young card grant the same benefits and are priced the same (32 euros), there is no particular incentive from a visitor's standpoint to buy either card and therefore to gather information; still, the Pyou card gives right to additional non museum-related benefits (see Section 2.1), which makes this card worth purchasing for a general customer. As a consequence, we use this figure to proxy for the stock of population in the Turin area randomly informed about the existence of the Pyou card, and thus subject

[19] In particular, a major category is represented by free cards granted to students of the artistic high school "Passoni", whose museum visits likely took place as school trips as established by their school's policy.

[20] The main excluded cards here are the student cards, representing 18% of the total.

[21] A prospective purchaser above age 27 who is not informed about the Pyou card would be charged the Standard card's fare (52 euros), and there would be no price discontinuity at the 30-years-old threshold for this kind of individual. Only those who are *informed* about the card are subject to the price change, irrespective of whether they purchase the card or not.

to the price change[22]. Being a selected sample, the (still large) sample size shrinks when compared to the other samples (roughly 1 million and a half). Figure 3 shows the actual price schedule nicely overlaps the theoretical one only below the threshold 27 (where the AAM and Pyou rules are identical and we only consider Young and Pyou cards, both priced the same). Between the age 27 ad 30, the sample averages the Pyou card's fare (32 euros) with the full-price and discounted Standard card prices (48 and 52 euros), which explains the discrepancy from the official price schedules; above age 30, the deviation from the (again overlapping) AAM and Pyou schedules is due to the presence of the discounted Standard cards (48 euros).

Finally, the sample around the cutoff 65 (henceforth, "Sample around 65") is constructed in a similar manner to the samples around 15 and 27, with the only difference that we build two different samples before and after November 2017 (when the Senior fare was raised from 37 to 45 euros). In addition to those who do not buy any card, this sample includes the Standard cards to the left of the cutoff, either at full or discounted price (72% of the total subscriptions), and the Senior cards to the right of the cutoff (95% of the total subscriptions). However, as highlighted by the AAM officers, the AAM stores usually agree to sell a Senior card to customers who have entered the calendar year of their 65th birthday, despite not having turned 65 yet. This results in a non-negligible portion of Senior cards being sold to individuals aged between 64 and 65 (12% of the total subscriptions of people aged 61-65), which are thus included in the sample, bringing the overall sample size to the left of the cutoff to 85.5% of the total subscriptions. The total sample size is above 6 millions for the period January 2015 - November 2017, and almost 4 millions for the period November 2017 - August 2019. Figure 3 shows that the correspondence with the official price schedule is perfect after the cutoff 65 (where we only consider the Senior cards), while the small discrepancy before age 64 is again due to the discounted Standard cards (48 euros). The informal sale of Senior cards to those who have already entered their 65th year despite not being 65 years old yet

[22]Note that this sample can be interpreted as the sample of individuals informed about the Pyou card, irrespectively of whether they purchase it or not before age 30.

is apparent from the graph in tha age range 64-65.

3.4.3 Treatment status

We next move to the description of the treatment status indicator, denoting whether an individual is subject to the official price as established by the age-based price schedule[23].
In the sample around 15, all the cards to the left and the right of the cutoff are paid the same (20 and 32 euros respectively); in addition, as both the Young and Pyou cards entail the same price rise at the same age cutoff 15, and there are no other discounts available, the non-purchasers are subject to the exact same prices, which results in a perfect jump in the probability of compliance at the threshold.
In the sample around 27, nobody located to the left of the cutoff and purchasing a card is charged a price different from 32 euros (the official price); this also applies to those who do not buy a card, as they are subject either to the Young or the Pyou's fares. When we move to the right of the cutoff, those purchasing a Standard card at full price (52 euros, the official price) are considered as compliers, while those paying differently (48 euros for a Standard card at reduced price, or 32 euros for a Pyou card) are considered non-compliers[24].
A key difficulty is the determination of the fraction of population not purchasing a card but *informed* about the Pyou card, and thus still subject to the reduced price (32 euros) despite being to the right of the cutoff. As we lack this type of information, consistently with the discussion in Section 3.4.2, we operate under the assumption of a random distribution of information among non-purchasers, and impute as "non-informed" a proportion equivalent to the share of non-Pyou cards below the cutoff 27; this results in roughly 73% of the overall sample to the right of the cutoff being denoted as complier with the official rule.
A similar line of reasoning can be applied to the sample around 65. Here, among card holders, only Senior cards (37 or 45 euros, depending on the specific period) are present to the right

[23]In particular, those individuals denoted by 0 when located to the left of the cutoff, and/or denoted by 1 when located to the right, are considered to be compliers with the official price schedule.

[24]Overall, roughly 46% of the card purchasers to the right of the cutoff 27 are denoted as compliers.

of the cutoff, and the same fares apply to those who don't purchase a card; as such, the whole sample to the right of the cutoff is denoted as complier. To the left of the cutoff, only those who purchase a Standard card at full price (52 euros, the official price) are denoted as compliers, while those who pay the reduced fare (48 euros) are obviously considered non-compliers. Additionally, as a non-negligible part of the card holders purchase a Senior card before turning 65, thereby paying the reduced fare before reaching the cutoff point, they are denoted as non-compliers as well[25]. In any case, since this only depends on the willingness of the AAM officers to grant a price discount beforehand, we believe it is very unlikely that non-purchasers of the card are aware of this possibility, and consistently consider all the non-purchasers to the left of the cutoff as compliers.

Finally, in the sample around 30, we again denote as compliers those who do not buy a full-price (52 euros) standard card before age 30, and those who do after age 30. As this is a selected sample, all the non-purchasers to the left of the cutoff are by definition considered to be informed about the Pyou card (therefore subject to the official price of 32 euros); additionally, all the non-purchasers to the right of the cutoff are considered to be subject to the full official price, as we believe it very unlikely that these selected people would not purchase a card, were they entitled to a significant price discount; as such, all the non-purchasers are denoted as compliers[26].

3.5 Summary statistics

Panel A of Table 1 contains summary statistics for both the total sample (purchasers and non-purchasers) and purchasers only, broken down by sample as outlined in Section 3.4.2. The probability of purchase tends to rise with age, ranging from a minimum of 0.2% for teenagers around age 15 to 0.7% for elderly around age 65. Depending on the specific age

[25] This results in roughly 10k cards in the period January 2015 - November 2017, and roughly 6k cards in the period November 2017 - August 2019, to be denoted as non-complier with the official price schedule.

[26] The small deviations from a perfect sharp design are due to a small number of people buying a full-price standard card before age 30, and to a non-negligible portion of previous holders of a Pyou card moving to a card different from a full-price standard card as they turn 30.

group, between 35% and 40% of the total sample is from Turin, and all the samples are well balanced in terms of gender, with a slight prevalence of males among younger cohorts and females in older ones. Limiting the attention to purchasers, we find that the card-level number of visits tends to increase with age, ranging from almost 5 for teenagers to 8.5 for elderly people; the equivalent cost of the visits follows the same trend, with a minimum of 20 euros for people around age 15, and a maximum of 41.5 for subscribers around 65, although members around the age cutoffs 27 and 30 still show averages in the neighborhood of 40. Consistently with the price schedules shown in Figure 1, the nominal and net card's price tend to increase with age as well, although this does not hold for the sample around 30, whose average card's price is about 5 euros less than what paid on average by subscribers around age 27. This can be readily explained by the larger share of subscribers purchasing a full-price card as they reach age 27, and by the stronger price response shown by the (informed) subscribers around 30, consistently with the higher degree of information at their disposal. Finally, irrespective of the specific age group, purchasers are shown to be mostly females, with more than half of them being from the Turin municipality.

Panel B of Table 1 summarizes the treatment status indicator, again broken down by sample and time period when relevant. Consistently with the discussion in Section 3.4.3, the results show that while the jump in the probability of getting treated is perfect for the sample around 15, the compliance with the official price schedules is still remarkable around the other age thresholds, implying strong first stage statistics. This holds both for total sample including subscribers and non-subscribers (rows 1-2), and the sample of purchasers only (rows 3-4).

4 Econometric Specification

4.1 The model

In order to estimate the average price impact on the AM probability of purchase and on museum visits (visits' cost), we employ a regression discontinuity (RD) model exploiting the price discontinuities at the age cutoffs 15, 27, 30 and 65, whose details are briefly presented. Except for the sample around 15, the received treatment is not a deterministic function of the running variable X_i, which calls for a fuzzy RD designs. Instead, the probability $\mathbb{P}(T_i = 1|X_i)$ is between zero and one on both sides, but undergoes a sharp change at the cutoff. When elected to treatment ($Xi \geq \underline{x}^{age}$), unit i's actual treatment status and outcome are represented by functions $T_i(1)$ and $Y_i(1)$; otherwise, they are $T_i(0)$ and $Y_i(0)$. Thus, the observed treatment status and outcome are

$$T_i = T_i(0)1(X_i < \underline{x}^{age}) + T_i(1)1(X_i \geq \underline{x}^{age}) \tag{1}$$

$$Y_i = Y_i(0)1(X_i < \underline{x}^{age}) + Y_i(1)1(X_i \geq \underline{x}^{age}) \tag{2}$$

where both are based on the individual subscriber's age X_i and the four age thresholds $\underline{x}^{age} \in \{15, 27, 30, 65\}$. The treatment effect is recovered by dividing the intent-to-treat (ITT) effect by the difference in the probabilities of getting treated (first stage)

$$\zeta = \frac{\mathbb{E}\left[Y_i\left(1\right) - Y_i\left(0\right)|X_i = \underline{x}^{age}\right]}{\mathbb{E}\left[T_i\left(1\right) - T_i\left(0\right)|X_i = \underline{x}^{age}\right]}, \tag{3}$$

where the intent-to-treat (ITT) effect is given by the difference in the counterfactual outcomes $Y_i\left(T_i\right)$ computed at the threshold. The identification of these sharp RD treatment effects relies on the assumption that the conditional expectation functions $\mathbb{E}\left[Y_i\left(t\right)|X_i = x\right]$ for $t \in \{0, 1\}$ and $\mathbb{E}\left[T_i\left(t\right)|X_i = x\right]$ for $t \in \{0, 1\}$ are continuous at the threshold (Hahn, Todd and Van der Klaauw (2001)).

Calonico et al. (2019) provide further conditions for non-parametric identification of the RD treatment effect with additional control variables (such as fixed effects) included in a vector $\mathbf{Z}_i$. We follow their approach, assuming additive separability between the running variable (i.e., age) and these covariates, and a linear specification for the latter but a fully non-parametric specification for the former.[27] Under these assumptions, the covariate-adjusted RD treatment effect estimator can be obtained through a weighted local linear regression of the form:

$$\hat{Y}_i = \hat{\alpha} + T_i\hat{\tau} + X_i\hat{\beta}_- + T_iX_i\hat{\beta}_+ + \mathbf{Z}_i'\hat{\gamma}. \tag{4}$$

which results in a consistent estimator as long as there is no RD treatment effect on the covariates.[28]. In order to control as much as possible for time trends and socioeconomic characteristics potentially correlated with cultural consumption, our baseline specification includes year and geographical fixed effects, the latter being defined as Area fixed effects when analyzing the probability of purchase (municipality for Turin, zip code for municipalities other than Turin), and Municipality fixed effects when analyzing the number (cost) of the visits[29]. As an additional specification, we also include Gender fixed effects.

The regression is local because it exploits only observations in a neighborhood of the threshold, i.e., with $X_i \in [\underline{x}^{age} - h_l, \underline{x}^{age} + h_r]$; we select the optimal bandwidths h_l and h_r through the data-driven procedure of mean square error optimization. In particular, when analyzing the probability of purchase, due to computational constraints we limit the samples to a neighborhood of 3 years around each age threshold, and employ a symmetric bandwidth on both sides of the cutoff; when studying the response of the visits (and visits' cost), we only restrict the samples until the previous and subsequent age cutoff, and allow for asymmetric bandwidths on each side[30]. The weighting of observations is determined by the choice of kernel $K\left(\left(X_i - \underline{x}^{age}\right)/h\right)$; we adopt a triangular kernel function, which down-weights observations linearly as a function of their distance from the threshold. While we have written

[27]This approach to RD covariate adjustment assumes linearity in parameters for the covariates, but otherwise allows for flexible transformations of the original covariates and admits regressors of all kinds, including discrete variables.

[28]This assumption is weaker than requiring $\mathbf{Z}_i(0)$ and $\mathbf{Z}_i(1)$ to have identical marginal distributions at the threshold, which is the usual assumption of predetermined covariates in an experimental setting.

[29]Due to the large sample sizes, it was computationally unfeasible to control for municipality fixed effects in the RD regressions on the probability of purchase.

[30]As the age cutoff 30 is very close the cutoff 27 and only relevant for the selected sample of informed individuals, we don't consider this threshold when determining the age range for the RD regressions around age 27 and 65.

Equation 4 linearly for simplicity, this approach can be used for a local polynomial estimator of arbitrary order; although our preferred specification employs a 1st order polynomial fit, we also test for a 2nd order fit as a robustness check. We cluster the standard errors at the year-municipality-gender level.

4.1.1 Donut approach

The continuity of the running variable's density around the threshold is the key identifying assumption for the RD treatment effect estimator. We assess the threat of such manipulative sorting both for the total sample (purchasers and non-purchasers) and the sample limited to subscribers only.

Figure 4 plots the histogram and the corresponding McCrary (2008) test of discontinuity in density for the probability of purchase, implemented by local polynomial density estimation methods (Cattaneo, Jansson and Ma (2020)). The figure shows that the sample construction detailed in 3.4.1 was successful in re-introducing non-subscribers into the sample, thus resulting in a balanced density around the relevant threshold. Consistently with the RD effects on the probability of purchase (see Section 5), Figure 5 shows instead i) spikes in the cards' density immediately before price rises and immediately after price drops, and ii) systematic changes in the cards' average density before and after the threshold, with larger mass where the price is smaller. We tackle the first issue by applying a Donut-Hole approach to both samples, and nevertheless interpret the RD estimates on visits' number and equivalent cost as purely descriptive. Figures 4 and 5 show the age bins which are excluded from the estimation[31].

[31] As the density spikes are always included in the first tenth of year before or after the age cutoff, the Donut approach applied to the probability of purchase simply entails dropping the closest age bin on either side of the cutoff.

4.2 Elasticity

Exploiting the RD treatment effects as outlined in the previous section, we can also compute the cutoff-specific price elasticities through a simple mid-point formula, which makes the calculation independent of the start and end price.

Let the price levels, the bandwidths and the first available age bins (taking the Donut approach into account) below and above the cutoff $\underline{x}^{age}$ be denoted as P_l and P_r, h_l and h_r, and x_l^{age} and x_r^{age} respectively. Furthermore, consider the population stock either within the RD bandwidths, or in the age bins closest to the Donut hole, defined as

$$Population = \begin{cases} \sum_i 1\left(\underline{x}^{age} + h_r \geq X_i \geq \underline{x}^{age} - h_l\right) \\ \sum_i 1\left(X_i \in \{x_l^{age}, x_r^{age}\}\right) \end{cases} \tag{5}$$

and the corresponding number of cards, defined as

$$Cards = \begin{cases} \sum_i 1\left(Card_i = 1, \underline{x}^{age} + h_r \geq X_i \geq \underline{x}^{age} - h_l\right) \\ \sum_i 1\left(Card_i = 1, X_i \in \{x_l^{age}, x_r^{age}\}\right) \end{cases} \tag{6}$$

The (absolute) elasticity can then be computed as

$$\epsilon_p = \frac{|\hat{\gamma}| * Population * (P_l + P_r)/2}{Cards * |P_l - P_r|} \tag{7}$$

where $\hat{\gamma}$ is the RD estimate of the price effect on the probability of purchase; given the large price variation on the two sides of the cutoff, we refer the elasticity to the mid-point price.

5 Results

5.1 Purchases

We begin our empirical analysis by evaluating how the purchase of the AM subscription reacts to exogenous changes in price. Figures 6 and 15 illustrate the probability of purchase around the age cutoffs 15, 27, 30 and 65, employing a 1st or 2nd order polynomial fit, respectively. Besides sharp jumps in the purchase probability, the figures are also indicative of strategic sorting around the threshold, which motivates the exclusion of the orange age bins from the RD estimation to address the imbalanced probability of purchase around the threshold (Donut approach, as outlines in Section 4).

Panel A of Table 2 contains our preferred Donut-Hole RD estimates for the samples around 15, 27 and 30 (January 2015 - August 2019) and for the sample around 65, separately for January 2015-November 2017 and November 2017-August 2019. All the RD models employ a 1st order polynomial fit and control for year, gender and area fixed effects. The reported estimates are already scaled by the first stage coefficient (second-stage), and comparable across thresholds in terms of a 10$ variation; for each (fuzzy) specification, we also report the estimates of the first stage model.

