Drip Pricing When Consumers Have Limited Foresight: Evidence from Driving School Fees*

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Abstract

This paper empirically investigates the add-on or "drip" pricing behavior of firms in the Portuguese market for driving instruction. We present a model along the lines of Gabaix and Laibson (2006) in which consumers purchase a base and, with some probability, an add-on product from the same firm, but are not always aware of the possible need for the add-on product. We show that a typical loss leader pricing strategy emerges whereby markups on the upfront product are artificially lowered, while firms price the add-on at monopoly levels. We then test the implications of the model using a detailed snapshot of industry data on student characteristics and preferences, school attributes including prices and costs, and market demographics for a cross-section of local markets with differing numbers of school competitors. We find significant evidence in support of the model predictions, including that firms face a substantial profit motive in the add-on market. Most notably, markups for the base product, but not the add-on products, decline in the number of competitors a firm faces, a prediction that has not been established in the empirical literature to date. Finally, we estimate an empirical version of the model to show that approximately one-quarter of students are not aware of the add-on when making their school choice. This result has important policy implications about the cross-subsidization from those students who are unaware of the add-on to those who are.

Keywords: market structure, loss-leader pricing, myopic consumers

JEL Classification: L10, L15, L80

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1 Introduction

In many industries, sellers advertise a low price for an upfront product in hopes of generating subsequent sales of other "add-on" products in greater numbers or at greater profit margins than the upfront product's sales. Rational-actor models typically explain the notion that multi-product firms might sell some products as low-markup "bargains" or loss leaders, only to recover these losses with high-markup "ripoffs" with search costs, price discrimination, or switching costs.[1]

Gabaix and Laibson (2006) formalize another explanation for high markups in add-on markets: high add-on prices may be optimal when consumers are naïve and do not anticipate that the price of the unadvertised add-on product is likely to be high. As an example, they point to tied products such as printers and toner cartridges in which consumer unawareness of the cartridge's high markup reduces the role that the tied product plays in the purchase process.[2]

To what extent are any of these theoretical predictions about add-on pricing borne out in reality? The empirical literature on add-on pricing in loss leader models is surprisingly scant. Several recent papers' findings are consistent with products serving as loss leaders. For instance, Chevalier et al. (2003) demonstrate declines in retail price margins for certain grocery store products during peak demand periods, which suggests that these products serve as loss leaders in driving store traffic. In studying online computer memory chip purchases, Ellison and Ellison (2009) show that a loss leader firm that shrouds add-ons is profitable by attracting a large number of customers who end up buying upgraded products at higher prices. In a field experiment, Chetty et al. (2009) find that demand falls when retailers "unshroud" by posting tax-inclusive prices for personal care products. In other field experiments, Hossain and Morgan (2006) and Brown et al. (2010) demonstrate that raising shipping charges increases revenues and the number of bidders attracted to eBay auctions.[3] There is little systematic evidence on add-on pricing in environments where consumers are not perfectly rational, however.

In this article, we empirically investigate firm competition in the Portuguese market for driving instruction. Here students initially purchase a base course of driving instruction, completion of which entitles them to one attempt at passing a theory and a practical driving exam. Should the student fail either exam, additional fees accrue for both lessons and a repeat exam. Schools are required to keep a full schedule of their add-on surcharges on-site, even though doing so does not rule out unawareness of these fees by at least some students at the time of their initial school choice. Our setting, as with professional testing and certification markets more generally, is one in which consumers might also systematically underestimate their probability of failing an exam and,

[1]See Ellison (2005) for a general framework that intersects these three explanations.

[2]Gabaix and Laibson (2006) form part of a broader literature that explores how biases in consumers' beliefs explain various pricing practices. Particular features of subscription pricing are consistent with quasi-hyperbolic discounting (Oster and Scott Morton 2005; DellaVigna and Malmendier 2006), lack of self control (DellaVigna and Malmendier 2004) or overconfidence (Grubb 2009); loss aversion might motivate bait-and-switch pricing (Köszegi and Rabin 2006; Heidhues and Köszegi 2010); and boundedly-rational heuristics can be applied to study how market equilibria exploit noise in consumer product evaluations (Jin and Leslie 2003; Spiegler 2006).

[3]This outcome contrasts with mixed results from several laboratory experiments (Morwitz et al. 1998; Bertini and Wathieu 2008).

thus, their demand for the add-on.[4] Among Portuguese driving school students, exam repetition is actually quite common; 45.6 percent of students fail either the theory or the practice exam the first time. The Portuguese regulator, the Instituto da Mobilidade e dos Transportes Terrestres (IMTT), asserts, however, that a significant share of students is unaware of these high failure rates when they first enroll in a school.

A unique feature of our setting is that we observe the universe of Portuguese driving school students over a three-year period, including information on the school they attend, the sequence of their exam outcomes, and demographic information such as their age, gender, and place of residence. We combine these data with information on school characteristics and hand-collected school fees for the basic driving course and for repeating either the theory or the practice portion. Such detailed data allow us to calculate the marginal cost to the school of each student for the basic and repeat courses and, consequently, to compute profit margins for schools' upfront and add-on services. Local markets further differ in the number of schools serving each market, which permits us to investigate the role of the competitive environment on pricing. Taken together, these data allow us to trace the entire sequence of purchases that students make and the prices they pay for each purchase, a feature that otherwise would render the empirical study of add-on pricing challenging.

To study the two-part pricing by driving schools, we first set up a basic model that builds on the Gabaix and Laibson (2006) model of add-on pricing with myopic consumers. On the demand side, we allow for two types of consumers who purchase an upfront and, with some probability, an add-on product from the same firm. Sophisticated consumers are rational in forming expectations about their likelihood of needing to purchase the add-on, and can engage in costly effort to reduce their purchase incidence. Myopic consumers, conversely, believe their demand for the add-on product is nonexistent and do not account for its price when choosing their school. We show that a typical loss-leader pricing strategy emerges in which firms sell the upfront product at or near competitive profit margins and simultaneously price the add-on at supra competitive levels.

As in Gabaix and Laibson, the assumption of Bertrand competition among symmetric firms results in profit neutrality across the two products, with add-on profits offsetting upfront losses. This feature has two consequences for the upfront product's price. First, a larger share of myopic consumers, who unexpectedly (to them) participate and generate profit in the add-on market, depresses the upfront product's price. Second, increases in the probability with which consumers require the add-on product similarly raise profitability, offset by a lower upfront product price and markup.

We then test several of these predictions in the driving school setting. First, we establish that the rates of failure across schools result in significant revenue and profit to schools from the add-on market; our data indicate that an estimated 14.0 percent of revenue and 24.4 percent of variable profit derive from repeat courses for the average school. In monetary terms, schools earn

[4] In consumer financial markets, consumers might similarly underestimate their future need for account features such as overdraft services or financing, at the time when they open a bank or credit card account (Stango and Zinman 2009).

an additional €0.81 for every €1 the average student generates in profit from its upfront service.

Second, while the Lerner index in the upfront market averages 28.7 percent, the corresponding indices in the theory and practice add-on markets average 86.5 and 56.6 percent, respectively: schools earn low markups in the upfront market, but simultaneously reap supra competitive markups in the add-on markets. Moreover, schools' upfront prices and markups strongly correlate with the number of schools in their municipality, pointing to the standard downward pressure on prices that additional competition exerts. On the other hand, schools' add-on prices and markups remain remarkably uncorrelated with the market structure across all specifications, a facet of competition, or the lack thereof, predicted by the theoretical model.

Since our data do not contain direct evidence on students' ex-ante perception of either their likelihood of failing or their understanding of the financial repercussions of having to retake the exam, we complement our primary data with survey evidence from a subsample of students who completed a short questionnaire as part of their theory exam session at a select testing center. The survey evidence suggests that students overestimate their probabilities of passing an exam, in particular in the case of the practice exam, on which students had limited information at the time of responded to the survey questions. At the same time, the survey responses identify a sizable group of students who either do not know whether they will or believe that they will not incur any fees for retaking an exam. These are two possible reasons why students would discount the price of the add-on at the time of their school choice.

In addition to providing descriptive evidence in support of the model's predictions, we estimate an empirical version of the model that relies on students' responses to schools' posted upfront and add-on prices to back out the proportion of students whose school choice is consistent with a failure to account for the add-on prices. Specifically, we detail a two-type mixture model of school choice in which the two types, as in the theoretical model, differ in their anticipated probabilities of failing an exam. Myopes and sophisticates make school choices based on whether they consider the upfront price only or the full price, which includes the expected repeat add-on fees. Our results demonstrate that schools' pricing behavior does not merely reflect students' differing price sensitivities across product markets; rather, schools' pricing is consistent with approximately one-quarter of the student population acting myopically when making their school choices.

That myopes constitute a nontrivial subset of the student population has important distributional consequences. If sophisticates can reduce their demand in the add-on market, they reap the benefits of low prices in the upfront market. Thus, myopic students – whose business in both markets comprises a significant portion of schools' profits – effectively subsidize sophisticates with lower prices in the upfront market.

The paper proceeds as follows. Section 2 presents a basic loss-leader model with boundedly-rational students. Section 3 introduces the data and the institutional setting of Portuguese driving schools. Section 4 and section 5 provide evidence to support some of the basic predictions and implications of the model based on our observational and survey data. Section 6 formalizes an empirical model using several of the model implications. Section 7 concludes.

2 A Model of Add-on Pricing with Myopic Students

Here, we outline a simple model of add-on pricing in the spirit of Gabaix and Laibson (2006) and Spiegler (2011) to illustrate that the loss-leader pricing strategies common to multi-product settings with search or switching costs can also arise when consumers have limited foresight of their demand for the add-on product.

Consider a two-period model of a market with n symmetric schools and a continuum of students. The schools offer an upfront or base service u – a course of instruction to prepare for the driving exam – and an add-on service a for an additional fee – a make-up course for exam re-takers. We assume that the add-on price takes the form of a surcharge: students who fail the exam do not have a choice but to purchase the add-on. As in classic repeat purchase models of pricing with switching costs (Klemperer 1987a; Beggs and Klemperer 1992; Farrell and Klemperer 2007), we assume that consumers are locked into purchasing both the upfront course and a possible repeat course from the same driving school.[5] In contrast to these models where firms are not able to commit to prices for subsequently purchased add-on products in the initial period, firms are required to keep at hand a full schedule of prices. We thus assume that schools commit to the add-on price when setting the price menu in the initial stage of the game.

In period 1, each school j simultaneously chooses and commits to a pricing strategy (p_j^u, p_j^a), where p_j^u and p_j^a are the prices of school j's upfront and add-on services. As in Gabaix and Laibson (2006), the add-on price p^a is effectively bounded above by $\overline{p}^a$. For example, if a student is forced to pay a high repeat-course price, he might choose not to continue with driving instruction or lodge a complaint with the regulatory body, the IMTT. While the IMTT does not directly regulate the price of repeat courses, its oversight likely also limits the fees that schools can charge. Firms face constant and nonnegative marginal costs of providing each service, (c^u, c^a). Students then choose a school to enroll in and purchase the upfront service u. In period 2, students learn whether or not they need to buy the add-on at its set price depending on their exam results from period 1. Students have a strictly positive, identical probability of $\overline{\lambda} \in (0, 1]$ of failing the initial driving exam.

We assume that there are two student types in the market: a share of $\pi \in (0, 1)$ sophisticates s and $(1 - \pi)$ myopes m. In period one, myopes have limited foresight about the add-on service; they only become aware of it ex-post when they fail the exam and are forced to purchase it. The assumption of limited foresight might reflect that myopic students assign zero probability to failing the exam – the students suffer from over-optimism, for example – or that students are unaware of the existence of makeup course fees simply because the school does not prominently advertise this information.

In contrast, sophisticated students recognize the possibility of having to retake the exam. We assume they form rational expectations over their probability of failing the exam, assessing it correctly at λ, and consider the add-on service when making their choice in the first period. Sophisticates

[5] We discuss below that we observe a negligible share of school transfer by students in our data, which we believe is consistent with the lock-in assumed here.

can engage in costly effort to reduce their probability of failing from $\overline{\lambda}$ to $\underline{\lambda} > 0$ at an effort cost e.[6]

In line with our empirical setting, we assume, as in Gabaix and Laibson (2006), that students make a discrete school choice, allowing for heterogeneous valuations of each school. For simplicity, we assume there are no systematic differences in valuations by type. The utility of student i of type $\{m, s\}$ from enrolling at school j is given by

$$\begin{aligned} u_{ij}^m &= v - p_j^u + \varepsilon_{ij} \\ u_{ij}^s &= v - p_j^u - \lambda p_j^a + \varepsilon_{ij}, \end{aligned} \tag{1}$$

where ε_{ij} denotes student i's heterogeneous valuation for the school j, such as the distance he travels to the school, and $\lambda = \{\underline{\lambda}, \overline{\lambda}\}$, depending on whether the sophisticate chooses to engage in effort.[7]

A student's demand for each school's services is given by the probability that the (expected) utility of school j exceeds that of all competing school $k \neq j$. Under the assumption that ε is distributed type I extreme value, this assumption results in common multinomial logit school choice probabilities:

$$\begin{aligned} D_j^m &= \left[1 + (n-1)\exp\left\{\frac{p_j^u - p_{-j}^u}{\sigma}\right\}\right]^{-1} \\ D_j^s &= \left[1 + (n-1)\exp\left\{\frac{p_j^u - p_{-j}^u + \lambda(p_j^a - p_{-j}^u)}{\sigma}\right\}\right]^{-1}, \end{aligned} \tag{2}$$

denoting as σ the scale parameter of the type I extreme value distribution.

Consider first the pricing in the add-on market. Since students are locked in to their school upon failing the initial exam, the school acts as a monopolist over its demand and optimally charges the highest possible price, $\overline{p}^a$.