Pooling all groups, the effects of an exogenous change in prices on purchases of the AM subscription are statistically significant and quantitatively sizable. On average, the probability to purchase an AM falls by 0.028 percentage points at the 15-years-old threshold, 0.114 percentage points at the 27-years-old threshold, and 0.301 percentage points at the 30-years-old threshold. At the 65-years-old threshold, the probability of purchase drops by 0.18 and 0.35 percentage points before and after November 2017 respectively, which is consistent with a larger demand response at a higher starting price (45 euros, as opposed to 37). Cumulating the effects over a 1-year period (the normal validity period of a card), the estimates imply roughly a 1.15% drop in the probability of holding a valid card at age 27, and a 3% drop at age 30 among informed people; for the elderly, these effects amount to 1.8%

and 3.5%, depending on the time period. In terms of elasticities, the informed sample in the neighborhood of age 30 is the most responsive, with a price elasticity around 2.6, while the teenagers around age 15 are the least responsive group, with a price elasticity around 0.5. Consistently with the lower amount of information at their disposal, the uniformed sample around age 27 is less elastic than its informed counterpart at age 30, with a price elasticity around 1.4. In parallel, the demand elasticity of the elderly after the Senior fare increase in November 2017 is more than double the one before November 2017, which implies a concave demand function under the assumption of no structural demand changes. In general, young people are shown to be quite elastic, and membership visitors are overall more elastic than simple ticket visitors. These findings are in general robust to increasing the order of the local polynomial fit and to the choice of the fixed effects, as shown in Table 3, Table 4, Table 5 and Table 6 ; the only exception are the 2nd order specifications in the sample around 15, where the point estimates rise in magnitude but also lose precision. In general, the choice of a 2nd order fit rises the elasticity's estimates at the age cutoff 27 and 65, but lowers the ones at age 30, with the final result of elasticities for both the uninformed and informed subscribers (cutoffs 27 and 30) in the range 2.1-2.3, and a maximum elasticity of 4 estimated on the post-November 2017 sample around 65.

5.2 Visits

We proceed to study whether there is any discontinuous pattern in museum visits by age group. The analyzed outcomes are twofold. First, we report our effect in terms of number of visits. Second, we construct a measure of their equivalent cost, where we recover the value of each visit in terms of admission fees through a normal ticket. Figures 7 and 8 illustrate the (sharp) RD effects on the number and cost of visits, respectively, employing a 1st order polynomial fit. Figures 16 and 17 show the same RD effects using a 2nd order fit.

Panel B and C of Table 2 present our preferred RD estimates for the number and cost of the visits, respectively, where we employ a 1st order fit and the full set of year, gender and municipality fixed effects. Although we don't find significant effects at the age cutoff 15 (column 1), the number and cost of the visits rise by around 0.4 and 4.9 per subscription at the 27-years-old threshold (column 2) in response to a 10 euros increase in the card's price, and the strong first stage confirms the presence of a discrete jump in the probability of paying the full price (52 euros). Although the first and second stage point estimates at the threshold 30 follow the same pattern, the large estimates' variability does not allow us to draw definite conclusions about this sample. This is likely due to the limited sample size to the right of the cutoff, as also confirmed by the large confidence intervals in Figure 7 and Figure 8. All these estimates are virtually identical when including or omitting the gender fixed effects and when raising the polynomial fit to the 2nd order in Table 7, Table 8 and Table 9, although the 2nd order effects at the threshold 27 are somewhat less precisely estimated. Columns 4 and 5 of Table 2 also show the corresponding estimates for the sample around 65, before and after November 2017, which are instead highly significant and economically sizable. In column 4 (pre November 2017), the museum visits falls by 1.125 per subscription, and the equivalent cost decreases by roughly 30 euros in response to a 10 euros price increase at the 65-years-old threshold. In column 5 (post November 2017), the effects are even higher, with the number and cost of the visits dropping by 2.3 and 51.4, respectively. Once again, Table 10 shows that these results are robust to increasing the order of the local polynomial fit and/or to the choice of the fixed effects. However, as subscribers start purchasing the Senior card as they turn 64 (see section 3.4.2), we also acknowledge that this could artificially lower the first stage estimate, thereby increasing the second stage results. As an alternative specification, we therefore apply an Asymmetric Donut-Hole approach, where the entire stock of subscribers in their 65th year is dropped from the estimation. The results are shown in table 11. As predicted, the first stage rises and the second stage drops, but the estimates remain highly significant and economically sizable (especially in terms of visits' cost): at minimum, the number and cost of visits decrease by 1 and 26 per subscription, respectively. On the whole, the results are fully robust to this alternative specification.

6 Behavioral effects vs pure selection

As far as the results in terms of visits' number and cost are concerned, they are interesting, but not conclusive: the jumps at the different thresholds could be either the effect of pure sample selection induced by the price shifts, or a true change in consumer behavior. To disentangle the two mechanisms, we provide further causal evidence shedding light on the pure behavioral component.

6.1 Diff-in-diff model

Specifically, we exploit the fact that the first card subscription (valid for 1 year) also determines the moment when the subscription can be potentially renewed. Our diff-in-diff strategy then consists in focusing on the age cutoff located 1 year (2 years) before the official age threshold (henceforth, diff-in-diff cutoff)[32], and comparing those purchasing a card just below this cutoff (thus able to renew before the official age threshold at the *same* fee) with those purchasing a card just after the diff-in-diff cutoff (thus able to renew only after the official age threshold at a *different* fee). Clearly, our identifying assumption is that there is *no anticipation effect*, meaning that the moment when a card is purchased is not strategically chosen so as to re-purchase the next one at a cheaper fee. In order to maximize the comparability between treatment and control, we keep track of the number of cards purchased until the individual enters the treatment or control group, and condition on that when comparing the two groups. As the necessary condition for entering the diff-in-diff specification is purchasing at least 2 cards, the sample sizes are not as large as the ones in Section 5.

In particular, our diff-in-diff specification is

$$Y_{it} = \alpha + Treat_i + Post_t + \delta * (Treat_i * Post_t) + \alpha_{cards} + \alpha_{year} + \alpha_{gender} + \alpha_{geo} + \epsilon_{it} \quad (8)$$

[32] Specifically, for the samples around 15, 27 and 30 we consider the cutoff ages 14, 26 and 29, 1 year earlier than the price shift. For the sample around 65, as a large portion of the sample already has a Senior card at age 64, we consider the age 63 as the diff-in-diff cutoff, and consider as treated those who after age 64 purchase a Senior card as their 2nd card. This maximizes the sample size, as it is relatively easier to find people with a full-price standard card around age 63 than around age 64.

where Y_{it} denotes the outcome of interest, $Treat_i$ is the treatment indicator, $Post_t$ in a dummy for the 2nd card, δ is the diff-in-diff estimate of interest, α_{cards} are "previous cards" fixed effects, and α_{year}, α_{gender} and α_{geo} are year, gender and geographical (either area or municipality) fixed effects. In particular, the individuals in the treatment group are those purchasing their first card right after the diff-in-diff cutoff; we consider both a margin of half year and a year around this cutoff. As as aside, the treatment indicator $Treat_i$ captures any difference in the endogenous behavior (either in terms of visits or visits' cost) across treatment's and control's *first cards*, thus indirectly testing for differences *before* any price change. The standard errors are clustered at the individual level.

6.2 Results

Table 12 shows the results on the sample around 15. Consistently with the results in Table 7, these teenagers are shown not to behaviorally respond to the change in price as they turn 15. However, as they purchase a new card, they tend to make fewer but more expensive visits to museums, irrespective of whether they belong to the treatment or control group.

Table 13 contains instead the results for the sample around 27. The results show that, employing a half-year margin around the diff-in-diff cutoff (26), a 20 euros increase in the card's price rises the average number of visits by more than 2 (columns 1-3), which translates in a 27 euro increase in equivalent cost (columns 4-6), although these effects are not precisely estimated. Importantly, the treatment indicator is never significant, suggesting a similar use of the first card across treatment and control subscribers, both in terms of quantity and quality of visits. Expanding the margin to a year around the diff-in-diff cutoff (columns 7-12), the behavioral responses in terms of visits and visits' quality are now more precisely identified, irrespective of the specification's choice. Although the treatment indicator becomes significant as well, this is not necessarily bad, as treated subscribers are shown to use *less* the first card when compared to control. In other words, *despite* a lower usage of the first card, the treatment (read, the price rise) is shown to completely revert this initial selection bias in the 2nd card, suggesting strong *behavioral effects*. Moreover, the effects in columns 7-12 are comparable in terms of magnitude to those in columns 1-6 (1.7 in terms of visits, 23 in terms of visits' cost), suggesting that the influence of the worse treatment-control comparability is negligible.

Although the price jump at the age cutoff 30 is shown not to induce a response in terms of visits (visits' cost) in Table 9, Table 14 shows that these subscribers still exhibit a behavioral response to the price change as they turn 30. In particular, employing a half-year margin around the diff-in-diff cutoff 29, the results show a 1.4 rise in the number of visits, and a 14 euros rise in the cost of visits in response to a 20 euros increase in the card's price. These responses are again robust to the specification choice. Moreover, consistently with the greater amount of information at their disposal, these (informed) 30-years-old's behavioral responses are smaller than the ones we find for the (uniformed) 27-years-old (Table 13).

Similarly, Table 15 reports the results for the sample around 65, separately for January 2015 - November 2017 (price variation 52-37, Panel A) and November 2017 - August 2019 (price variation 52-45, Panel B). Using either a half-year (columns 1-6) or a 1-year margin (columns 7-12) around the diff-in-diff cutoff 63, a 15 euros decrease in the card's price is shown to reduce the card utilization by an (imprecisely estimated) 0.3 visits per subscription, which also translate in a (better identified) 10/12 euros reduction in the visits' equivalent cost. The absence of systematic treatment-control differences in the pre-treatment card in columns 1-6, both in terms of visits and equivalent cost, are reassuring of an appropriate definition of the control group. However, when extending the margin around the diff-in-diff cutoff to a whole year (columns 7-12), the treatment and control samples lose evidence of balance in the first card's utilization; for this reason, our preferred estimates are the ones in columns 1-6. Consistently with the smaller price variation across treatment's and control's second cards from November 2017 (7 euros), we don't find evidence of behavioral responses in this time period (panel B).

When comparing the RD effects on the visits (visits' cost) with the diff-in-diff behavioral responses, we conclude that a mechanism of pure sample selection may be relatively more important in explaining the results on the senior sub-sample, while the results on the youth are mostly consistent with strong behavioral responses. For instance, after re-scaling the diff-in-diff estimates for the 27-year-olds in Table 13 to represent the effect for a 10 euros price increase, we find that the behavioral effects are more than double the RD estimates, suggesting that the latter are driven by those re-purchasing a card at a 20-euros surcharge. On the contrary, the behavioral effects in Table 15 account for only 25% of the RD estimates in Table 11, and even less when considering Table 10. These findings are consistent with a mechanism of price-induced selection getting more important among the older cohorts, where the larger time availability arguably translates into more systematic price search's efforts.

7 Validity Tests

Our estimates of the RD treatment effects crucially rely on the testable identifying assumption that subscribers around the threshold are similar in observable characteristics, except for the price effect on purchases and visits. We first formally test the validity of this assumption through covariate-balance exercises around the threshold, where we replicate the econometric model detailed in 4 using a variety of municipality-level outcomes; as these variables only show variation by municipality and year, we omit municipality and year fixed effects.

First, we focus on *per-capita* taxable income and net taxes. The results for these income-related variables are shown in Table 16, where we find strong evidence of income being balanced around the threshold. The results are fully robust to the choice of the local polynomial fit's order, and to the inclusion of gender fixed effects. This confirms the RD design was successful in identifying the price elasticity while ruling out income effects. The same conclusions also apply to Table 17, where we perform a second balance exercise on the individual-level residency's latitude, longitude and distance from Turin, as well as on the municipality-level residency's *per-capita* vehicles, proxing for the ease of movement across the Turin district. Once again, the results suggest a perfect sample balance around the threshold. The results in Table 17, where we check how the per-capita number of university students are sorted around the threshold, are perfectly balanced as well.

Next, we present placebo tests that replicate our main result from Table 2 for irrelevant cutoffs above and below the 4 thresholds (15, 27, 30 and 65). In particular, in order to stay sufficiently far away from the true age cutoffs, we limit our attention to age thresholds which are at least 1 year before and after each true cutoffs; as senior subscribers start purchasing the Senior card as they turn 64, we consider a margin of 2 years before age 65. Following Cattaneo, Idrobo and Titiunik (2019), we perform these tests separately for treated and untreated observations, to rule out contamination from the actual treatment effect[33]. The results on the probability of purchase, the number of visits and the equivalent cost of the visits are presented in Figure 9, Figure 10 and Figure 11, respectively. Reassuringly, virtually all the point estimates of the RD treatment effects at placebo thresholds are below our true estimate, with p-values usually above .05.

As a final validity check, we also expand the Donut hole to 0.2 years before and after each threshold and test for the results's robustness, both in terms of probability of purchase (Appendix Tables A1 - A4) and visits' number/cost (Appendix Tables A5 - A8). Except for Table A1, the results are fully in line with those presented in Section 5, with the 1st order specifications in Table A5 now better identifying an effect on the visits' equivalent cost for the sample around 15. The standard errors on the visits' number and cost around the age 27 slightly rise in Table A6 when compared to Table 8, but the overall conclusions hold unchanged. On the whole, the results are robust to this alternative specification.

[33] If the regression function is truly continuous for a given treatment status, this placebo design guarantees by construction that the treatment effect is zero at every artificial threshold.

8 Local demand identification

One the main advantages of our RD quasi-experimental setting is to provide for price discontinuities at the age threshold, allowing us to identify the changes in demand only due to the price shift, and to rule out income effects or structural breaks in the demand curve. Focusing on a neighborhood of the age threshold, the perfectly elastic supply curves to the left and to the right of the cutoff are then sufficient to (locally) identify two points of the demand curve. Additionally, the RD estimate at the threshold provides for an additional condition, namely the local slope of the demand curve. Admittedly, the large price changes at the threshold are not ideal to estimate the local demand slope, as they pose the problem as to where the RD slopes should be located. For this reason, we operate under the two extreme scenarios where the local RD slope applies to either of the previously identified points, and build a confidence interval-like region where the demand curve is arguably located. Under the assumption of a quadratic demand curve, this procedure results in a (local) identification of the demand curve for museum cards.

Specifically, let P_l and P_r be the official price levels to the left and right of the cutoff, respectively. Let $\hat{\gamma}$ be the RD estimate, and define the local probabilities of purchase to the left and right of the cutoff as

$$Prob_l = \frac{\sum_i 1\left(Card_i = 1, \underline{x}^{age} > X_i \geq \underline{x}^{age} - h_l\right)}{\sum_i 1\left(\underline{x}^{age} > X_i \geq \underline{x}^{age} - h_l\right)} \tag{9}$$

$$Prob_r = \frac{\sum_i 1\left(Card_i = 1, \underline{x}^{age} + h_r \geq X_i \geq \underline{x}^{age}\right)}{\sum_i 1\left(\underline{x}^{age} + h_r \geq X_i \geq \underline{x}^{age}\right)} \tag{10}$$

where h_l and h_r are the RD bandwidths, and $\underline{x}^{age}$ is the relevant age threshold. The unknown parameters a, b and c are then found by solving the following linear system

$$\begin{cases} P_l = aProb_l^2 + bProb_l + c \\ P_r = aProb_r^2 + bProb_r + c \\ 1/\hat{\gamma} = 2aProb_{l/r} + b \end{cases} \tag{11}$$

where the first two conditions identify the intersections with the pre-cutoff and post-cutoff perfectly elastic supply curves, and the third condition provides a slope condition as estimated in Table 2.

The local demand curves around the age cutoffs 15, 27 and 30 are shown in Figure 12. Consistently with our previous discussion, the (informed) subscribers around the age threshold 30 are the most elastic, while teenagers around the age cutoff 15 exhibit the most rigid demand curve. Consistently with the lower amount of information at their disposal when compared to their 30-years-old counterparts, the subscribers around the age 27 are somewhat in between. Figure 13 shows the demand curves around the age threshold 65, both before and after November 2017. Interestingly, the two demand curves are almost perfectly overlapping, which could be indicative of the absence of structural demand changes over the entire period 2015-2019. This reinforces our confidence in the estimates' suitability for policy prescription.

9 Substitution effects

In this section, we explore whether a price change in the AAM card triggers a consumers' response in terms of purchased tickets. In order to test for this, we employ the aggregated museum-level data on tickets sold over the period 2012-2020 and provided by the Osservatorio Culturale del Piemonte (OCP). In particular, the OCP dataset records the sales of 3 different categories of tickets: full-price, discounted, and free tickets. In order to allow for a cleaner comparison and provide for a control group, we focus on the price change episode on November 2017, where only the Senior card fare was affected (8 euros rise), while the others were left unchanged. As potential senior card holders would be entitled to age-based discounts on ticket purchases, we would expect a substitution effect (if any) to affect the stock of discounted tickets, and to find no effect on the stock of full-price and free tickets. Unfortunately, the OCP dataset does not identify the reason for the price discounts, and we acknowledge that reasons other than age might be partially responsible for the price reduction. In particular, the stock might also include tickets sold to young or special categories of visitors. However, as the price schedule on the Young card was left unchanged, we can safely ascribe any *change* in the stock of discounted tickets to the Senior card price change; additionally, the age structure of the Turin population, as well as the age distribution of the typical card purchasers, make this concern of second-order magnitude. Still, the results should be interpreted with caution.