Now consider pricing of the base service. We analyze the symmetric case, and assume that firms compete on price. In the Appendix we prove there is a unique symmetric equilibrium characterized by the following pricing strategies:

$$\begin{aligned} (p_j^a)^* &= \overline{p}^a \\ (p_j^u)^* &= c^u + \frac{\sigma n}{n-1} - \left[(1-\pi)\overline{\lambda} + \pi\underline{\lambda}\right](\overline{p}^a - c^a) \end{aligned} \tag{3}$$

[6] For example, sophisticates might study more for the theory exams or try harder at their practice lessons so as to minimize their probability of failing and the likelihood they will be required to purchase the add-on service. Unlike similar models, whereby sophisticates face a perfect substitute for the add-on service, however, we assume that sophisticates cannot reduce their probability of needing to purchase the add-on service to zero despite their best efforts to avoid it.

[7] Note that we do not model the school's choice of whether to unshroud or publicize the upfront prices. We show in the Appendix that, in our setting where add-ons are unavoidable, the shrouded and unshrouded equilibria are equivalent if sophisticates form rational expectations about add-on prices and unshrouding is costless. We therefore simply assume that sophisticates are aware of the add-on price and form expectations solely with regard to their demand for the add-on, but not the firms' prices.

provided effort costs e are at most equal to $(\overline{\lambda}-\underline{\lambda})\overline{p}^a$. We make the following observations about the equilibrium prices:

1. Schools set the price of the add-on service to be the same and equal to the ex-post monopoly price for the add-on service.

2. The add-on price does not depend on the fraction of myopes or the probability of failing because demand is perfectly inelastic in the aftermarket.

3. The price of the upfront service is increasing (decreasing) in the fraction of sophisticates (myopes), or

$$\frac{\partial (p_j^u)^*}{\partial \pi} = \left(\overline{\lambda}-\underline{\lambda}\right)\left(\overline{p}^a - c^a\right) \geq 0. \tag{4}$$

   Thus, as the fraction of myopes (sophisticates) increases, the upfront price decreases (increases) to reflect that schools anticipate larger (smaller) profits from the add-on service; schools want to attract more *myopes* upfront with their loss-leader service, only to recoup these losses in the aftermarket.[8]

4. The price of the upfront service is monotonically decreasing in the average probability of failing the exam, $\left[(1-\pi)\overline{\lambda}+\pi\underline{\lambda}\right]$. The greater the number of students schools can attract in the aftermarket, the lower the price they charge in the upfront market to entice students to choose its service in the first place.

5. Finally, markups in the upfront market decline as the number of firms increases. With large n and a sizable aftermarket, the model allows for the possibility that margins in the upfront market are negative and are offset by large, positive markups in the add-on market.

The equilibrium pricing strategies in (3) reflect that sophisticated students engage in costly effort to reduce their exposure to the add-on market. Such effort is not necessarily efficient. The firm foregoes profit in the amount of $(\overline{p}^a - c^a)\left(\overline{\lambda}-\underline{\lambda}\right)$ on every sophisticate. The choice to engage in effort, thus, is only efficient if $e \leq c^a\left(\overline{\lambda}-\underline{\lambda}\right)$, whereas the student's choice to do so reflects the prices he pays for, rather than the cost of providing, the add-on service.

In section 4 we investigate the extent to which these properties of the equilibrium pricing strategies are borne out by the pricing patterns we observe in our data. Moreover, in section 6 we estimate an empirical model based on the theoretical model presented. Beforehand we briefly describe driving instruction and schools in Portugal and summarize our sources of data.

[8]This conclusion depends on the relative ordering of the probabilities of failing by myopes and sophisticates. If sophisticated students had a strictly higher probability of failing than myopes, regardless of their expended effort, the price of the upfront service would increase in the share of myopes.

3 Background and Data

3.1 The Portuguese Market for Driving Instruction

We begin with an overview of the process of obtaining a driver's license in Portugal, the market for driving instruction, and the role of the IMTT as the regulatory agency that oversees driving instruction.

To obtain a driver's license, learner drivers aged 18 years or older must first enroll in an IMTT-authorized driving school.[9] There, candidates must complete 28 theory lessons, the curriculum of which is set by the IMTT, and a minimum of 32 on-road driving lessons. After completing the required theory lessons, students take a computerized theory exam. Subsequently, they perform an on-road driving test. Both exams are administered at one of 35 exam centers. Twenty-two exam centers are managed by the IMTT, while private organizations operate the remainder. An IMTT certified examiner oversees the on-road driving test. Upon successful completion of both exams, the IMTT issues a probationary license to the new driver. The license converts to an unrestricted one automatically should the driver avoid serious driving violations during an initial five-year probationary period. In 2011 the IMTT issued a total of 95,556 new driver's licenses, of which approximately 85 percent are the category B passenger vehicle licenses we study. For these students the process from registering at a school to receiving the probationary license takes 8.7 months to complete on average.

As of the end of 2011, there are 1,119 driving schools on mainland Portugal and 27 schools in the archipelagos of Madeira and the Azores. The industry's current size reflects significant growth in the number of firms since 1998, when only 527 schools served the population of 9.9 million individuals. Entry resulted from significant liberalization efforts of a broad number of professional services in the late 1990s. Previously, the regulatory framework restricted the number of schools serving each municipality to be a step function of the municipality's population and placed ceilings on school fees for instruction. Legislative reforms lifted both entry and price restrictions in 1998, resulting in an immediate increase in the number of schools by 25 percent and a stabilization at current levels by 2005, with virtually no exit of existing schools. A number of regulatory restraints remain in place, including territorial restrictions limiting all business to be conducted within the municipality covered by the owner's license and regulations governing the sharing of resources between commonly-owned schools that limit the presence of multi-outlet chains of schools. Eighty-seven percent of owners operate a single school, and another nine percent operate two schools. Figure 1 plots the locations of all driving schools in mainland Portugal by municipality population density.

[9]Initial authorization by the IMTT requires, among other things, proof that the proposed school owner holds at least five years of experience in driving instruction, that the school is financially viable, and that the fleet and facilities satisfy certain IMTT standards.

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Insert Figure 1 about here

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Since the deregulation in 1998, each school has set its own prices for services. A flat fee covers the base course of instruction, including classroom time, materials, practice theory exams, on-road driving lessons, and any fees the student must pay to the exam center to take the two exams. The schools handle the submission of fees to the exam center, as well as the scheduling of exams. If a learner driver fails the theory exam, he must pay the school a fee to retake the exam. Similarly, should a student fail the practice exam, he must pay an extra fee to complete five additional driving lessons and to retake the practice exam. We summarize the schools' fees for enrolling in the base course, retaking the theory exam, and preparing for and retaking the on-road driving test, as well as the frequent instances of failing either of the exams next.

3.2 Data

Our empirical analysis combines a number of data sets at the school, student, and municipality level. First, we collected data on non-price attributes of schools from the IMTT. These data, which are collected as part of each school's licensing process and which are updated periodically, include information about the school's facilities, the number and tenure of its instructors, the number of license classes offered, and characteristics of its fleet of instruction vehicles.[10] We geocoded school addresses using GIS software to derive detailed location information. Lastly, we added hand-collected school prices and estimated costs. More details about our price and cost data follow below.

Second, we obtained individual student-level school enrollment and driving exam information from the IMTT. The comprehensive, retrospective database includes the full universe of learner driver candidates who obtained their driver license's sometime in 2009 or 2010 (having started as far back as early 2008). We observe the date on which the student obtained his learner's permit and the permit's license category, the dates, times, exam centers and outcomes of each exam, the final licensing date, as well as the candidate's age, gender, and home postal code. We assume that each student resides at the centroid of his postal code area to compute his distance to his chosen school, and to the other schools in his consideration set.

Finally, we obtain demographic and other data at the level of the municipality from the market research company, GrupoMarktest, the Ministério do Trabalho e da Solidariedade Social, and Statistics Portugal.[11]

[10] The age of a school's driving fleet is determined by mapping its vehicles' license plates to the year of initial registration using a key published by the ACAP (Associação Automóvel de Portugal).

[11] Much of these data derive from Portugal's censuses of 2001 and 2011.

3.2.1 Price Collection and Sample Markets

While the IMTT collects various pieces of information about the schools it oversees, it does not collect price or fee information. We thus complement the IMTT data with hand-collected, detailed price information. To keep the data collection process manageable, we focus on 13 of the 18 Portuguese districts, excluding most notably the districts of Lisbon and Porto.[12] In our empirical work below, we focus on the effect of competition on prices and treat a municipality – the area covered by a school license – as the relevant market area within which firms compete. While schools are required to conduct their business within the municipality covered by their license, students are free to frequent a school outside of their municipality of residence. Lisbon and Porto are large urban districts made up of densely populated municipalities in close proximity, where the assumption of a single municipality comprising the relevant market area is likely unreasonable.

To collect price information in the remaining districts, we employed a team of 14 mystery shoppers who visited each school in person between November 2011 and March 2012. Each shopper used the same script to query school employees for price information, including both the upfront prices and the add-on surcharges. We include in our final sample all municipalities for whom our mystery shoppers were able to collect a complete fee schedule, consisting of the base course, the theory repetition, and the practice repetition, for all schools in the local market.[13] Our sample covers 158 municipalities with a total of 420 schools. These are displayed in panel (b) of Figure 1.

Table 1 contains descriptive statistics for our sample of markets. The average (median) municipality contains three (two) driving schools. They range in population from 3,445 to 160,825 residents, with an average population of 26,356 people, 13.8 percent of whom are aged 15 to 24 years.

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Insert Table 1 about here

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In our descriptive analysis in Section 4, we incorporate information on these and a number of other market demographics. The lower portion of Table 1 summarizes these municipality-level demographics. The age and monthly wage income of the average resident is 40.3 years and €888.74 per month (for employed residents). The average illiteracy rate in our markets is 10.5 percent of the population aged 14 or higher, slightly above the national average of nine percent, and 35.3 percent of residents have completed at least compulsory secondary education, compared to 38 percent nationwide. A little more than half of all residents use cars on a daily basis, spending approximately 19.6 minutes in commuting time on average.

[12] The other excluded districts include Braga, Viana do Castelo, and Vila Real.

[13] We were forced to drop some municipalities where at least one school was unable or unwilling to reveal the prices of the add-on services. We do not discern any systematic patterns in the frequency of such instances across districts or the territories assigned to each of our mystery shoppers. In total we dropped 31 municipalities out of the 189 municipalities with at least one school in our subset of districts.

The price for the base course typically covers the exam center fees for both exams, all the requisite materials for the theory exam, and the required number of driving lessons from one of the school's instructors. If the student fails either exam, he pays an additional fee to cover the next exam center fee; the practice exam add-on surcharge further covers the required additional driving lessons. Since schools differ somewhat in what items are included in the base course price, we standardize prices to be comparable across schools. We use the full price of the standard course of instruction as our price measure for all schools.

Panel (a) of Table 2 summarizes the distribution of prices across schools and markets. The median school charges €726 for its base driving course, with an interquartile range of €145. There is thus significant variation in prices. A large share of this variation is likely due to cost and demand differences across municipalities. Accordingly, the between-municipality standard deviation is 1.63 times the within-municipality standard deviation in upfront prices. The average practice exam add-on surcharge of €275.44 is more than double that of the theory exam add-on, €133.90, which is driven by the fact that the practice exam add-on includes five additional lessons.

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Insert Table 2 about here

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3.2.2 Marginal Cost Calculation

Our model makes predictions for variation in markups across the upfront and add-on markets. To test these predictions we require estimates of markups and, thus, marginal costs. An advantage to our setting is the relative simplicity of the service offered, which allows us to construct reliable estimates of the marginal cost a school incurs for serving an additional student in the main driving course, as well as in the repeat markets. In constructing our measures, we exploit information contained in a template that the industry association Associação Nacional dos Industriais do Ensino da Condução Automóvel (ANIECA) provides to potential entrants to estimate annual costs of operation, including both total and unit costs.

We use the cost template to compute marginal costs for each of the offered services: the upfront and the add-on services. The per student upfront service marginal cost consists of several individual components, including (i) the fees paid to the exam center for one theory and one practice test administration, (ii) the cost of instructional materials for the theory lessons, (iii) the instructor salary for 32 driving lessons and for the final on-road driving exam (which he also needs to attend to), and (iv) the vehicle operating costs of driving one of the school's vehicles during the practice lessons. According to ANIECA, vehicle operating costs consist of the cost of gasoline, depreciation expenses, maintenance and repairs, tolls and other road fees and taxes, and other expenses. The theory repeat service entails the minimal marginal cost to the school of having to cover the student's renewed theory exam fee, which is identical to the fee it pays to the exam center the first time the student takes the exam. Lastly, in offering the practice repeat course, the school incurs driving exam administration fees, as well as labor and vehicle maintenance costs equivalent to five additional driving lessons.

We use information on exam center fees, municipality-level salaries scaled to fall within the range of typical instructor pay, local gasoline prices, the estimated distance traveled in kilometers during a 32-lesson and a five-lesson course of instruction, as well as the aggregate annual usage in kilometers of each school's fleet of cars to derive marginal cost estimates. In the Appendix we describe the explicit procedure we employ to calculate each of the cost components. Our detailed data allows us to recognize both spatial and firm-level variation in costs.

Here, we briefly summarize the magnitude of the different cost sources. Per student, the average school pays €54.48 in exam fees to cover the cost of one theory and one practice exam. Some amount of variation in costs reflects differences in fees charged by private and publicly run exam centers. The cost of instructional materials is minimal and standardized, amounting to €10 per student. We estimate the school's labor cost of an instructor amounts to €236.94 and €43.08 for driving lessons during the upfront and practice repeat driving courses, respectively; we assume no marginal labor costs arise from the in-class time spent by the instructor due to the common spare capacity in classroom space. The standard deviation in the base course labor costs of €18.24 captures cost-of-living differences reflected in municipality-level incomes across municipalities. Vehicle operating costs represent the largest source of marginal costs, with gasoline costs of €0.09 per kilometer, depreciation costs of €0.15 per kilometer, maintenance and repair costs of €0.02 per kilometer, and tire expenses of €0.01 per kilometer.[14] When scaled by the 722.9 kilometers the average student covers during the driving course and exam itself, the marginal vehicle operating cost for the base course of instruction amounts to €201.36 on average. The equivalent figure is €34.17 for the practice repeat course.