We employ a panel event study approach, where we analyze the monthly evolution of the stock of discounted price tickets following the 8 euros rise in the Senior card fare. We restrict attention to those museums included in the AAM subscription. Our time series display both a stagionality and a trend component, which we tackle by a 12-months difference, and by differencing with respect to the control group, respectively. That is, we double-difference the series according to

$$(Y_{i,t}^{disc} - Y_{i,t-12}^{disc}) - (Y_{i,t}^{j} - Y_{i,t-12}^{j}), \quad j \in \{full\text{-}price, free\} \tag{12}$$

Figure 14 shows the results. While we managed to smooth-out most of the pre-trend and the stagionality component, we find limited evidence of a substitution effect across museum cards and tickets. Consistently with the stagional pattern of the card purchases, we see a lag in the response of tickets, which is likely due to most of the cards being still valid at the moment of the price change. Moreover, this response is only temporary, and decays to almost zero already one year after the policy change. The results point to the very special nature of the subscription product and the congestion effects of museum visits, whereby changes in the subscription's price can trigger a response in terms of single product pruchases only limited to a very restricted group of fully committed consumers.

10 Policy implications

Our estimates allow for specific evaluation of price policies. One typical problem that social planners face is the low participation of younger generation. A desirable price policy without the funding of external subsidy from the local government should patronize younger subscribers. From our estimates, a 10 euros reduction policy for the younger cohorts will increase the probability of young eligible people to buy a membership by 0.0114%. It translates in 895 more annual subscriptions (785472, which is the eligible annual population between 23 and 27, times 0.00114), which translates into 82715 euros of total revenues in the end ($(895 + 2865) * 22$, where 2865 is the pre-intervention subscribers population). Overall, the policy requires an external funding of 5184 euros, taking into account both the decrease in earnings and the additional cost of higher visits. Fortunately, such policies can be supported, lowering the price for older cohorts, which is currently excessively expensive. To subsidize the same revenue drop, a policymaker should set the price for elder membership extremely near to 44.5, lowering the price by only 0.5 euros. Overall, because of the increase in total revenues and the decrease in average visits, it would be a sustainable strategy. Moving around the price bands of young membership pricing (+/-20 euros), within which we are confident of our elasticities estimations, we conclude that a price of 30 euros should maximize profits. For old membership, a price of 37 euros maximizes profits within the pricing bands (+/- 7 euros).

11 Conclusion

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Tables

Table 1: Summary statistics and treatment status

	Sample around 15			Sample around 27			Sample around 30			Sample around 65					
	Jan. 2015 - Aug. 2019			Jan. 2015 - Aug. 2019			Jan. 2015 - Aug. 2019			Jan. 2015 - Nov. 2017			Nov. 2017 - Aug. 2019		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
A. Summary statistics															
Total sample															
Card	0.002	(0.041)	7371932	0.003	(0.057)	9964053	0.004	(0.062)	1577215	0.007	(0.085)	6199847	0.007	(0.081)	3900895
Turin	0.350	(0.477)	7371932	0.399	(0.490)	9964053	0.428	(0.495)	1577215	0.350	(0.477)	6199847	0.347	(0.476)	3900895
Female	0.482	(0.500)	7371932	0.487	(0.500)	9964053	0.491	(0.500)	1577215	0.521	(0.500)	6199847	0.519	(0.500)	3900895
Purchasers only															
Number of visits	4.783	(4.358)	12149	7.166	(6.467)	32166	7.502	(6.213)	6108	8.462	(7.199)	44965	7.813	(7.885)	25859
Cost of the visits	19.306	(20.036)	12149	38.387	(34.404)	32166	40.136	(32.888)	6108	41.555	(35.159)	44965	39.475	(39.501)	25859
Nominal card price	25.260	(5.954)	12149	40.662	(9.910)	32166	36.472	(8.679)	6108	42.296	(7.169)	44965	47.788	(3.427)	25859
Net card price	25.260	(5.954)	12149	40.183	(9.436)	32166	35.320	(9.357)	6108	41.643	(6.396)	44965	47.029	(2.794)	25859
Turin	0.520	(0.500)	12149	0.616	(0.486)	32166	0.674	(0.469)	6108	0.559	(0.497)	44965	0.550	(0.498)	25859
Female	0.585	(0.493)	12149	0.576	(0.494)	32166	0.619	(0.486)	6108	0.573	(0.495)	44965	0.575	(0.494)	25859
B. Treatment status															
Total sample															
Treated - pre cutoff	0.000	(0.000)	3670734	0.000	(0.002)	3665539	0.000	(0.009)	754132	0.003	(0.059)	3017606	0.003	(0.056)	1985411
Treated - post cutoff	1.000	(0.000)	3701198	0.728	(0.445)	4149125	0.999	(0.026)	823083	1.000	(0.000)	3182241	1.000	(0.000)	1915484
Purchasers only															
Treated - pre cutoff	0.000	(0.000)	6824	0.001	(0.031)	13367	0.012	(0.111)	4771	0.549	(0.498)	18918	0.540	(0.498)	11714
Treated - post cutoff	1.000	(0.000)	5325	0.458	(0.498)	12322	0.581	(0.494)	1337	1.000	(0.000)	26047	1.000	(0.000)	14145

Notes: Summary statistics by sample (around 27, around 30, around 65). For each sample, the table reports the mean, standard deviation and sample size. The first panel refers to the entire dataset (purchasers and non-purchasers), the second panel to purchasers only.

Table 2: RD summary table

	Cutoff 15	Cutoff 27	Cutoff 30	Cutoff 65	
	Prices: 20-32 (Jan. 2015 - Aug. 2019)	Prices: 32-52 (Jan. 2015 - Aug. 2019)	Prices: 32-52 (Jan. 2015 - Aug. 2019)	Prices: 52-37 (Jan. 2015 - Nov. 2017)	Prices: 52-45 (Nov. 2017 - Aug. 2019)
	(1)	(2)	(3)	(4)	(5)
A. Probability of purchase					
RD estimate	-0.00028**	-0.00114***	-0.00301***	0.00179***	0.00347***
	(0.00014)	(0.00036)	(0.00083)	(0.00053)	(0.00079)
1st stage estimate	-	0.72664***	0.99925***	0.99413***	0.99519***
	-	(0.00098)	(0.00014)	(0.00065)	(0.00050)
Elasticity	0.536**	1.420***	2.614***	1.010***	2.382***
N (within bandwidth)	1545826	1835614	387265	964406	613487
B. Number of visits					
RD estimate	0.036	0.401*	1.379	-1.125***	-2.312***
	(0.240)	(0.458)	(2.541)	(0.242)	(0.559)
1st stage estimate	-	0.333***	0.473***	0.408***	0.325***
	-	(0.025)	(0.056)	(0.005)	(0.016)
N (within bandwidth)	6808	20298	2257	92869	32036
C. Cost of the visits					
RD estimate	5.186	4.918**	6.952	-37.725***	-51.390***
	(3.340)	(4.724)	(17.707)	(8.454)	(4.188)
1st stage estimate	-	0.335***	0.495***	0.157***	0.381***
	-	(0.025)	(0.041)	(0.010)	(0.013)
N (within bandwidht)	4400	20038	2148	55707	37954
Polynomial order	1	1	1	1	1
Geo F.E.	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
Gender F.E.	YES	YES	YES	YES	YES

Notes: Sharp RD estimates (column 1) and fuzzy RD estimates (columns 2-5). Columns 1, 2 and 3 refer to the samples around the age cutoffs 15, 27 and 30 respectively, for the entire period January 2015 - August 2019; columns 4 and 5 refer to the sample around the age cutoff 65, for the periods January 2015 - November 2017 and November 2017 - August 2019, respectively. The dependent variables are: a dummy for card's purchasers (panel A), the card-level number of visits (panel B), the card-level equivalent cost of the visits (panel C). The RD estimates are rescaled to represent the change in the dependent variable for a 10 euros variation in the card's price. All the models employ a 1st order local polynomial fit, control for Geographical, Year and Gender fixed effects, and apply a Donut-Hole approach. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: † $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Probability of purchase - Donut-Hole sharp RD - Sample around 15

	Jan. 2015 - Aug. 2019			
	(1)	(2)	(3)	(4)
RD estimate	-0.00028*	-0.00035	-0.00028**	-0.00037
	(0.00015)	(0.00039)	(0.00014)	(0.00041)
Elasticity				
Pop. in the last bin	0.531	0.677	0.542	0.703
Pop. within bandwidth	0.519	0.669	0.536	0.695
polynomial order	1	2	1	2
cutoff	15	15	15	15
Bandwidth	1.054	0.942	0.972	0.917
Mean	0.00186	0.00186	0.00186	0.00186
Effective N	1727815	1545826	1545826	1545826
Total N	5370319	5370319	5370319	5370319
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole sharp RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Probability of purchase - Donut-Hole fuzzy RD - Sample around 27

	Jan. 2015 - Aug. 2019			
	(5)	(6)	(7)	(8)
RD estimate	-0.00114***	-0.00160***	-0.00114***	-0.00160***
	(0.00047)	(0.00088)	(0.00036)	(0.00080)
1st stage estimate	0.72664***	0.72708***	0.72664***	0.72708***
	(0.00098)	(0.00098)	(0.00098)	(0.00097)
Elasticity				
Pop. in the last bin	1.500	2.093	1.502	2.094
Pop. within bandwidth	1.418	1.989	1.420	1.991
polynomial order	1	2	1	2
cutoff	27	27	27	27
Bandwidth	1.021	0.943	1.020	0.945
Mean	0.00364	0.00364	0.00364	0.00364
Effective N	1835614	1642177	1835614	1642177
Total N	5698417	5698417	5698417	5698417
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Probability of purchase - Donut-Hole fuzzy RD - Sample around 30

	Jan. 2015 - Aug. 2019			
	(1)	(2)	(3)	(4)
RD estimate	-0.00301***	-0.00246***	-0.00301***	-0.00246***
	(0.00088)	(0.00150)	(0.00083)	(0.00146)
1st stage estimate	0.99925***	0.99927***	0.99925***	0.99927***
	(0.00014)	(0.00026)	(0.00014)	(0.00026)
Elasticity				
Pop. in the last bin	2.856	2.338	2.859	2.336
Pop. within bandwidth	2.610	2.136	2.614	2.135
polynomial order	1	2	1	2
cutoff	30	30	30	30
Bandwidth	0.836	0.857	0.841	0.858
Mean	0.00625	0.00625	0.00625	0.00625
Effective N	387265	387265	387265	387265
Total N	1525584	1525584	1525584	1525584
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Probability of purchase - Donut-Hole fuzzy RD - Sample around 65

	Jan. 2015 - Nov. 2017				Nov. 2017 - Aug. 2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD estimate	0.00170***	0.00224***	0.00179***	0.00233***	0.00322***	0.00567***	0.00347***	0.00567***
	(0.00055)	(0.00098)	(0.00053)	(0.00109)	(0.00082)	(0.00131)	(0.00079)	(0.00125)
1st stage estimate	0.99418***	0.99414***	0.99413***	0.99407***	0.99505***	0.99595***	0.99519***	0.99586***
	(0.00063)	(0.00090)	(0.00065)	(0.00101)	(0.00050)	(0.00083)	(0.00050)	(0.00084)
Elasticity								
Pop. in the last bin	1.002	1.319	1.054	1.376	2.324	4.099	2.510	4.098
Pop. within bandwidth	0.961	1.276	1.010	1.319	2.223	3.921	2.382	3.919
polynomial order	1	2	1	2	1	2	1	2
cutoff	65	65	65	65	65	65	65	65
Bandwidth	0.794	0.838	0.701	0.796	0.835	0.860	0.778	0.832
Mean	0.00284	0.00284	0.00284	0.00284	0.00272	0.00272	0.00272	0.00272
Effective N	964406	1112544	964406	964406	707899	707899	613487	707899
Total N	4474690	4474690	4474690	4474690	2816119	2816119	2816119	2816119
Area F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. Columns 1-4 refer to the period January 2015 - November 2017, columns 5-8 to November 2017 - August 2019. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. In each period, the first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Visits - Donut-Hole Sharp RD estimates - Sample around 15

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
RD estimate	0.037	0.141	0.036	0.142	5.213	3.528	5.186	3.491
	(0.241)	(0.294)	(0.240)	(0.294)	(3.348)	(3.737)	(3.340)	(3.724)
cutoff	15	15	15	15	15	15	15	15
polynomial order	1	2	1	2	1	2	1	2
Price (left)	20	20	20	20	20	20	20	20
Price (right)	32	32	32	32	32	32	32	32
Bandwidth (left)	2.366	4.346	2.366	4.345	1.056	2.250	1.055	2.249
Bandwidth (right)	2.745	3.480	2.746	3.479	2.574	3.548	2.574	3.548
Mean	5.341	5.341	5.341	5.341	29.592	29.592	29.592	29.592
Effective N	6806	11733	6808	11720	4400	7796	4400	7787
Total N	46464	46464	46464	46464	46464	46464	46464	46464
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Sharp RD estimates. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Visits - Donut-Hole Fuzzy RD estimates - Sample around 27

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
	0.401*	0.449	0.406*	0.451	4.918**	5.605†	4.965**	5.615†
	(0.458)	(0.635)	(0.456)	(0.632)	(4.724)	(6.525)	(4.724)	(6.484)
1st stage estimate	0.333***	0.269***	0.336***	0.272***	0.335***	0.269***	0.337***	0.271***
	(0.025)	(0.030)	(0.024)	(0.029)	(0.025)	(0.030)	(0.024)	(0.029)
cutoff	27	27	27	27	27	27	27	27
polynomial order	1	2	1	2	1	2	1	2
Price (left)	32	32	32	32	32	32	32	32
Price (right)	52	52	52	52	52	52	52	52
Bandwidth (left)	3.140	5.502	3.129	5.495	3.128	5.435	3.117	5.427
Bandwidth (right)	3.371	7.410	3.265	7.300	3.300	7.435	3.206	7.337
Mean	6.238	6.238	6.238	6.238	67.813	67.813	67.813	67.813
Effective N	20298	40348	19932	39988	20038	40231	19733	39893
Total N	222035	222035	222035	222035	222035	222035	222035	222035
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Visits - Donut-Hole Fuzzy RD estimates - Sample around 30

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
RD estimate	1.530	2.251	1.379	2.293	6.660	4.456	6.952	5.236
	(2.708)	(4.354)	(2.541)	(4.607)	(18.018)	(20.563)	(17.707)	(20.864)
1st stage estimate	0.468***	0.412***	0.473***	0.407***	0.494***	0.500***	0.495***	0.495***
	(0.061)	(0.089)	(0.056)	(0.093)	(0.041)	(0.048)	(0.041)	(0.049)
cutoff	30	30	30	30	30	30	30	30
polynomial order	1	2	1	2	1	2	1	2
Price (left)	32	32	32	32	32	32	32	32
Price (right)	52	52	52	52	52	52	52	52
Bandwidth (left)	1.338	2.249	1.342	2.243	1.033	2.001	1.032	1.943
Bandwidth (right)	0.682	1.033	0.721	1.002	1.033	2.001	1.032	1.943
Mean	6.619	6.619	6.619	6.619	71.329	71.329	71.329	71.329
Effective N	2217	3799	2257	3743	2153	3839	2148	3695
Total N	16321	16321	16321	16321	16321	16321	16321	16321
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Visits - Donut-Hole Fuzzy RD estimates - Sample around 65