Panel (b) of Table 2 summarizes the sum of the marginal cost components and the aggregate marginal cost of serving each student in the upfront and repeat driving courses. The average school incurs a marginal cost of €507.78 per student in the base course, with a standard deviation of €42.26. As a robustness check we computed a simplified marginal cost measure that assumes constant annual usage and characteristics of schools' fleets, which results in a similar average marginal cost of €499.29 for the base course. See Appendix Table B-1. We further verified the reliability of our cost estimates using feasibility studies that potential entrants prepare for the IMTT as part of the licensing process. These allow us to compare our marginal cost estimates to the schools' own estimates for a country-wide sample of schools; the comparison suggests our estimates are reasonable. We also talked to a few driving school managers across the country to confirm the validity of some of our estimates. The add-on services generate estimated marginal costs of €16.66 and €116.06 for the theory and practice repeat courses, respectively.

[14] In total we thus estimate a vehicle operating cost of €0.28 per kilometer. This compares to estimates of vehicle operating and ownership costs provided by the Automóvel Club de Portugal (ACP), which is Portugal's equivalent of AAA in the USA.

3.2.3 Other School Characteristics

Here, we summarize other school characteristics, the size of the schools' student body, and market shares for the schools in our sample and for the universe of driving schools in general. Table 2 summarizes the most pertinent information we observe about schools.

Over the three-year period from 2008 to 2010, the average of our 420 sample schools enrolled 450 students, or approximately 150 students per year.[15] There is significant variation in enrollment figures across schools, however; the interquartile range of enrollment spans from 270 to 563 students. The number of a school's local competitors ranges from zero to 14 schools, with a typical municipality containing three schools. We use enrollment at the school and in the municipality to measure market shares. The average school's market share is 34.4 percent; the presence of monopoly markets skews the market share distribution – the median market share amounts to 23.7 percent.

The median school's age is 10.6 years at the end of 2010, which reflects that approximately half of all sampled schools entered the market after deregulation in 1998. The schools have a driving fleet consisting of, at the median, three passenger vehicles, for which we observe characteristics such as an average displacement of 1.5 liters and an age of 5.3 years. Their median of four instructors have an average of 7.8 years of teaching experience at the school. Twenty-six percent of schools have a functional website.

Furthermore, we record the straight-line distance of the school to the nearest district-wide IMTT office and to its most used exam center to proxy for costs of interacting with the IMTT and of transporting students to the exam center. The average school is 28.2 kilometers from the closest IMTT office. It also is 25.2 kilometers from its most commonly used exam center; two-thirds of schools use at least one private exam center.

The schools in the pricing sample are representative of schools nationwide. Since we exclude the two urban districts of Lisbon and Porto, the sample schools are slightly smaller than the average school nationwide. Our markets are typically also more concentrated; as a result, the sample schools control a larger share of the market, relative to the average school's market share of 23.8 percent. The remaining school attributes, however, including the characteristics of the fleet and instructors, are very similar.

3.2.4 Student Attributes

There are 57,329 unique learner driver candidates in our data. We only follow candidates for whom we have a complete history profile from enrollment at a school to completion of the practice exam, which eliminates approximately 28.4 percent of the full data set due to left or right truncation. The profile of an average student in our sample is representative of the entire Portuguese population of student drivers, however.

[15] We employ data over a three-year period to smooth large fluctuations in the numbers of students for a small group of schools that faced such events as temporary closures due to repairs, and so on.

The demographic attributes we observe for the students are limited. The average (median) student in our sample is 21.8 years (19.1 years) old. There is an even split of male and female students: 50.6 percent of our sample are females. We further observe the detailed location of the student's residence based on his seven-digit postal code, which approximately designates a city block. We calculate the straight-line distance from the postal code to the school that the student has chosen to attend. According to this measure, not only are a majority of students located less than three kilometers to their schools (2.8 kilometers), but also 44.3 percent of students choose the school from those in their consideration set closest to home; both facts allude to the importance of distance to students' consideration and choice of schools. See Table 3. Clearly, in addition to competition from schools located within the same municipality, spatial differentiation is an important dimension that contributes to the variation in prices we see in the data.

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Insert Table 3 about here

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4 Pricing in the Upfront and Add-on Markets

Our theoretical model implies that the retake market exhibits monopoly- or collusive-like markups and that the upfront market exhibits competitive markups that decline in the number of market competitors. We provide suggestive evidence that supports these model predictions in what follows.

While repeat courses are clearly additional services that add to a student's cost of driving instruction in the spirit of the add-on products studied by Ellison (2005) and others, their economic relevance would be minimal unless they were to generate significant profit for schools. Our model predicts that schools earn substantial markups from add-on services, and a casual comparison of prices and marginal costs in Table 2 suggests this to be the case. If few students actually require add-on services, however, then there is only limited scope for substantive profits. We therefore begin by summarizing students' exam outcomes and school pass rates.

4.1 Incidence of Exam Repetitions

Figure 2 and Table 3 quickly dispel any notion that the add-on market is small. Among 57,329 students from 420 schools in our sample, 76.3 and 70.6 percent pass the theory and practice exams on the first attempt, respectively. More importantly, however, only 54.4 percent pass both exams on the first attempt. The average student takes the theory and practice exams approximately 1.35 and 1.41 times, respectively. This results in the driving school process being lengthy; the median student takes around 7.5 months from start to finish. Given that just under half of all students retake at least one exam, the retake market has the potential to serve as a significant source of profit for schools.

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Insert Figure 2 about here
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The data also provide evidence to support our model assumption that students are locked into the school by their initial choice of where to take the base course and that any exam repeat course can be treated as an unavoidable add-on to the base course: students rarely switch schools. Only 1.8 and 0.1 percent of all students transfer schools during the theory and practice exam phases, respectively, while only 0.7 percent transfer in between the theory and practice exam phases. The majority of these, or 64.5 percent, transfer to schools outside their original school's municipality, suggesting that exogenous reasons such as moving explain a significant share of transfers. Schools engage in several practices that make it prohibitively costly for students to transfer: first, the fee for the upfront course of instruction is non-refundable, making it unlikely that students switch before reaching their first practice exam. Transferring schools further requires restarting the base course from the beginning at a new school. Schools price their repeat courses significantly below their own and their competitors' base courses, so that students who consider transferring schools comparison shop their current schools' add-on prices to competitor schools' higher base prices (see Miao (2010) for a theoretical analysis of such aftermarket competition between firms that simultaneously compete over the primary good.)

The theoretical model also proposes that schools' add-on prices would be set at their market's "walkway" price, or the maximum supportable price in the market. The data provide evidence that this assumption is reasonable. First, conditional on failing at least one exam, students are more likely to quit than to transfer. While 0.9 percent of students at schools in our sample switch schools within the same municipality, more than double – or 2.6 percent of students – actually quit.[16] Second, conditional on failing at least one exam, students who quit also behave in ways we would expect. Conditional logit regressions of the decision to quit reveal that, for the theory exam, older males are more likely to quit at schools with higher theory exam add-on prices and, for the practice exam, older females are more likely to quit schools with higher practice exam add-on prices. Importantly, students are more likely to quit at schools with higher add-on prices, and this statistically and economically significant finding is robust to adding school- and municipality-level controls. Note that, if price is correlated with other components of school quality not captured by our controls, the estimated price effect would be downward biased.

4.2 Markups

To assess the per-student profitability of offering the three services, we consider two common measures of profit margins: the traditional markup or price-cost margin, and the percentage markup or Lerner index, which equals the ratio of markup to price. Table 4 reports a summary of both

[16]Quitters are defined as those students for whom more than a year passes between successive exams, conditional on failing the last exam taken, or as those students who disappear altogether after their last instance of failing an exam.

measures across schools; Figure 3 illustrates the distribution of the percentage markups.[17] The markups for the add-on services are higher on average in percentage terms than those of the upfront service.

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Insert Figure 3 about here

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Insert Table 4 about here

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The average Lerner index for the upfront service is 28.7 percent, while in contrast, the percentage markups in the add-on markets average to 86.5 percent and 56.6 percent in the theory and practice add-on markets, respectively, suggesting differential degrees of market power in the primary and add-on markets.

Moreover, the variation in markups differs significantly across the primary and secondary markets. If schools act according to the stylized model above, we might expect there to be limited variation in add-on markups to reflect that schools charge the highest sustainable price in the market. The standard deviation of upfront markups across markets is €110.79, or 11.6 percent for the Lerner index, while the standard deviation of theory and practice add-on markups across markets is €28.85 (7.6 percent for the Lerner index) and €46.44 (8.9 percent), respectively.

Six schools, or 1.4 percent of the sample, have negative markups in the upfront market, pricing below estimated cost. All but one of these schools garner positive effective markups across the three services, however; they are able to cover their total variable costs with the revenues they earn from the add-on markets despite the losses they incur in the upfront market. We compute effective markups as the total fees paid by each student less the total variable cost incurred in serving the student, averaging across students at each school. For every euro the average school earns in profit from offering the base course, it earns an additional €0.71 in effective markup on the full cost of serving its average student. At the student level the average student in the sample yields an additional €0.81 for every €1 he generates in profit for the upfront service. Thus, schools with a larger student population tend to have higher effective markups on average than smaller schools. According to the effective markup measure, a school earns €329.95, or 34.2 percent of fees paid by the student, on the average student.[18]

Implicitly, our model posits that the upfront and add-on markets are distinct: the upfront market prices and markups depend on a number of consumer- and market-related factors, while the add-on market surcharges and markups are independent of these. Evidence points to little

[17] A plot of the distribution of markups in levels reveals greater variation across the base service markups, but otherwise has no economic interpretation.

[18] We estimate that one school has a negative effective markup of −€18.07. We are unable to determine whether this is because of error in our marginal cost estimate or because this school truly incurs a loss.

relationship between the upfront and add-on prices: only a weak association exists between the upfront prices and the theory exam add-on prices (0.071) and the practice exam add-on prices (0.091). On the other hand, there is a strong and positive association between each of the add-on prices (0.405). Similarly, for markups, the correlations between base markup and the theory and practice markups are 0.072 and 0.102, respectively, but 0.407 between the theory and practice markups themselves. These correlations provide indirect evidence that factors affecting the setting of schools' upfront prices differ from those affecting their add-on prices.

4.3 Sources of Profit

Perhaps most compelling to the add-on market profit motive is that a significant portion of schools' variable profits derive from add-on fees. The average (median) school derives 9.9 percent (8.8 percent) and 14.4 percent (13.0 percent) of total variable profits from the theory and practice exam add-on services, respectively, or 24.4 percent (22.2 percent) of profit overall. At the same time, schools earn a smaller share of total revenues from add-on services: the average (median) school derives 4.4 percent (4.4 percent) and 9.5 percent (9.0 percent) of total revenues from the two add-on services for a total of 14.0 percent (13.4 percent) of revenue. This suggests that schools face relatively lower variable costs for add-ons compared to the cost of the corresponding base course, and, thus, more revenue is passed on as variable profits to schools in the add-on market.

Figure 4 reveals significant variation in the percentage of total variable profits derived from the add-on services. Nine schools (2.1 percent of the sample) earn more than 20 percent of their variable profits from the theory exam add-on service, with 4 of these earning more than 30 percent from theory exam retakes. The interquartile range for the share of profits stemming from the theory exam retake market is 6.2 to 12.0 percent. Typically, the share of profit from practice exam retakes further exceeds these magnitudes with an interquartile range of 8.8 to 18.5 percent. Seventy-seven schools (or 18.3 percent of the sample) earn more than 20 percent of their variable profits from the practice exam add-on service, with 10 and 3 of these schools earning more than 30 and 40 percent from practice exam retakes, respectively. The variation in the two add-on markets translates into significant variation in the share of profit stemming from add-ons in aggregate, with an interquartile range of 17.5 to 28.0 percent.

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Insert Figure 4 about here

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4.4 Determinants of Markups

The previous section establishes that schools have a profit motive in the add-on market in which significantly higher markups are earned relative to the base course. We now test whether the observed markups for the upfront and retake services are consistent with the basic predictions of the bargains-then-ripoffs model from Section 2. The model predicts that variation in markups on the upfront base service, but not the add-on surcharges, depend on the number of competitors in the market, the proportion of myopes, and the type-specific probability of failing the exams. We consider a number of reduced form models of markups to test these predictions, while controlling for heterogeneity in demand conditions across schools that might introduce variation in prices and markups unrelated to the competitive environment.

We regress school markups on the number of competitors within the municipality as well as a number of other school- and municipality-related controls. While we benefit from an accurate measure of the number of market competitors and the overall probability of failing on both exams, we do not have separate proxies for the proportion of myopes and the probability of failing by consumer type. In Section 6 we estimate an empirical version of the demand model above, using the consumers' responses to variation in upfront and add-on prices to pin down the share of myopic consumers consistent with the observed school choices. A direct benefit to estimating such a model is that it allows us to derive estimates of variation in consumer types across markets and demographic groups.