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Nov. 2017								
RD estimate	-1.125***	-1.420**	-1.125***	-1.408**	-38.144***	-78.543*	-37.725***	-81.438*
	(0.305)	(0.945)	(0.242)	(0.871)	(9.672)	(51.700)	(8.454)	(52.773)
1st stage estimate	0.406***	0.200***	0.408***	0.197***	0.151***	0.042	0.157***	0.040
	(0.005)	(0.011)	(0.005)	(0.011)	(0.010)	(0.014)	(0.010)	(0.014)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	37	37	37	37	37	37	37	37
Bandwidth (left)	11.943	8.014	12.153	7.944	3.125	4.299	3.205	4.255
Bandwidth (right)	8.200	9.310	7.340	9.093	7.673	9.655	7.251	9.541
Mean	8.090	8.090	8.090	8.090	86.567	86.567	86.567	86.567
Effective N	95136	83196	92869	82090	56920	68657	55707	68121
Total N	190085	190085	190085	190085	190085	190085	190085	190085
B. Nov. 2017 - Aug. 2019								
RD estimate	-2.350***	-2.732**	-2.312***	-2.663**	-50.634***	-57.827***	-51.390***	-57.366***
	(0.544)	(0.745)	(0.559)	(0.745)	(4.551)	(6.106)	(4.188)	(5.655)
1st stage estimate	0.338***	0.285***	0.325***	0.289***	0.389***	0.332***	0.381***	0.335***
	(0.016)	(0.020)	(0.016)	(0.020)	(0.013)	(0.018)	(0.013)	(0.017)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	45	45	45	45	45	45	45	45
Bandwidth (left)	5.670	8.561	5.287	8.731	7.969	10.892	7.480	11.055
Bandwidth (right)	4.794	9.094	5.217	9.384	5.122	9.027	5.336	9.203
Mean	7.259	7.259	7.259	7.259	79.124	79.124	79.124	79.124
Effective N	31537	51437	32036	52375	38457	57161	37954	57978
Total N	114074	114074	114074	114074	114074	114074	114074	114074
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Visits - Asymmetric Donut-Hole Fuzzy RD estimates - Sample around 65

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Nov. 2017								
	-1.012***	-1.118***	-1.029***	-1.116***	-26.465***	-27.902***	-26.606***	-27.885***
	(0.240)	(0.264)	(0.218)	(0.240)	(2.681)	(2.783)	(2.655)	(2.776)
1st stage estimate	0.548***	0.551***	0.548***	0.551***	0.549***	0.550***	0.549***	0.550***
	(0.009)	(0.011)	(0.009)	(0.011)	(0.010)	(0.012)	(0.009)	(0.011)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	37	37	37	37	37	37	37	37
Bandwidth (left)	6.325	12.755	6.449	12.564	5.585	11.505	5.714	11.409
Bandwidth (right)	8.607	9.576	7.780	9.381	7.842	9.804	7.426	9.750
Mean	7.981	7.981	7.981	7.981	85.207	85.207	85.207	85.207
Effective N	68727	98873	66301	97431	62655	94541	61641	93984
Total N	185454	185454	185454	185454	185454	185454	185454	185454
B. Nov. 2017 - Aug. 2019								
RD estimate	-1.236*	-1.163	-1.113*	-1.123	-39.957***	-39.584***	-37.709***	-39.468***
	(0.479)	(0.679)	(0.464)	(0.635)	(5.442)	(7.524)	(5.537)	(7.192)
1st stage estimate	0.521***	0.511***	0.514***	0.510***	0.518***	0.510***	0.512***	0.510***
	(0.012)	(0.020)	(0.015)	(0.019)	(0.014)	(0.021)	(0.016)	(0.020)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	45	45	45	45	45	45	45	45
Bandwidth (left)	5.925	8.487	5.283	8.349	5.643	8.335	5.057	8.317
Bandwidth (right)	4.518	8.810	4.782	8.988	4.812	8.990	4.949	9.096
Mean	7.108	7.108	7.108	7.108	77.182	77.182	77.182	77.182
Effective N	28360	47833	27723	47836	28728	47814	27643	48004
Total N	111269	111269	111269	111269	111269	111269	111269	111269
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Asymmetric Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ an asymmetric Donut-Hole approach, where we drop all the subscribers aged 64, in addition to the bins highlighted in Figure 5. Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Behavioral effects - Diff in Diff - Sample around 15

	Half year margin around 14						1 year margin around 14					
	Number of visits			Cost of the visits			Number of visits			Cost of the visits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Jan. 2015 - Aug. 2019												
post	-1.394***	-1.309***	-1.238**	14.608***	15.187***	15.496***	-1.408***	-1.420***	-1.479***	7.827***	7.583***	7.057***
	(0.447)	(0.472)	(0.489)	(3.616)	(3.815)	(3.967)	(0.295)	(0.305)	(0.310)	(2.368)	(2.393)	(2.428)
treatment	-0.276	-0.469	-0.562	7.582**	6.376*	5.945†	-0.340	-0.398	-0.474†	13.407***	12.914***	12.683***
	(0.517)	(0.534)	(0.581)	(3.390)	(3.505)	(3.859)	(0.293)	(0.306)	(0.309)	(2.209)	(2.304)	(2.342)
treatment*post	0.142	0.181	0.193	-0.370	-0.049	-0.006	0.274	0.270	0.259	-0.029	-0.096	-0.191
	(0.497)	(0.513)	(0.526)	(4.218)	(4.360)	(4.459)	(0.370)	(0.377)	(0.383)	(3.171)	(3.242)	(3.291)
N	730	730	730	730	730	730	1582	1582	1582	1582	1582	1582
Previous cards F.E	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Area F.E.	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
Municipality F.E.	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: Diff-in-diff estimates. Treatment and control are defined according to when they buy their first card in the neighbourhood of the diff-in-diff cutoff (26). Columns 1-6 use a margin of half a year, columns 7-12 use a margin of one year around the diff-in-diff cutoff (26). The dependent variable is the number of visits in columns 1-3 and 7-9, the equivalent cost of the visits in columns 4-6 and 10-12. Columns 2, 5, 8 and 11 also include area fixed effects (municipality for Turin, zip-code for municipalities outside Turin); columns 3, 6, 9 and 12 include instead municipality fixed effects. The standard errors are robust to heteroskedasticity and clustered at the individual level. Significance levels: † $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Behavioral effects - Diff in Diff - Sample around 27

	Half year margin around 26						1 year margin around 26					
	Number of visits			Cost of the visits			Number of visits			Cost of the visits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Jan. 2015 - Aug. 2019												
post	-2.300***	-2.350***	-2.307***	-24.013***	-24.546***	-24.580***	-2.264***	-2.282***	-2.311***	-24.579***	-24.818***	-25.612***
	(0.558)	(0.558)	(0.570)	(5.840)	(5.945)	(6.169)	(0.408)	(0.392)	(0.402)	(4.323)	(4.220)	(4.366)
treatment	-0.847	-0.507	-0.367	-8.860	-4.746	-3.540	-0.938**	-0.929**	-1.000**	-11.360**	-11.165**	-11.877**
	(0.726)	(0.750)	(0.802)	(7.294)	(7.685)	(8.497)	(0.457)	(0.472)	(0.492)	(4.732)	(4.894)	(5.125)
treatment*post	2.170	2.199	2.168	27.554	27.719	27.232	1.728*	1.767*	1.735*	22.760*	23.075*	22.551*
	(1.694)	(1.765)	(1.807)	(21.641)	(22.555)	(23.103)	(0.938)	(0.961)	(0.984)	(11.833)	(12.133)	(12.433)
N	728	728	728	728	728	728	1494	1494	1494	1494	1494	1494
Previous cards F.E	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Area F.E.	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
Municipality F.E.	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: Diff-in-diff estimates. Treatment and control are defined according to when they buy their first card in the neighbourhood of the diff-in-diff cutoff (26). Columns 1-6 use a margin of half a year, columns 7-12 use a margin of one year around the diff-in-diff cutoff (26). The dependent variable is the number of visits in columns 1-3 and 7-9, the equivalent cost of the visits in columns 4-6 and 10-12. Columns 2, 5, 8 and 11 also include area fixed effects (municipality for Turin, zip-code for municipalities outside Turin); columns 3, 6, 9 and 12 include instead municipality fixed effects. The standard errors are robust to heteroskedasticity and clustered at the individual level. Significance levels: † $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Behavioral effects - Diff in Diff - Sample around 30

	Half year margin around 29						1 year margin around 29					
	Number of visits			Cost of the visits			Number of visits			Cost of the visits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Jan. 2015 - Aug. 2019												
post	-1.997***	-1.855***	-2.035***	-20.204***	-19.037**	-20.892***	-1.300***	-1.314***	-1.395***	-14.511***	-14.830***	-15.639***
	(0.690)	(0.713)	(0.717)	(7.348)	(7.604)	(7.647)	(0.403)	(0.406)	(0.410)	(4.311)	(4.332)	(4.378)
treatment	-1.000†	-0.964	-1.271*	-11.032†	-10.775	-14.476*	-0.082	0.023	-0.073	-1.215	-0.347	-1.307
	(0.691)	(0.738)	(0.759)	(7.206)	(7.733)	(7.938)	(0.409)	(0.421)	(0.431)	(4.352)	(4.461)	(4.548)
treatment*post	1.397**	1.387*	1.434**	14.244*	14.231*	14.806*	0.466	0.465	0.476	5.174	5.120	5.254
	(0.691)	(0.711)	(0.720)	(7.404)	(7.611)	(7.705)	(0.446)	(0.452)	(0.456)	(4.772)	(4.831)	(4.875)
N	662	662	662	662	662	662	1688	1688	1688	1688	1688	1688
Previous cards F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Area F.E.	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
Municipality F.E.	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: Diff-in-diff estimates. Treatment and control are defined according to when they buy their first card in the neighbourhood of the diff-in-diff cutoff (29). Columns 1-6 use a margin of half a year, columns 7-12 use a margin of one year around the diff-in-diff cutoff (29). The dependent variable is the number of visits in columns 1-3 and 7-9, the equivalent cost of the visits in columns 4-6 and 10-12. Columns 2, 5, 8 and 11 also include area fixed effects (municipality for Turin, zip-code for municipalities outside Turin); columns 3, 6, 9 and 12 include instead municipality fixed effects. The standard errors are robust to heteroskedasticity and clustered at the individual level. Significance levels: † $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Behavioral effects - Diff in Diff - Sample around 65

	Half year margin around 63						1 year margin around 63					
	Number of visits			Cost of the visits			Number of visits			Cost of the visits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Jan. 2015 - Nov. 2017												
post	-0.197	-0.291	-0.253	-2.066	-3.443	-3.093	0.209	0.222	0.206	2.405	2.303	2.295
	(0.875)	(0.927)	(0.958)	(10.005)	(10.659)	(11.097)	(0.509)	(0.515)	(0.524)	(5.716)	(5.782)	(5.905)
treatment	-0.322	-0.289	-0.376	-2.458	-2.098	-3.031	-0.740**	-0.671**	-0.791**	-7.127**	-6.357*	-7.606**
	(0.573)	(0.600)	(0.630)	(6.078)	(6.408)	(6.732)	(0.333)	(0.334)	(0.345)	(3.534)	(3.551)	(3.653)
treatment*post	-0.267	-0.281	-0.273	-9.664**	-9.863**	-9.791**	-0.346	-0.344	-0.344	-12.369***	-12.369***	-12.350***
	(0.436)	(0.448)	(0.454)	(4.696)	(4.821)	(4.889)	(0.312)	(0.316)	(0.319)	(3.415)	(3.454)	(3.491)
N	1280	1280	1280	1280	1280	1280	3018	3018	3018	3018	3018	3018
B. Nov. 2017 - Aug. 2019												
post	-4.024**	-3.662**	-3.391*	-38.896**	-33.599*	-30.333	-4.338***	-4.299***	-4.309***	-43.903***	-43.701***	-43.529***
	(1.567)	(1.722)	(1.871)	(17.830)	(19.587)	(21.174)	(0.870)	(0.957)	(1.015)	(9.557)	(10.695)	(11.311)
treatment	-0.656	-1.189	-1.166	-5.832	-11.952	-11.738	0.118	-0.055	-0.053	3.109	1.160	1.210
	(1.199)	(1.319)	(1.361)	(12.746)	(13.993)	(14.419)	(0.888)	(0.917)	(0.957)	(9.387)	(9.670)	(10.085)
treatment*post	1.177	1.257	1.317	10.086	11.256	11.966	0.299	0.299	0.320	-2.989	-3.026	-2.785
	(1.087)	(1.152)	(1.180)	(11.709)	(12.397)	(12.710)	(0.702)	(0.716)	(0.727)	(7.613)	(7.732)	(7.854)
N	454	454	454	454	454	454	1126	1126	1126	1126	1126	1126
Previous cards F.E	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Area F.E.	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO
Municipality F.E.	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: Diff-in-diff estimates. Treatment and control are defined according to when they buy their first card in the neighbourhood of the diff-in-diff cutoff (63). Columns 1-6 use a margin of half a year, columns 7-12 use a margin of one year around the diff-in-diff cutoff (63). The dependent variable is the number of visits in columns 1-3 and 7-9, the equivalent cost of the visits in columns 4-6 and 10-12. Columns 2, 5, 8 and 11 also include area fixed effects (municipality for Turin, zip-code for municipalities outside Turin); columns 3, 6, 9 and 12 include instead municipality fixed effects. The standard errors are robust to heteroskedasticity and clustered at the individual level. Significance levels: † $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Covariate balancedness - Income

	Sample around 27				Sample around 65							
	Jan. 2015 - Aug. 2019				Jan. 2015 - Nov. 2017				Nov. 2017 - Aug. 2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Property	-18.934	-14.795	-18.965	-14.893	11.373	4.830	11.806	5.085	12.118	-8.095	11.341	-8.246
	(114.205)	(134.260)	(112.878)	(133.538)	(118.079)	(122.261)	(117.438)	(121.694)	(89.358)	(94.801)	(88.206)	(93.647)
Employment	-72.963	-74.365	-73.932	-75.573	15.585	-13.309	17.077	-11.203	-62.690	-63.631	-61.015	-61.041
	(476.079)	(643.159)	(473.150)	(642.838)	(422.242)	(449.515)	(419.510)	(447.689)	(655.793)	(703.139)	(650.228)	(697.989)
Pension	3.585	-23.329	3.103	-23.697	-59.456	-114.531	-58.821	-111.741	29.096	-62.616	30.796	-61.704
	(262.505)	(307.369)	(260.200)	(305.183)	(353.016)	(418.170)	(350.129)	(412.933)	(275.000)	(310.526)	(272.738)	(307.509)
Self-employment	-25.593	-14.042	-26.104	-15.062	24.190	-7.937	25.622	-5.914	55.703	-0.651	55.605	-0.456
	(290.088)	(332.211)	(286.290)	(330.562)	(302.829)	(359.887)	(300.552)	(355.937)	(243.823)	(263.985)	(241.019)	(260.870)
Financial	-26.406	-21.742	-26.375	-21.934	4.169	1.315	4.309	0.887	-1.724	0.901	-1.965	0.518
	(109.139)	(140.384)	(108.114)	(140.403)	(112.259)	(131.155)	(111.916)	(130.815)	(112.378)	(130.838)	(111.210)	(130.105)
Taxable income	-139.841	-133.113	-141.503	-136.886	78.592	-6.907	82.924	-4.416	-0.606	-102.151	2.185	-102.835
	(1074.715)	(1388.890)	(1064.259)	(1383.101)	(1205.800)	(1237.332)	(1198.893)	(1230.586)	(1289.980)	(1369.101)	(1276.276)	(1354.227)
Net tax	-55.692	-49.331	-56.455	-51.017	37.417	1.754	39.426	3.552	3.547	-12.950	4.829	-10.942
	(471.122)	(591.830)	(465.644)	(589.053)	(510.186)	(531.499)	(507.167)	(526.963)	(530.344)	(561.763)	(524.484)	(555.644)
cutoff	27	27	27	27	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2	1	2	1	2
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The Table reports the second-stage RD estimate (standard errors in parenthesis). Columns 1-4 refer to the sample around 27, columns 5-8 to the sample around 65. The dependent variable are from ISTAT and vary at the municipal-year level. All the models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each sample, the first 2 columns control for Year and Gender fixed effects, the last 2 columns also include Area fixed effects (Municipality fixed effects for Turin, Zip-code fixed effects for municipalities outside Turin). Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Covariate balancedness - Location and vehicles

	Sample around 27				Sample around 65							
	Jan. 2015 - Aug. 2019				Jan. 2015 - Nov. 2017				Nov. 2017 - Aug. 2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Latitude	0.001	0.002	0.001	0.001	0.003	0.005	0.003	0.005	0.002	0.001	0.002	0.001
	(0.013)	(0.017)	(0.013)	(0.017)	(0.013)	(0.016)	(0.013)	(0.016)	(0.012)	(0.015)	(0.012)	(0.015)
Longitude	0.006	0.008	0.006	0.008	-0.003	-0.012	-0.003	-0.012	-0.003	-0.017	-0.003	-0.017
	(0.034)	(0.043)	(0.034)	(0.043)	(0.032)	(0.042)	(0.032)	(0.042)	(0.033)	(0.040)	(0.033)	(0.039)
Distance	-0.875	-0.791	-0.873	-0.794	0.931	2.917	0.914	2.904	1.204	2.667	1.206	2.657
	(7.800)	(9.168)	(7.752)	(9.151)	(7.221)	(9.853)	(7.182)	(9.797)	(7.310)	(8.870)	(7.282)	(8.835)
Cars	-1.867	-2.028	-2.070	-2.085	0.177	0.102	0.194	0.114	0.002	0.003	0.002	0.003
	(12.256)	(13.397)	(12.581)	(13.499)	(11.549)	(13.368)	(11.526)	(13.341)	(0.011)	(0.012)	(0.011)	(0.013)
Bus/Filobus	-0.007	-0.008	-0.008	-0.008	0.001	0.000	0.001	0.000	0.000	-0.000	0.000	-0.000
	(0.048)	(0.051)	(0.049)	(0.052)	(0.044)	(0.051)	(0.044)	(0.051)	(0.001)	(0.001)	(0.001)	(0.001)
Motorbikes	-0.248	-0.270	-0.274	-0.277	0.023	0.014	0.025	0.016	0.000	0.005	0.000	0.005
	(1.607)	(1.759)	(1.649)	(1.772)	(1.511)	(1.741)	(1.508)	(1.738)	(0.014)	(0.016)	(0.014)	(0.016)
cutoff	27	27	27	27	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2	1	2	1	2
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The Table reports the second-stage RD estimate (standard errors in parenthesis). Columns 1-4 refer to the sample around 27, columns 5-8 to the sample around 65. The dependent variable are from ISTAT and vary at the municipal-year level. All the models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each sample, the first 2 columns control for Year and Gender fixed effects, the last 2 columns also include Area fixed effects (Municipality fixed effects for Turin, Zip-code fixed effects for municipalities outside Turin). Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

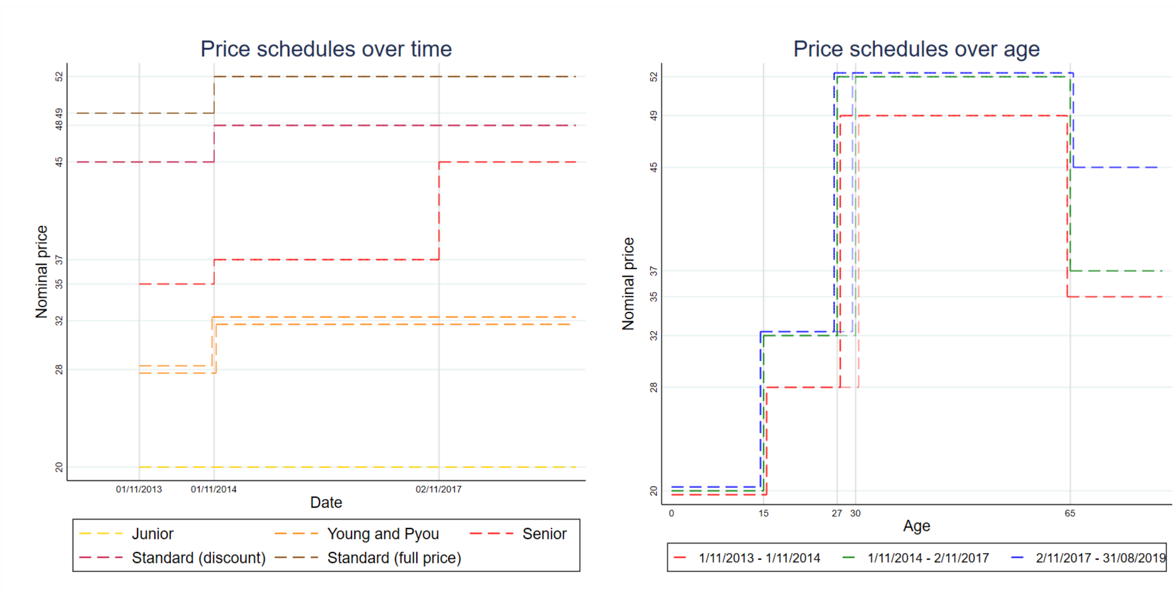
Table 18: Covariate balancedness - Education

	Sample around 27				Sample around 65							
	Jan. 2015 - Aug. 2019				Jan. 2015 - Nov. 2017				Nov. 2017 - Aug. 2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Scientific	-0.005	-0.005	-0.006	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.031)	(0.032)	(0.032)	(0.033)	(0.018)	(0.021)	(0.018)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)
Chemistry	-0.004	-0.004	-0.005	-0.004	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.026)	(0.028)	(0.027)	(0.028)	(0.016)	(0.018)	(0.016)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Biology	-0.003	-0.003	-0.004	-0.003	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.020)	(0.021)	(0.021)	(0.022)	(0.012)	(0.014)	(0.012)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Medicine	-0.014	-0.013	-0.015	-0.013	0.001	0.000	0.001	0.001	0.000	-0.000	0.000	-0.000
	(0.082)	(0.087)	(0.085)	(0.088)	(0.049)	(0.056)	(0.048)	(0.056)	(0.000)	(0.000)	(0.000)	(0.000)
Engineering	-0.020	-0.019	-0.023	-0.020	0.001	0.001	0.001	0.001	0.000	-0.000	0.000	-0.000
	(0.124)	(0.131)	(0.127)	(0.133)	(0.073)	(0.085)	(0.073)	(0.085)	(0.001)	(0.001)	(0.001)	(0.001)
Architecture	-0.008	-0.007	-0.009	-0.008	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.047)	(0.050)	(0.049)	(0.051)	(0.028)	(0.033)	(0.028)	(0.033)	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture	-0.004	-0.004	-0.005	-0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.027)	(0.028)	(0.027)	(0.028)	(0.016)	(0.018)	(0.016)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Economics/Statistics	-0.019	-0.017	-0.021	-0.018	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000
	(0.113)	(0.119)	(0.116)	(0.121)	(0.067)	(0.077)	(0.067)	(0.077)	(0.000)	(0.000)	(0.000)	(0.000)
Political science	-0.015	-0.014	-0.017	-0.015	0.001	0.000	0.001	0.001	0.000	0.000	0.000	0.000
	(0.093)	(0.099)	(0.096)	(0.100)	(0.055)	(0.064)	(0.055)	(0.064)	(0.000)	(0.000)	(0.000)	(0.000)
Law	-0.012	-0.011	-0.014	-0.012	0.001	0.000	0.001	0.000	-0.000	-0.000	-0.000	-0.000
	(0.074)	(0.079)	(0.077)	(0.081)	(0.044)	(0.051)	(0.044)	(0.051)	(0.000)	(0.000)	(0.000)	(0.000)
Literature	-0.009	-0.008	-0.010	-0.008	0.000	0.000	0.001	0.000	-0.000	-0.000	-0.000	-0.000
	(0.052)	(0.055)	(0.054)	(0.056)	(0.031)	(0.036)	(0.031)	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)
Languages	-0.006	-0.006	-0.007	-0.006	0.000	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.037)	(0.039)	(0.038)	(0.040)	(0.022)	(0.025)	(0.022)	(0.025)	(0.000)	(0.000)	(0.000)	(0.000)
Teaching	-0.006	-0.006	-0.007	-0.006	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.036)	(0.039)	(0.037)	(0.039)	(0.021)	(0.025)	(0.021)	(0.025)	(0.000)	(0.000)	(0.000)	(0.000)
Psychology	-0.005	-0.004	-0.005	-0.005	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.028)	(0.030)	(0.029)	(0.031)	(0.017)	(0.020)	(0.017)	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)
Physical education	-0.003	-0.002	-0.003	-0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.015)	(0.016)	(0.016)	(0.016)	(0.009)	(0.010)	(0.009)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
Defense	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
cutoff	27	27	27	27	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2	1	2	1	2
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The Table reports the second-stage RD estimate (standard errors in parenthesis). Columns 1-4 refer to the sample around 27, columns 5-8 to the sample around 65. The dependent variable are from ISTAT and vary at the municipal-year level. All the models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each sample, the first 2 columns control for Year and Gender fixed effects, the last 2 columns also include Area fixed effects (Municipality fixed effects for Turin, Zip-code fixed effects for municipalities outside Turin). Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

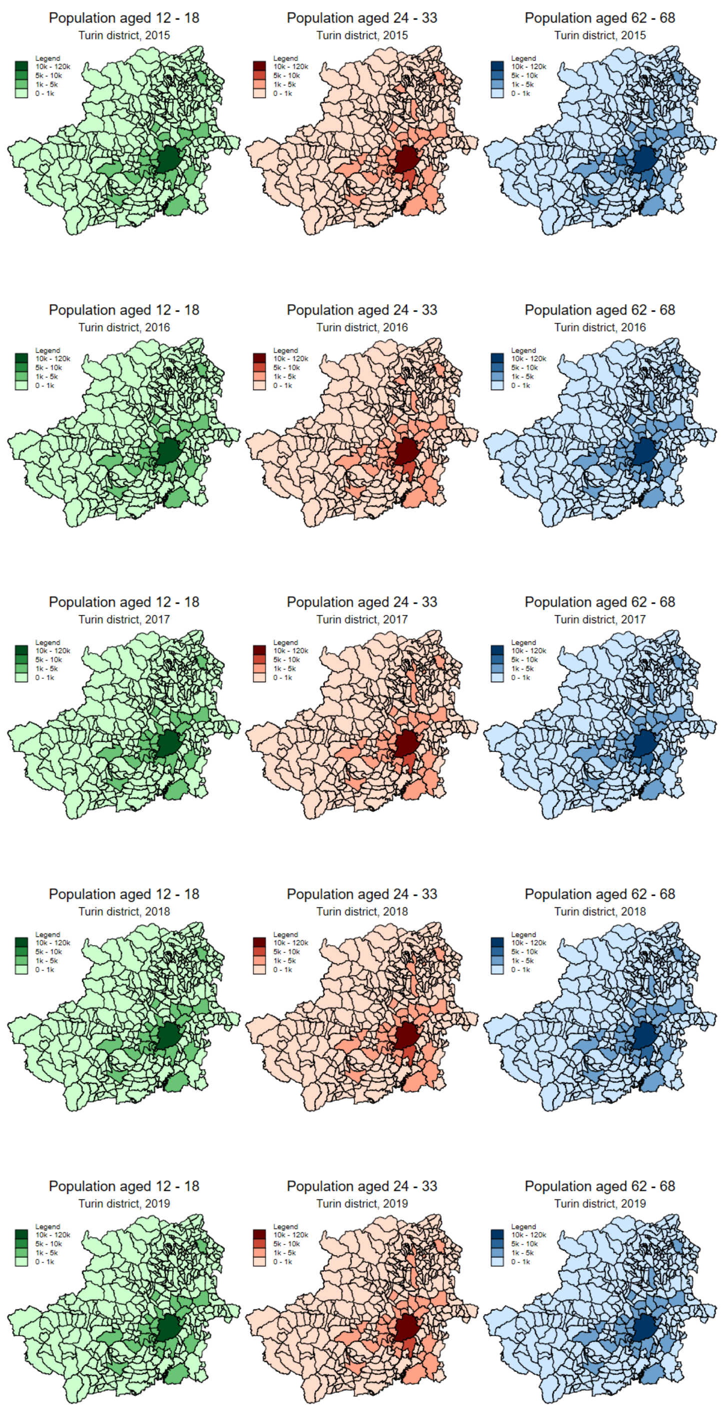
Figures

Figure 1: Price schedules, over time and age



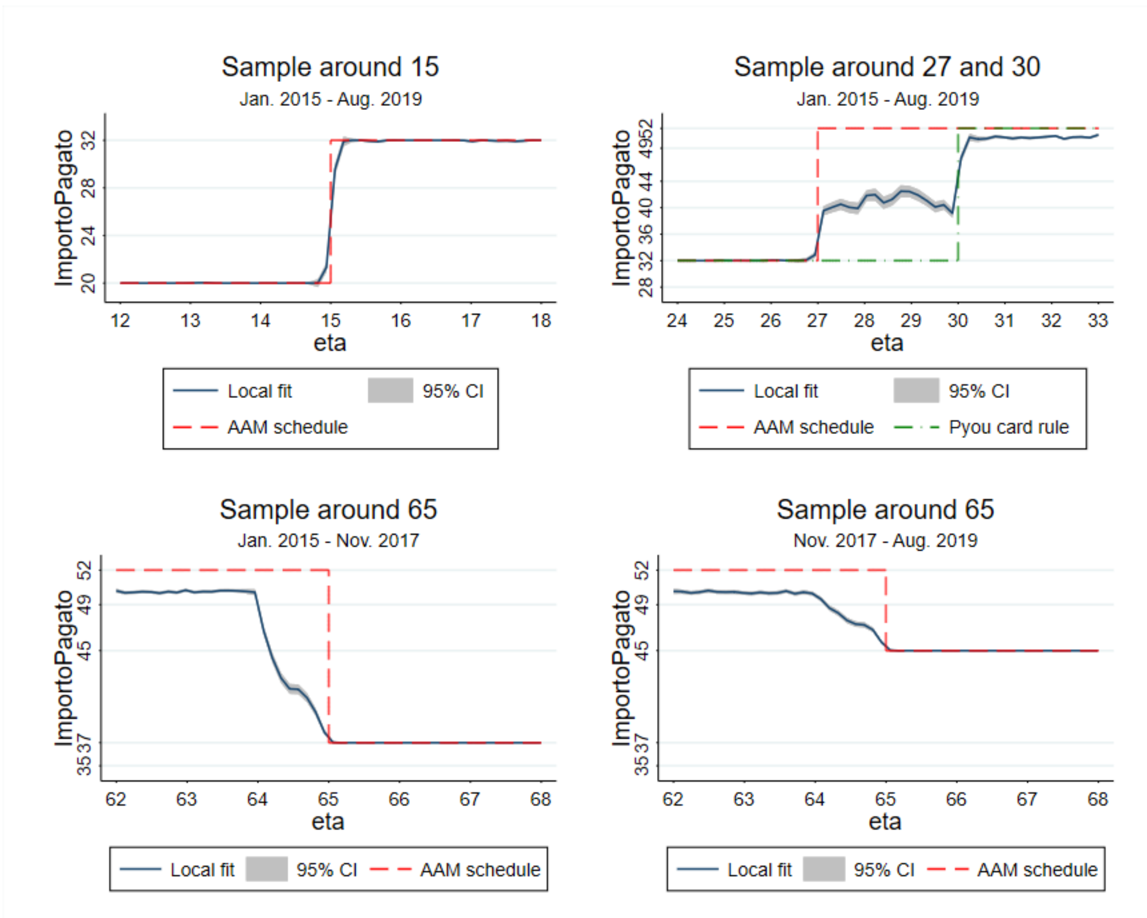
Notes: on the left panel, the evolution over time of the card prices, by card type. On the right panel, the resulting age-based price schedules for the period 2013-2019. The opaque lines refer to purchasers of the Pyou card.

Figure 2: Population, by age group and year



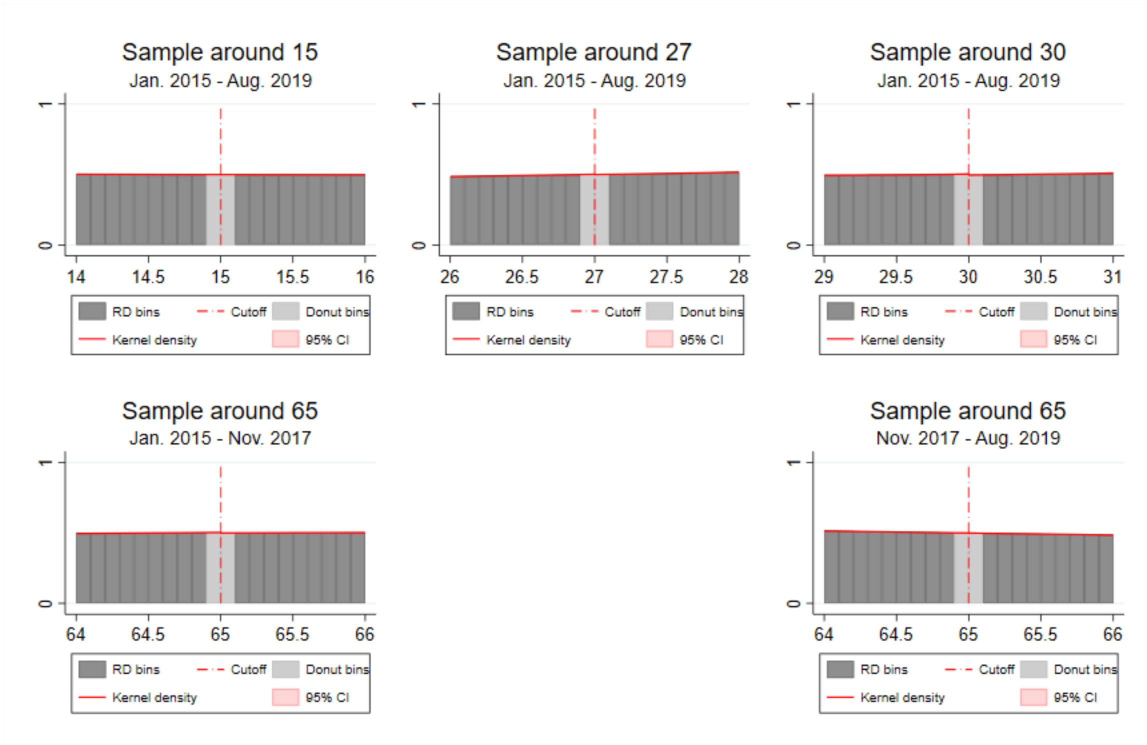
Notes: The figure shows the geographical distribution of the population in the Turin district for the period 2015-2019. Column 1 refers to the age interval 12-18, column 2 to the age interval 24-33, column 3 to the age interval 62-68.