In our regression analysis, we employ both OLS and two-stage least squares techniques to control for the possibility that the number of schools in the municipality are endogenous to schools' markups. As discussed in Section 3.1, the driving school industry faced municipality-based entry restraints prior to being deregulated in 1998. These restraints were closely tied to the municipality's population, stipulating that each licensed school serves a minimum of 25,000 residents in the chosen municipality or is the sole provider in a municipality with less than 25,000 residents. The regulated number of schools in each municipality prior to liberalization thus serves as a good instrument for the number of firms: by being tied to population alone, it is likely uncorrelated with unobserved profit shifters that are reflected in both markups and entry in the unregulated regime, but is related to the number of schools in the municipality under free entry, post deregulation.[19]

The results of the regressions of the upfront profit margins on the number of market competitors with school- and municipality-level controls are shown in Table 5. While the first-stage F-statistics and partial R-squared statistics for the instrumental variables regressions imply a strong instrument, the endogeneity concerns do not seem to drive the results, which themselves appear to be robust across all specifications (including the specification that incorporates the share of the population under the age of 25 as an instrument for the number of market competitors). Similarly, the introduction of a number of school- and municipality-related controls do not change the coefficient on the number of market competitors significantly. Across specifications, the number of schools in the municipality has a strong and significantly negative impact on the upfront markups of schools

[19] As a robustness check (not shown) we further incorporated the share of the population above the age of 15 but below the age of 25 as an instrument for the number of firms: the vast majority of students in our sample (83.6 percent) are below age 25 and the size of that age category in the municipality thus represents a good proxy for the size of the municipality's market. (Note that, while students need to at least be of age 18 to enroll in driving school, we were not able to obtain data for finer age bins from Statistics Portugal.) While the market size shifts total variable profit in the market, and thus the profitability of entering, it should not affect the markup charged per student if marginal costs are near constant and economies of scale are small.

in that municipality. For every school added to the market, the upfront markup decreases by approximately €23.08, corresponding to 10.5 percent of the average upfront markup. This result aligns with the theoretical prediction that upfront markups should fall in the number of competitors because of the highly competitive nature of the upfront market. The competition-related controls also suggest that a school's markups are higher the farther away is its competition.

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Insert Table 5 about here

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The results for the equivalent regressions of the add-on profit margins on the number of market competitors with school- and municipality-level controls are shown in Table 6. As with the upfront markup regressions, the results are robust to instrumenting for the number of firms and introducing school- and municipality-level controls. In each of these specifications, the number of schools in a school's own municipality is statistically insignificant in affecting both add-on markups, and has an economically much smaller effect on both markups for each additional competitor. Note too that the competition-specific controls are insignificantly associated with the add-on markups. These results are thus suggestive of there being no competitive influence on either retake markup, with schools benefitting from highly localized market power. Moreover, the one control that represents a student's outside option, e.g., public transportation, is significantly associated with add-on markups.

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Insert Table 6 about here

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Note that the endogenous variable is a discrete count of the number of schools in the market, but our linear regression models treat this regressor as continuous, and furthermore assume that the effect of an incremental entrant on markups remains constant regardless of how many schools end up in the market. We investigate the sensitivity of the results to these assumptions by estimating a specification that models the number of schools as an ordered probit model, allowing the unobservable market-level error that drives entry decisions to be correlated with an unobserved market-level error that affects markups. This correlation represents the possible correlations between unobserved market structure shifters and unobserved markup determinants that we worry might bias the estimated effect of the number of schools on prices. We estimate the resulting nonlinear two-equation model using full information maximum likelihood (FIML) and derive the likelihood in the Appendix.

Further note that potential measurement error in computing the marginal costs may have induced spurious results. Additionally, we might worry that the competition effects are driven solely by the cost side. In Tables D-1 and D-2 of the Appendix we estimate equivalent specifications using prices instead of markups as the dependent variables. The results from using markups are robust to using prices instead.

One market where we might expect higher upfront markups, but similar add-on markups compared to other markets, is a monopoly market. Fifty-four schools, or approximately 12.9 percent of sampled schools, serve as the only school in their municipality; these schools should wield monopoly power in both upfront and add-on markets. In fact, the average (median) school in a monopoly market earns €289.45 (€287.73) in upfront markups, compared to €208.82 (€203.42) earned by the average (median) school in an oligopoly market (p-value of test of the equality of means of 0.0000). Schools in both monopoly and oligopoly markets earn about the same markups in the add-on market, however: the average (median) school in a monopoly market garners €120.99 (€129.00) and €163.09 (€163.62) in theory and practice add-on markups, respectively, while the average (median) school in a oligopoly market receives €116.70 (€121.00) and €158.77 (€161.02) in theory and practice add-on markups, respectively, and we cannot reject the hypothesis of equal means, with p-values of 0.2562 and 0.5474, respectively. The similarity of add-on markets across monopoly and oligopoly markets, combined with the demonstrated decline in markups as the number of competitors rises, in particular from monopoly to oligopoly markets, thus bear out the model predictions of loss-leader pricing.

5 Survey of Students' Exam Outcome Expectations

The evidence presented so far supports the hypothesis that firms use loss-leader pricing in the upfront market, with significantly higher, and largely competition-invariant, margins in the add-on market. Since the data do not contain direct information on students' expectations of the cost or incidence of exam failures, we complement this analysis with a short survey administered to students in the process of obtaining their drivers licenses in the Setúbal district. We developed the survey jointly with the IMTT, and IMTT representatives administered the survey to all students who took the theory driving exam at Setúbal's public exam center during the months of December 2012 and January 2013. The students were given the opportunity to answer the survey immediately after having taken the theory exam, and prior to learning their outcomes on the exam. The survey was voluntary, and was presented to students as being part of a general study on driver education and testing. The IMTT shared with us the anonymized compiled survey responses, together with information on the students' ultimate performance on the immediately following theory exam and the later practice exam. Figure 5 depicts the survey.

In total, 797 students took the theory exam in Setúbal during the two-months window of the survey, and 782 students participated in the survey, entailing a 98% response rate. In the following analyses, we focus on first-time theory exam takers of the passenger vehicle license exam only, resulting in a sample of 465 respondents. The resulting sample is representative of the country-wide student population: 47.31% are female; the mean (median) age at the time of the theory exam is 22.7 (19.7) years with a standard deviation of 7.1 years. We use the survey responses to investigate two questions. First, do students have correct expectations of their likelihood of failing the exam? Second, do students understand the financial repercussions of failing the theory exam? We present evidence speaking to each of these questions in turn.

Similar to the nationwide results, in the sample of survey respondents failing a driving exam is common: 27.7% fail the theory exam at first try, while 24.8% fail the subsequent practice exam at first try. In aggregate, students have near correct expectations regarding the likelihood of failing the theory exam at 30.8%, but are overly optimistic regarding the fail incidence on the practice exam. Only 16.2% of students state that they believe they will fail the exam, compared to the 24.8% ultimate fail rate. Note that students have different amounts of information when answering the two questions: their assessment of passing the theory exam is based on having just taken the actual exam, while for the average student in the sample, the actual driving exam takes place only 3 months after having answered the survey. To the extent that the students' initial school choice is similarly made without direct evidence of the difficulty of each of the exams, this suggests that students may underestimate their propensity of needing to purchase the add-on repeat course.

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Insert Table 8 about here

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We also find systematic differences in exam outcome beliefs between those students who ultimately pass and those who fail the exam. Among the students who pass the theory exam, 76.2% believed that they would pass the exam prior to obtaining their results, above the aggregate pass rate. More pronounced, students who pass the practical exam believe to have a 87.1% chance of passing, significantly above the average pass rate of 75.2%. This suggests that, on average, this group of students has some understanding of how their ability compares to the exams' passing standards. Students who fail in contrast appear to be overly optimistic of passing, in particular on the practice exam, where 73.6% of students state that they believe they will pass it, near identical to the average pass rate in the sample.