Figure 3: Price discontinuities



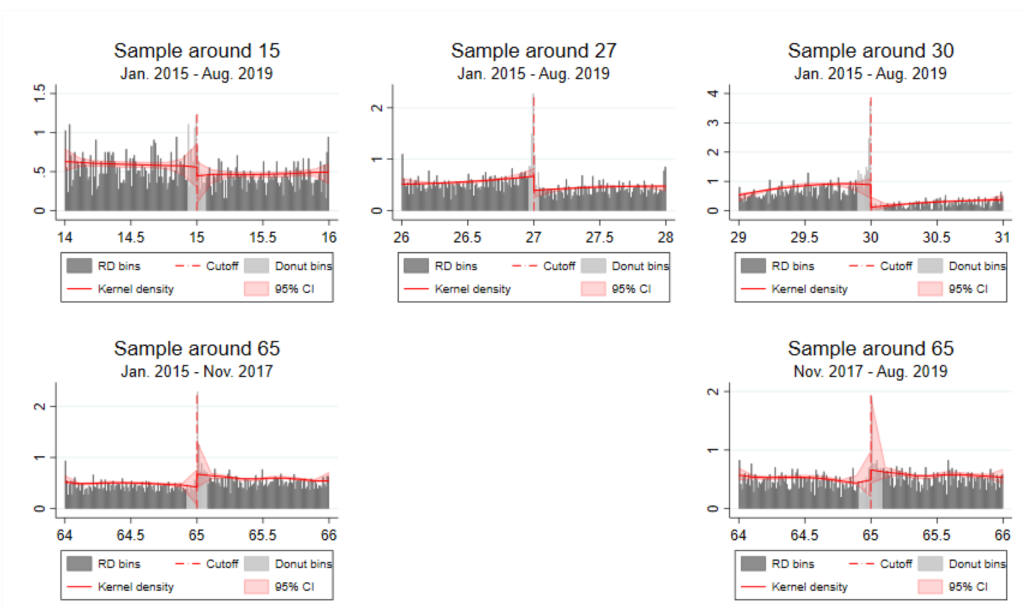
Notes: The figure shows a local polynomial approximation of the card's price for the samples around the age cutoffs 15 (panel 1), 27 and 30 (panel 2), and 65, the latter separately for Jan. 2015 - Nov. 2017 (panel 3) and Nov. 2017 - Aug. 2019 (panel 4). The figures also show the AAM price schedule, and the Pyou card rule when relevant.

Figure 4: McCrary test - Probability of purchase



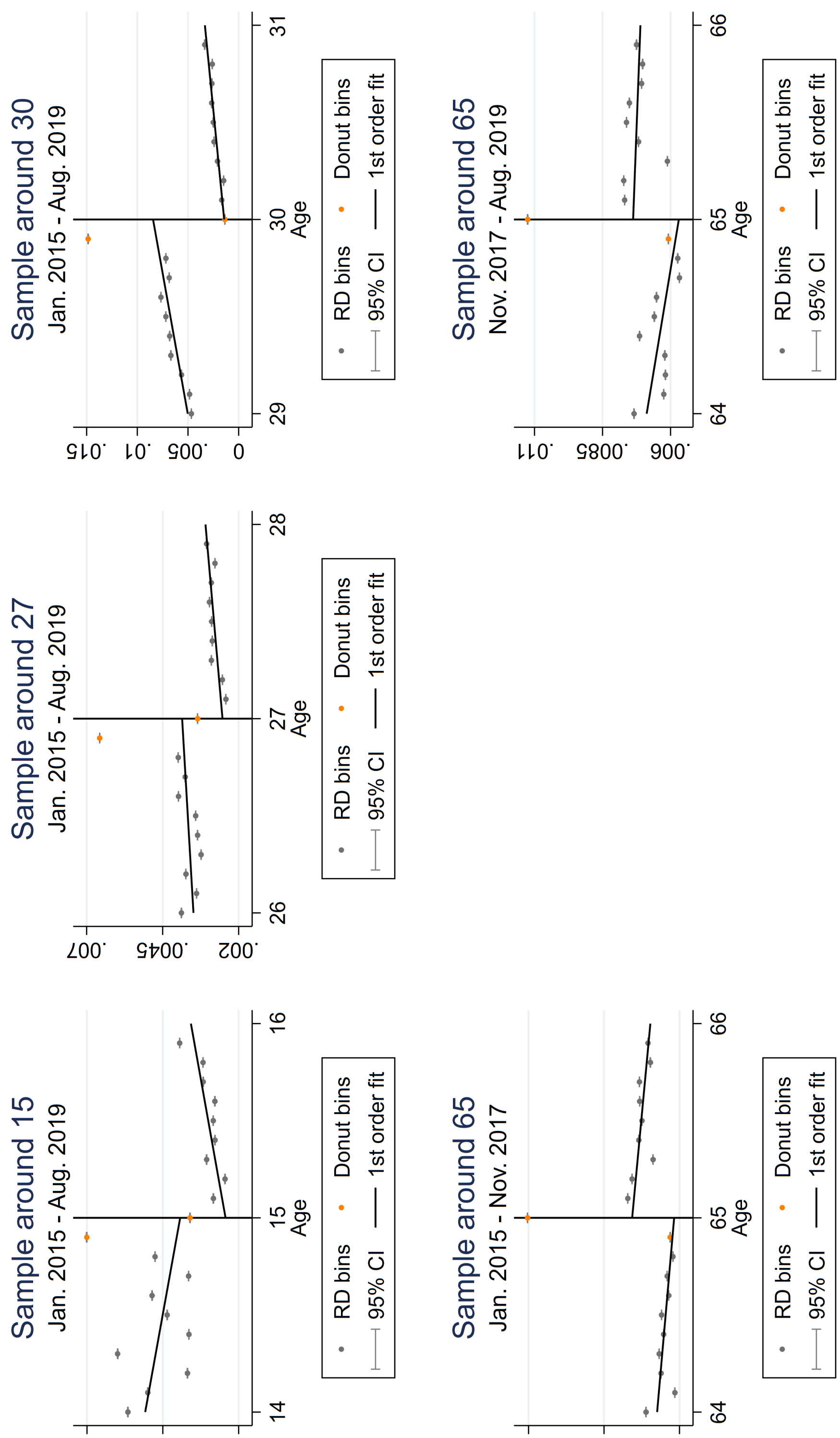
Notes: McCrary's sorting tests around the cutoffs 15, 27, 30 (Jan. 2015 - Aug. 2019) and 65 (separately for Jan. 2015 - Nov. 2017 and Nov. 2017 - Aug. 2019). The figure reports the histogram, the kernel densities and the 95% confidence intervals. The lighter bins are those excluded from the RD estimation following a Donut-Hole approach.

Figure 5: McCrary test - Visits



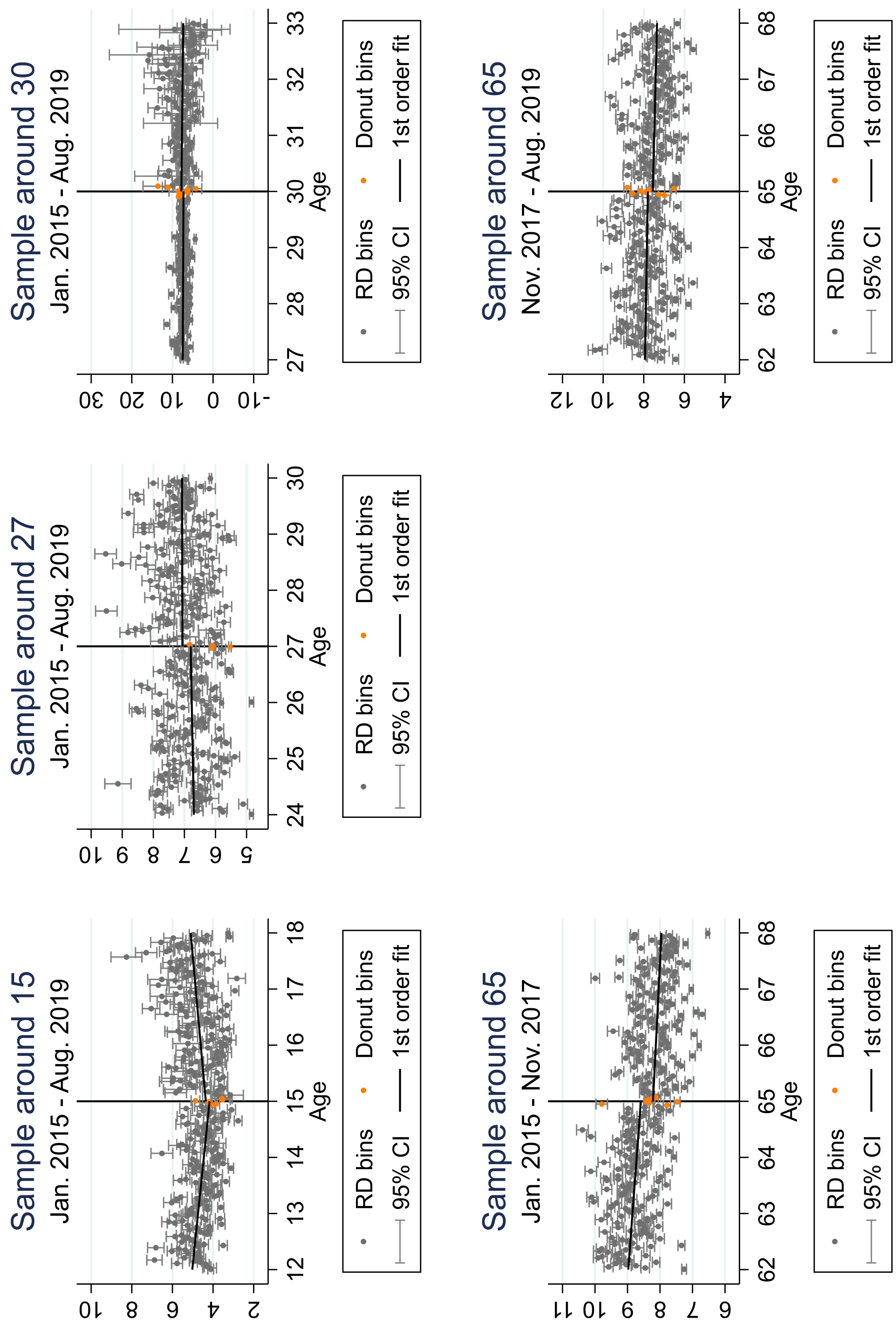
Notes: McCrary's sorting tests around the cutoffs 15, 27, 30 (Jan. 2015 - Aug. 2019) and 65 (separately for Jan. 2015 - Nov. 2017 and Nov. 2017 - Aug. 2019). The figure reports the histogram, the kernel densities and the 95% confidence intervals. The lighter bins are those excluded from the RD estimation following a Donut-Hole approach.

Figure 6: Probability of purchase - Order 1



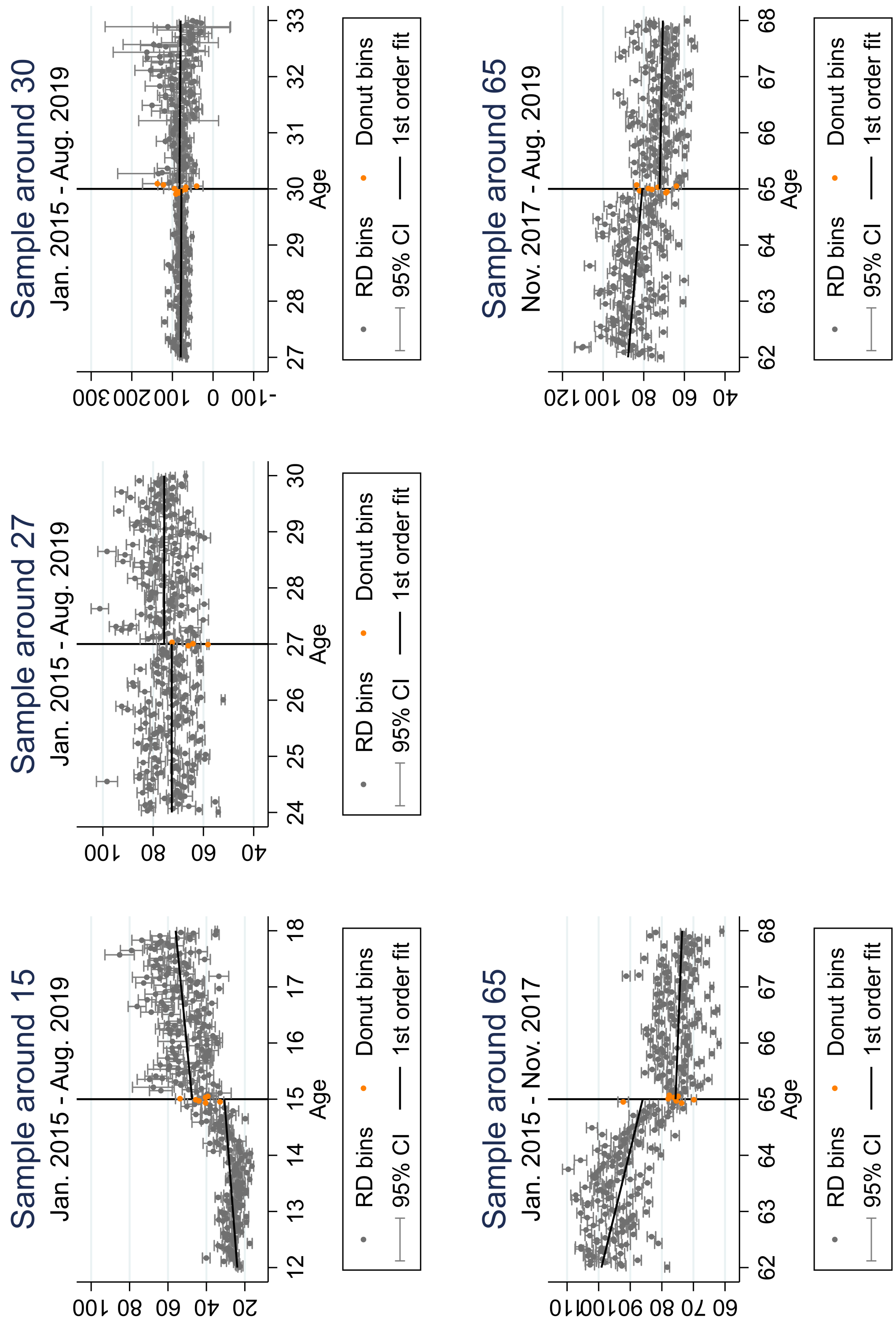
Notes: Reduced form relationship between the age level and the probability of purchase. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 1st order local polynomial fit does not consider these observations.

Figure 7: Number of visits - Order 1



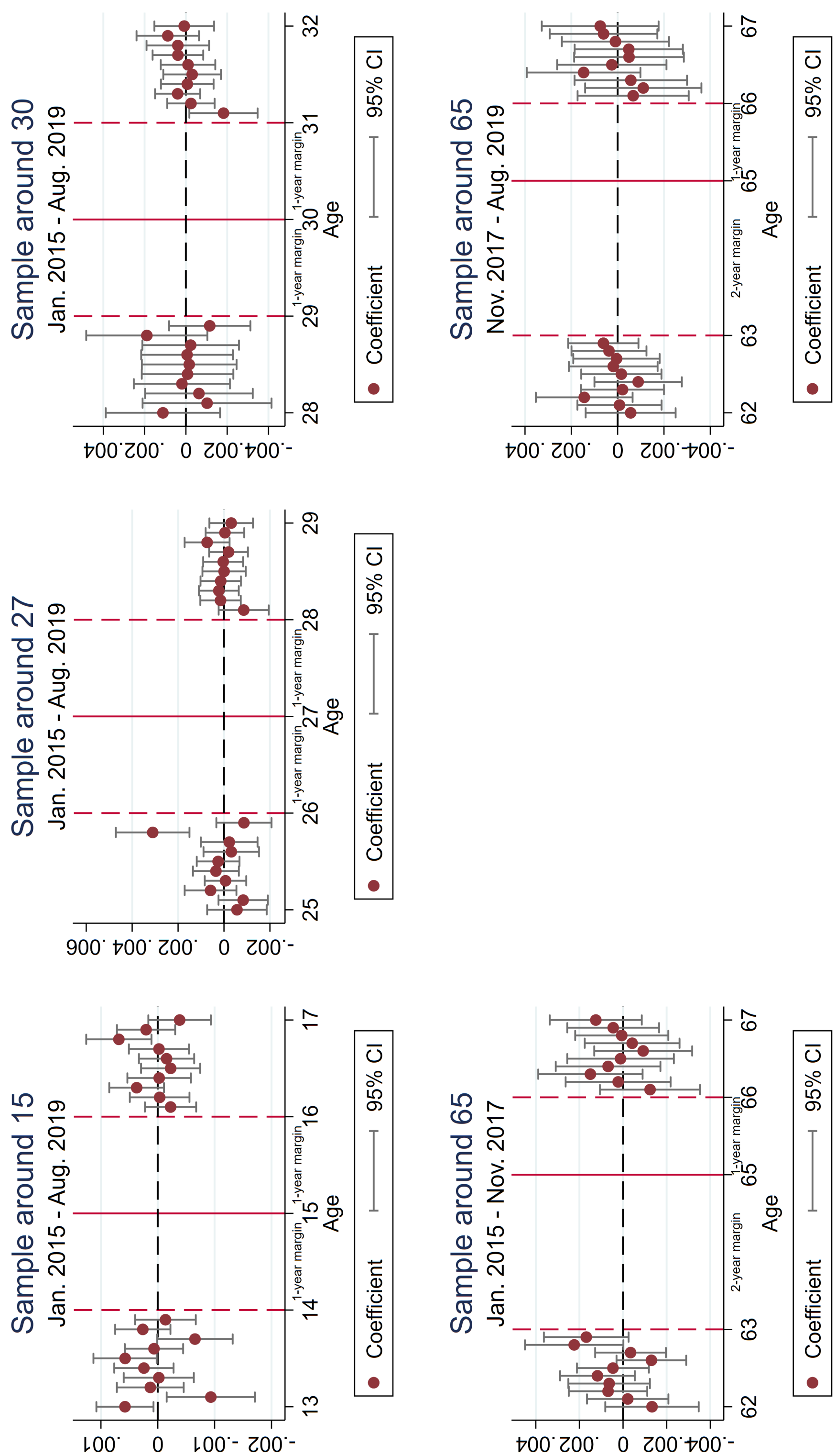
Notes: Reduced form relationship between the age level and the number of visits. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 1st order local polynomial fit does not consider these observations.

Figure 8: Cost of the visits - Order 1



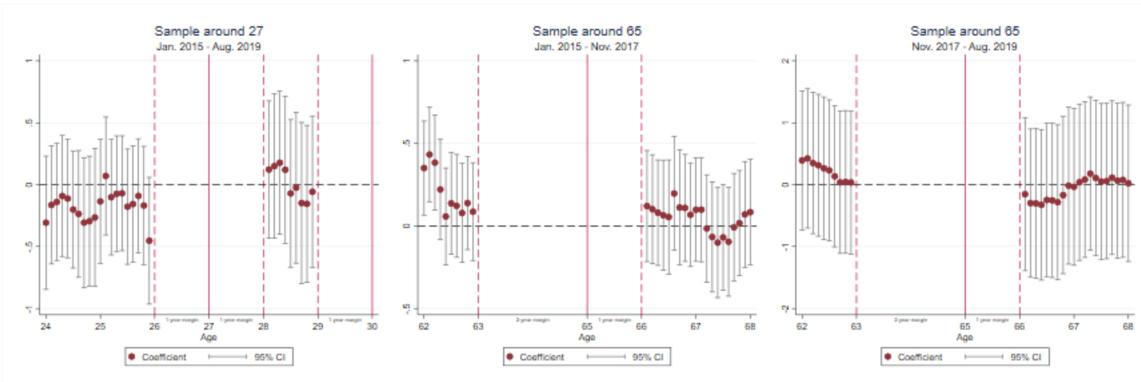
Notes: Reduced form relationship between the age level and the cost of visits. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 1st order local polynomial fit does not consider these observations.

Figure 9: Placebo cutoff - Probability of purchase



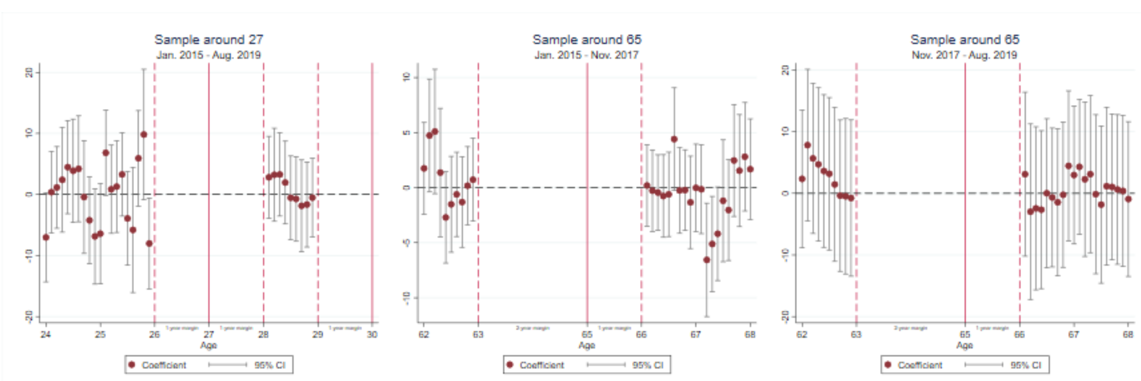
Notes: (Sharp) RD point estimates and 95% confidence intervals for the probability of purchase in the 4 main samples (around 15, 27, 30 and 65), the latter separately for Jan. 2015 - Nov. 2017 and Nov. 2017 - Aug. 2019. The samples around 15, 27 and 30 consider those placebo age levels outside a 1-year margin from the true cutoff; the sample around 65 consider the placebo age levels outside a 2-years margin on the left, and a 1-year margin on the right (as subscribers start purchasing the Senior card as they turn 64).

Figure 10: Placebo cutoff - Visits



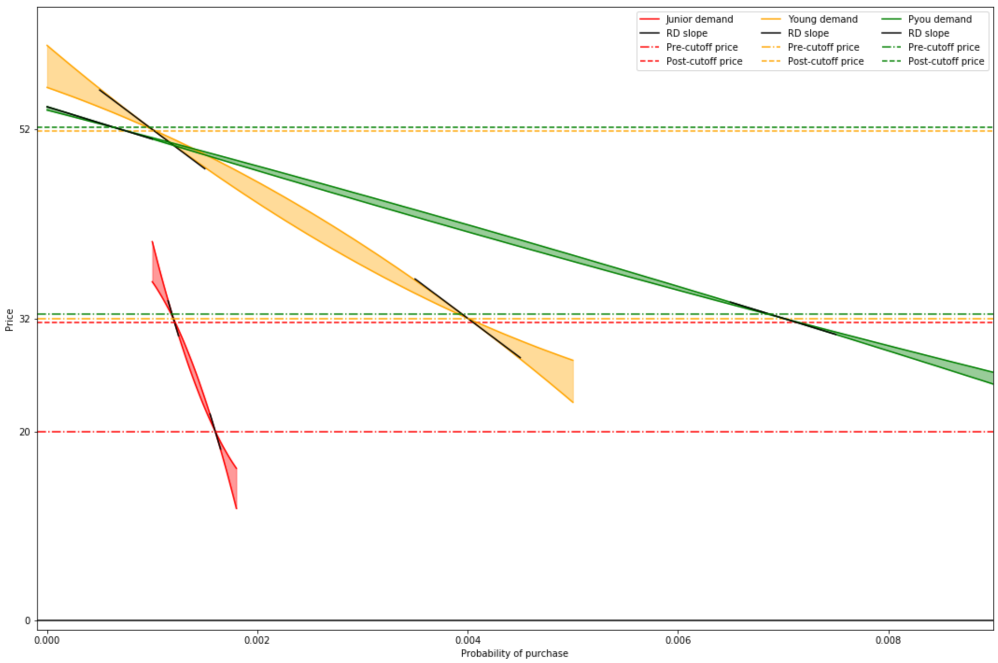
Notes: The figure shows the (sharp) RD point estimates and 95% confidence intervals for the number of visits in the 3 main samples (around 27, 30 and 65), with a 1 year margin around each true threshold.

Figure 11: Placebo cutoff - Equivalent visits' cost



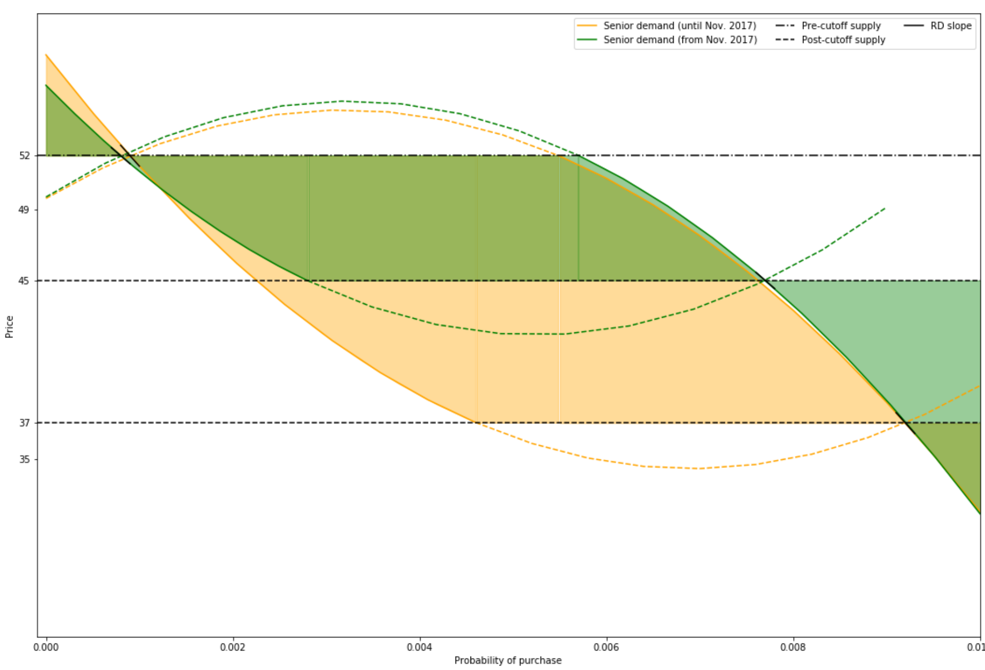
Notes: The figure shows the (sharp) RD point estimates and 95% confidence intervals for the equivalent cost of the visits in the 3 main samples (around 27, 30 and 65), with a 1 year margin around each true threshold.

Figure 12: Demand for Junior, Young and Pyou cards



Notes: The figure shows the (sharp) RD point estimates and 95% confidence intervals for the equivalent cost of the visits in the 3 main samples (around 27, 30 and 65), with a 1 year margin around each true threshold.

Figure 13: Demand for Senior cards



Notes: The figure shows the (sharp) RD point estimates and 95% confidence intervals for the equivalent cost of the visits in the 3 main samples (around 27, 30 and 65), with a 1 year margin around each true threshold.

Figure 14: Substitution effects

Notes: The figure shows the (sharp) RD point estimates and 95% confidence intervals for the equivalent cost of the visits in the 3 main samples (around 27, 30 and 65), with a 1 year margin around each true threshold.

Appendix

Table A1: Probability of purchase - Larger Donut-Hole sharp RD - Sample around 15

	Jan. 2015 - Aug. 2019			
	(5)	(6)	(7)	(8)
RD estimate	-0.00013	0.00005	-0.00016	0.00006
	(0.00024)	(0.00051)	(0.00026)	(0.00051)
Elasticity				
Pop. in the last bin	0.287	0.118	0.354	0.123
Pop. within bandwidth	0.253	0.104	0.312	0.108
polynomial order	1	2	1	2
cutoff	15	15	15	15
Bandwidth	0.754	0.982	0.717	0.970
Mean	0.00186	0.00186	0.00186	0.00186
Effective N	1000158	1364070	1000158	1364070
Total N	5188563	5188563	5188563	5188563
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole sharp RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Probability of purchase - Larger Donut-Hole fuzzy RD - Sample around 27

	Jan. 2015 - Aug. 2019			
	(5)	(6)	(7)	(8)
RD estimate	-0.00128***	-0.00177***	-0.00128***	-0.00177***
	(0.00062)	(0.00100)	(0.00056)	(0.00095)
1st stage estimate	0.72763***	0.72904***	0.72763***	0.72903***
	(0.00093)	(0.00087)	(0.00093)	(0.00087)
Elasticity				
Pop. in the last bin	1.714	2.359	1.715	2.360
Pop. within bandwidth	1.582	2.189	1.584	2.190
polynomial order	1	2	1	2
cutoff	27	27	27	27
Bandwidth	0.779	1.097	0.779	1.098
Mean	0.00364	0.00364	0.00364	0.00364
Effective N	1062737	1642849	1062737	1642849
Total N	5505652	5505652	5505652	5505652
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Probability of purchase - Larger Donut-Hole fuzzy RD - Sample around 30

	Jan. 2015 - Aug. 2019			
	(1)	(2)	(3)	(4)
RD estimate	-0.00308***	-0.00043	-0.00308***	-0.00043
	(0.00115)	(0.00595)	(0.00114)	(0.00595)
1st stage estimate	0.99960***	1.00115***	0.99960***	1.00115***
	(0.00016)	(0.00070)	(0.00016)	(0.00070)
Elasticity				
Pop. in the last bin	3.098	0.428	3.099	0.432
Pop. within bandwidth	2.619	0.358	2.620	0.362
polynomial order	1	2	1	2
cutoff	30	30	30	30
Bandwidth	0.775	0.654	0.778	0.655
Mean	0.00625	0.00625	0.00625	0.00625
Effective N	284112	232311	284112	232311
Total N	1474062	1474062	1474062	1474062
Area F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. The first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Probability of purchase - Larger Donut-Hole fuzzy RD - Sample around 65

	Jan. 2015 - Nov. 2017				Nov. 2017 - Aug. 2019			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RD estimate	0.00119***	0.00208	0.00129***	0.00213	0.00484**	0.01145**	0.00517**	0.01170**
	(0.00064)	(0.00215)	(0.00065)	(0.00220)	(0.00154)	(0.00307)	(0.00153)	(0.00328)
1st stage estimate	0.99389***	0.99294***	0.99407***	0.99296***	0.99690***	0.99997***	0.99692***	0.99945***
	(0.00067)	(0.00177)	(0.00070)	(0.00181)	(0.00077)	(0.00202)	(0.00079)	(0.00239)
Elasticity								
Pop. in the last bin	0.696	1.220	0.755	1.247	3.509	8.300	3.751	8.482
Pop. within bandwidth	0.685	1.176	0.734	1.202	3.304	7.854	3.532	8.025
polynomial order	1	2	1	2	1	2	1	2
cutoff	65	65	65	65	65	65	65	65
Bandwidth	0.969	0.753	0.881	0.738	0.596	0.720	0.563	0.705
Mean	0.00284	0.00284	0.00284	0.00284	0.00272	0.00272	0.00272	0.00272
Effective N	1112191	815947	964085	815947	330080	518998	330080	518998
Total N	4326231	4326231	4326231	4326231	2721630	2721630	2721630	2721630
Area F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole fuzzy RD estimates. The dependent variable is a dummy for card's purchasers. Columns 1-4 refer to the period January 2015 - November 2017, columns 5-8 to November 2017 - August 2019. The RD estimate is rescaled to represent the change in the probability of purchase for a 10 euros variation in the card's price. The models employ a Donut-Hole approach, thereby dropping the first age bin before and after the relevant threshold (see also Figures **??** and **??**). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. In each period, the first 2 columns control for Area and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Visits - Larger Donut-Hole Sharp RD estimates - Sample around 15

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
	0.128	0.347	0.128	0.349	7.949**	5.733	7.927**	5.707
	(0.282)	(0.358)	(0.282)	(0.358)	(3.433)	(4.300)	(3.425)	(4.295)
cutoff	15	15	15	15	15	15	15	15
polynomial order	1	2	1	2	1	2	1	2
Price (left)	20	20	20	20	20	20	20	20
Price (right)	32	32	32	32	32	32	32	32
Bandwidth (left)	2.038	3.913	2.039	3.911	1.151	2.199	1.151	2.196
Bandwidth (right)	2.617	3.500	2.605	3.495	2.553	3.594	2.547	3.590
Mean	5.338	5.338	5.338	5.338	29.478	29.478	29.478	29.478
Effective N	5787	10509	5776	10497	4201	7416	4196	7410
Total N	46150	46150	46150	46150	46150	46150	46150	46150
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Sharp RD estimates. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Visits - Larger Donut-Hole Fuzzy RD estimates - Sample around 27

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
	0.476†	0.546	0.472†	0.547	6.130*	7.302	6.141*	7.263
	(0.593)	(0.898)	(0.595)	(0.897)	(6.075)	(9.517)	(6.069)	(9.517)
1st stage estimate	0.348***	0.246***	0.347***	0.248***	0.347***	0.236***	0.348***	0.238***
	(0.025)	(0.031)	(0.025)	(0.031)	(0.025)	(0.031)	(0.025)	(0.031)
cutoff	27	27	27	27	27	27	27	27
polynomial order	1	2	1	2	1	2	1	2
Price (left)	32	32	32	32	32	32	32	32
Price (right)	52	52	52	52	52	52	52	52
Bandwidth (left)	2.516	5.154	2.507	5.144	2.507	4.851	2.500	4.818
Bandwidth (right)	3.125	7.964	3.042	7.860	3.215	8.504	3.133	8.387
Mean	6.227	6.227	6.227	6.227	67.714	67.714	67.714	67.714
Effective N	16602	40190	16362	39838	16817	41094	16572	40641
Total N	220997	220997	220997	220997	220997	220997	220997	220997
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Visits - Larger Donut-Hole Fuzzy RD estimates - Sample around 30

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Aug. 2019								
	0.062	1.689	0.085	1.686	1.712	0.183	2.465	0.425
	(1.532)	(2.897)	(1.505)	(2.833)	(18.213)	(23.262)	(18.048)	(23.208)
1st stage estimate	0.612***	0.789***	0.612***	0.823***	0.601***	0.619***	0.602***	0.619***
	(0.043)	(0.143)	(0.043)	(0.148)	(0.050)	(0.060)	(0.050)	(0.061)
cutoff	30	30	30	30	30	30	30	30
polynomial order	1	2	1	2	1	2	1	2
Price (left)	32	32	32	32	32	32	32	32
Price (right)	52	52	52	52	52	52	52	52
Bandwidth (left)	1.151	2.026	1.151	2.023	1.083	1.910	1.070	1.904
Bandwidth (right)	1.279	1.070	1.276	1.037	1.083	1.910	1.070	1.904
Mean	6.563	6.563	6.563	6.563	70.580	70.580	70.580	70.580
Effective N	2193	3261	2191	3234	2010	3412	1988	3407
Total N	16093	16093	16093	16093	16093	16093	16093	16093
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

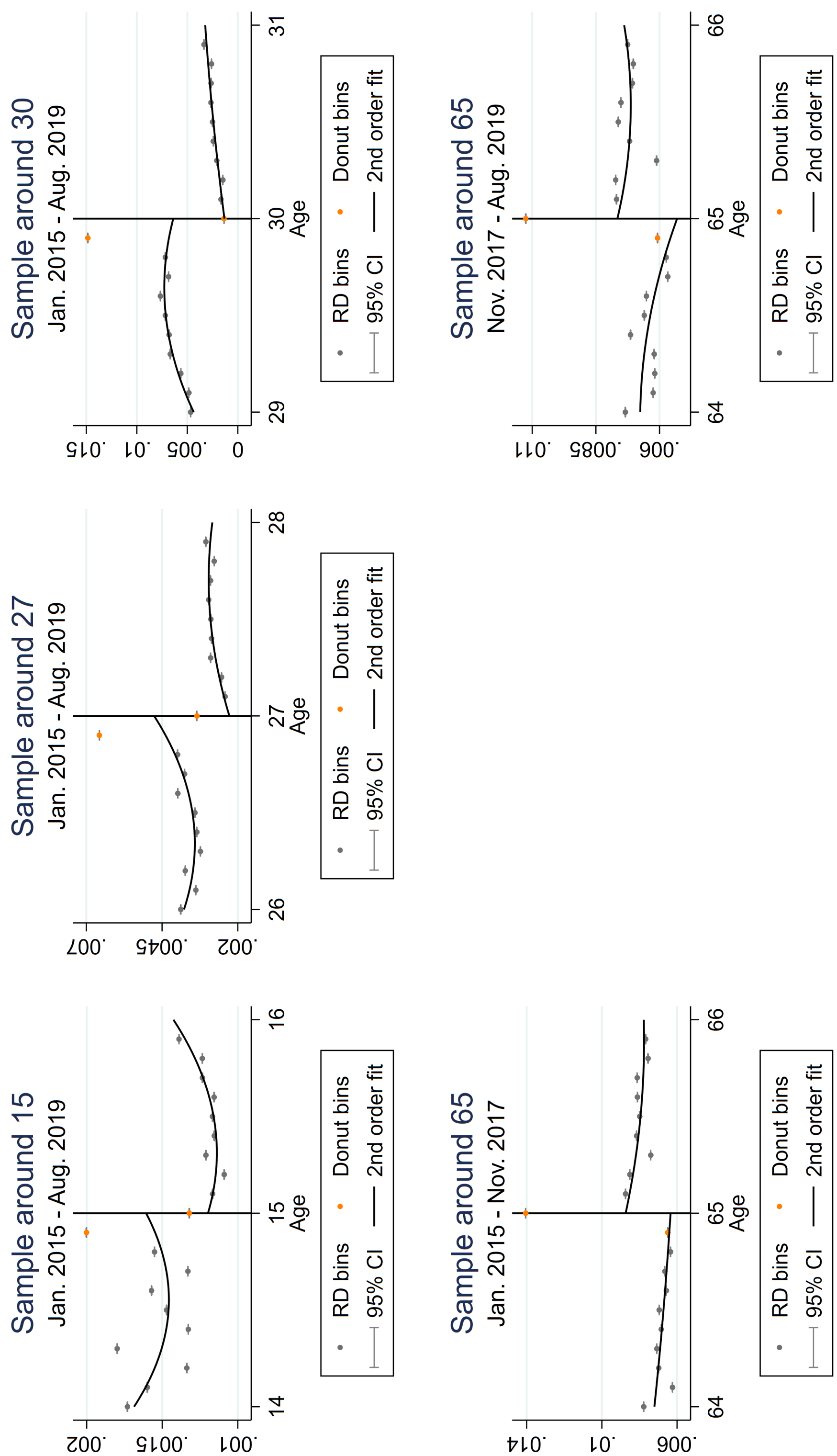
Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Visits - Larger Donut-Hole Fuzzy RD estimates - Sample around 65

	Visits				Equivalent cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Jan. 2015 - Nov. 2017								
	-1.074***	-1.206***	-1.050***	-1.183***	-32.225***	-57.172***	-31.745***	-53.332***
	(0.247)	(0.388)	(0.202)	(0.334)	(4.973)	(24.854)	(4.689)	(20.635)
1st stage estimate	0.413***	0.344***	0.422***	0.356***	0.247***	0.072*	0.264***	0.080**
	(0.006)	(0.008)	(0.005)	(0.008)	(0.009)	(0.015)	(0.009)	(0.015)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	37	37	37	37	37	37	37	37
Bandwidth (left)	10.676	13.348	11.571	14.225	4.241	4.718	4.594	4.844
Bandwidth (right)	7.965	8.753	7.301	8.637	7.304	9.183	6.832	9.157
Mean	7.982	7.982	7.982	7.982	85.218	85.218	85.218	85.218
Effective N	87874	101745	89038	104888	58555	67097	57851	67444
Total N	188791	188791	188791	188791	188791	188791	188791	188791
B. Nov. 2017 - Aug. 2019								
RD estimate	-1.432**	-1.577*	-1.386**	-1.539†	-40.723***	-46.146***	-41.922***	-45.887***
	(0.466)	(0.630)	(0.475)	(0.620)	(3.924)	(5.411)	(3.809)	(5.156)
1st stage estimate	0.376***	0.331***	0.352***	0.333***	0.419***	0.358***	0.404***	0.360***
	(0.015)	(0.020)	(0.016)	(0.019)	(0.012)	(0.018)	(0.012)	(0.018)
cutoff	65	65	65	65	65	65	65	65
polynomial order	1	2	1	2	1	2	1	2
Price (left)	52	52	52	52	52	52	52	52
Price (right)	45	45	45	45	45	45	45	45
Bandwidth (left)	6.051	9.253	5.280	9.369	8.573	10.755	7.472	10.883
Bandwidth (right)	4.989	8.660	5.469	8.949	4.974	8.748	5.317	8.951
Mean	7.107	7.107	7.107	7.107	77.178	77.178	77.178	77.178
Effective N	32448	51548	32133	52420	38806	55509	37176	56272
Total N	113376	113376	113376	113376	113376	113376	113376	113376
Municipality F.E	YES	YES	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Gender F.E.	NO	NO	YES	YES	NO	NO	YES	YES

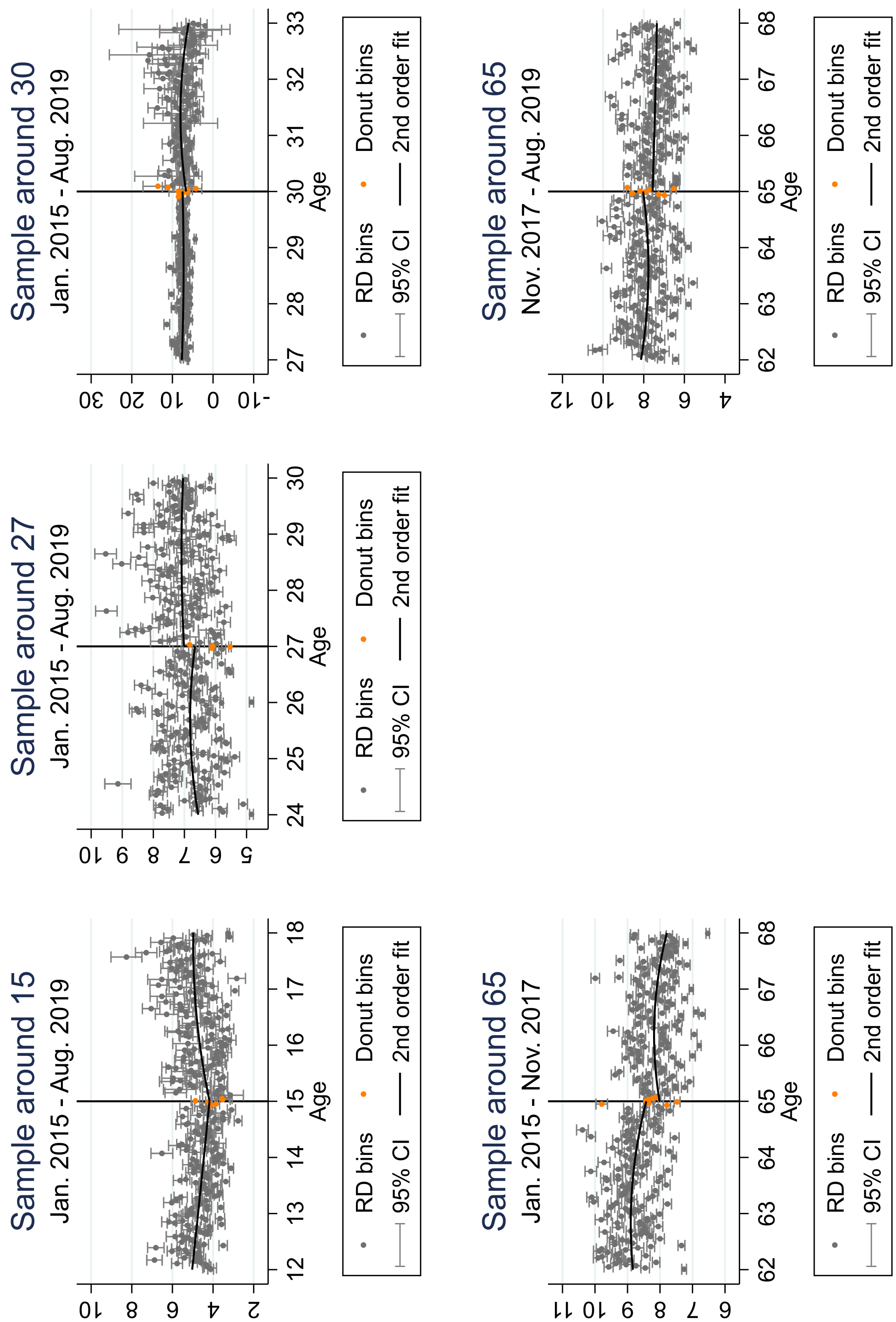
Notes: Donut-Hole Fuzzy RD estimates. The RD estimate refers to the ratio between the reduced form and the first stage estimate, which is also reported. The dependent variable is the number of visits in columns 1-4, the equivalent cost of the visits in columns 5-8. The RD estimate is rescaled to represent the change in the number of visits (visits' cost) for a 10 euros variation in card's price. All the models employ a Donut-Hole approach (see also Figure 5). Odd and even columns refer to a 1st and 2nd order local polynomial fit, respectively. For each dependent variable, the first 2 columns control for Municipality and Year fixed effects, the last 2 columns also include Gender fixed effects. Robust standard errors are clustered at the Year-Gender-Municipality level.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 15: Probability of purchase - Order 2



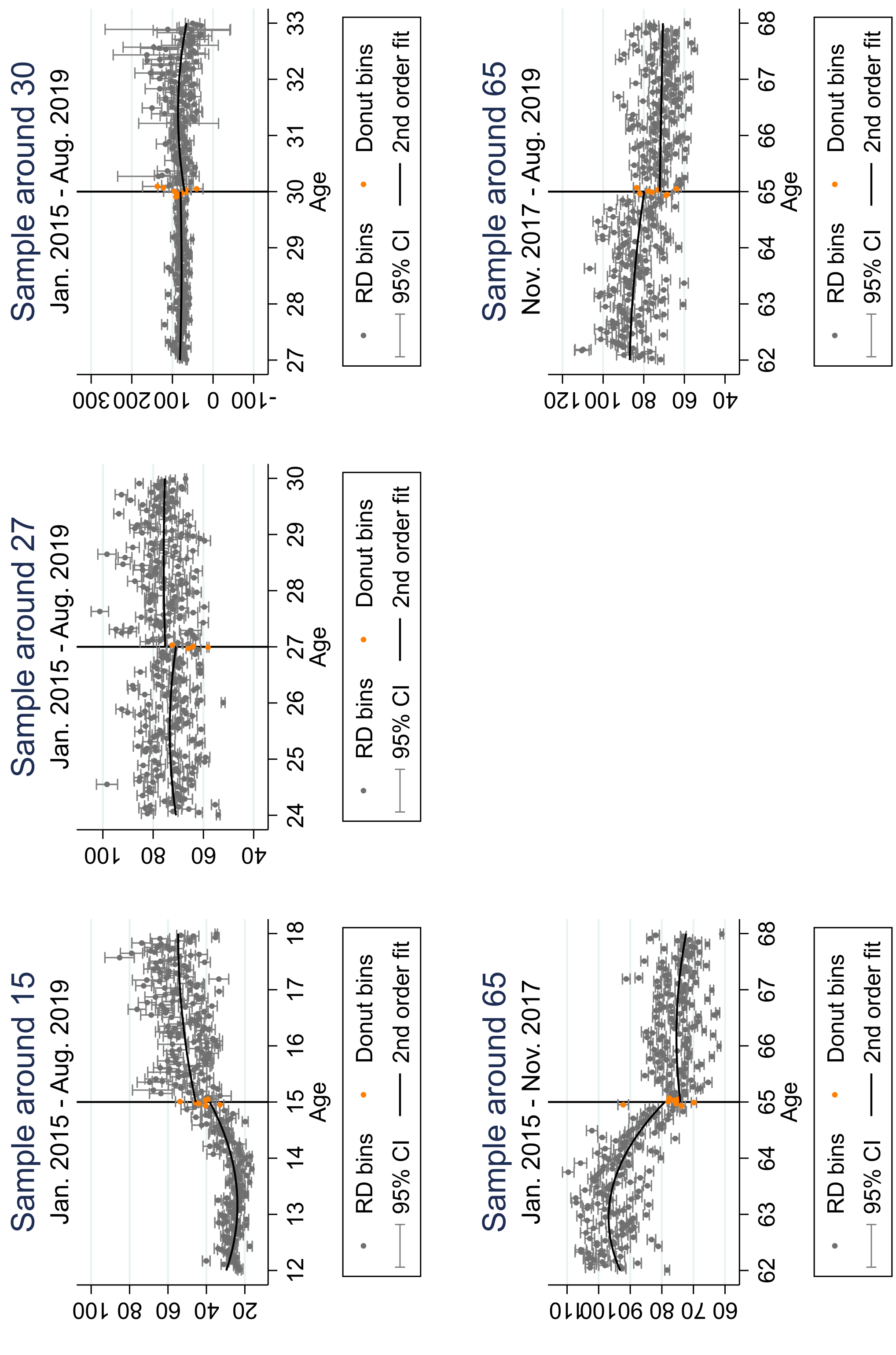
Notes: Reduced form relationship between the age level and the probability of purchase. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 2nd order local polynomial fit does not consider these observations.

Figure 16: Number of visits - Order 2



Notes: Reduced form relationship between the age level and the number of visits. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 2nd order local polynomial fit does not consider these observations.

Figure 17: Visits' equivalent cost - Order 2



Notes: Reduced form relationship between the age level and the visits' equivalent cost. The red bins are those excluded from the RD estimation following a Donut-Hole approach. The 2nd order local polynomial fit does not consider these observations.