There are also significant gender differences. Regardless of ultimate exam outcome, female students are less optimistic about their pass probabilities. Among theory exam failers, 55.2% of female students believed they would fail, compared to 41.8% of male students, while among theory exam passers, only 70.0% of female students thought they would pass compared to 82.1% of male students. Similarly, among practical exam failers, 35.0% of female students believed they would fail, compared to only 14.6% of male students, and 82.5% of female practice exam passers thought they would pass compared to the vast majority of 91.6% of male students in that category. At the same time, aggregate pass probabilities favor male students slightly, but not to the same extent as suggested by students' beliefs: 69.0% and 72.7% of female students pass the theory and practice exams at first try, respectively, compared to 74.4% and 76.7% of male students.

In sum, we thus find evidence of optimism in the survey responses, in particular among male students and regarding the passing of the practical exam, on which the students have limited information at the time of completing the survey. This optimism could serve as a source of myopia in the model above, resulting in students discounting the price of exam repeat courses in their school choice.

We also use the survey to investigate the extent to which the students understand the financial cost of repeating one or both exams. We asked the students whether they would have to pay an additional amount to retake the theory exam in case they failed the exam they just took. 3.8% of students stated they would not have to pay anything; 17.7% did not know; and 78.4% said that they would have to pay some amount. 26.9% of these students state that they asked the school whether they would have to pay, and 43.3% state that the school informed them directly that additional fees would accrue. However, only 66.5% of the students who expect to pay for a retake, or 52.1% in aggregate, stated that they knew the amount they would have to overpay. The students who claim knowledge of the retake fees are close to correct, underestimating the retake fees by only 4.1% on average.[20] The survey responses thus indicate that only a subset of students is aware of the fees they will have to pay if they need to repeat an exam. Similarly to the optimism in passing documented above, this might lead them to base their school choice primarily on the upfront fee for the base course, rather than the full expected price to be paid to the school.

6 Empirical Model

In this section we present and estimate an empirical model based on the theoretical model discussed in Section 2.

6.1 Overview

In order to maximize utility a student makes a choice among all the schools located in the municipality in which he resides.

The utility of student i from attending school j is conditional on the student's type h (i.e., myope or sophisticate) and is defined as

$$u_{ij|h} = \mathbf{X}_j' \beta_X + \mathbf{Z}_i' \beta_Z + f(D_{ij}) - \alpha \mathbb{E} p_{ih|j} + \xi_j + \varepsilon_{ij}, \quad (5)$$

where $\mathbf{X}_j$ is a vector of observed school attributes (that does not include price) and $\mathbf{Z}_i$ is a vector of student-specific attributes such as demographics; D_{ij} is the distance from student i's location to the location of school j; $\mathbb{E} p_{ih|j}$ is the price that each student expects to pay for his training at each school; ξ_j denotes school fixed effects for all schools that belong to student i's choice set; and ε_{ij} is an unobservable (to the econometrician) error term that we assume to be mean independent of the included right-hand side variables.

To control for students' preferences for distance, we allow distance to enter nonlinearly into the utility function in a flexible way as

[20] While it would be interesting to test whether students who are more pessimistic about failing an exam have better knowledge of retake fees, the sample is too small to do so conclusively.

$$f(D_{ij}) = \beta_{d_1} D_{ij} + \beta_{d_2} D_{ij}^2 + \beta_{d3} \mathbb{I}_{\{j=\text{closest}\}}, \tag{6}$$

where $\mathbb{I}_{\{j=\text{closest}\}}$ is an indicator variable equal to 1 if school j is closest to the student in the choice set of student i.

Since in our data we do not observe individuals who chose not to obtain a driver's license, we model students' choices between schools only and normalize one fixed effect in each municipality to zero.

The variable $\mathbb{E}p_{ih|j}$ varies by student i and is defined as

$$\mathbb{E}p_{ih|j} = p_j^u + \phi_h \lambda_{ij} p_j^a, \tag{7}$$

where p_j^u is the price of the upfront instruction course at school j; λ_{ij} is student i's fail probability at school j; p_j^a is the price of the add-on service at school j (i.e., the price associated with retaking the exam); and ϕ_h is a scale parameter that reflects the assessment of a type h student of his own probability of failing. If the student is a myope, then $\phi_h = 0$ and he neglects the add-on prices when making his school choice. A sophisticate, with $\phi_h = 1$, on the other hand, accounts for the possibility that he may fail the exams, which will have an effect on the final price he ultimately pays to obtain his driver's license.

6.2 Fail Probabilities

A key component of our model involves the assessment that each sophisticated student makes of his own probability of failing each exam at each of the schools in his choice set. We estimate a conditional logistic regression model of the fail probability given by

$$\ln\left(\frac{\lambda_{ij}}{1-\lambda_{ij}}\right) = \delta_j + \mathbf{Z}_i' \beta_Z, \tag{8}$$

where λ_{ij} is the probability that student i of school j fails his exam; $\mathbf{Z}_i$ are characteristics of student i; and δ_j is the effect of school j on the student's probability of failing.

Student-specific variables include each student's age and gender, as well as variables that are specific to the parish in which the student resides, namely, the illiteracy rate and whether that location is considered rural or urban. Interactions between these variables are also used. In addition, for the practice exam fail probability regression, we also include a dummy for whether the student took the exam at a public or private exam center because there is the perception in the industry that private center examiners are somewhat more lenient than those at public centers.

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Insert Table 7 about here

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We assume each student can fail each of the theory and practice exams at most one time. This is consistent with the observation that most students rarely fail more than once. After estimating the parameters in (8), which we show in Table 7, we compute predicted probabilities of failing for each exam/student/school combination and use these as inputs in the choice model.

6.3 Specification of School Choice Model

Assuming that ε_{ij} in (5) is an i.i.d. Weibull random variable, the probability that student i chooses to attend school j is conditional on the student's type h (myope or sophisticate), and can be written as

$$P_{ij|h} = \frac{\exp\left\{\mathbf{X}_j'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ij}\right) - \alpha\left(p_j^u + \phi_h \lambda_{ij} p_j^a\right) + \xi_j\right\}}{\sum_{k=1}^{J} \exp\left\{\mathbf{X}_k'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ik}\right) - \alpha\left(p_k^u + \phi_h \lambda_{ik} p_k^a\right) + \xi_k\right\}} \tag{9}$$

Since we do not observe any student's degree of sophistication, given by h, we estimate a finite mixture model in which the probability of belonging to each of two possible segments (i.e., myopes or sophisticates) is given by π_h. More formally, suppose that ϕ_h is drawn from a discrete distribution with two points of support such that

$$\phi_h = \begin{cases} 0 & \text{with probability } \pi_m \\ 1 & \text{with probability } \pi_s \end{cases} \tag{10}$$

and π_s and $\pi_m = 1 - \pi_s$ are parameters to be estimated. This specification of the model allows the unobserved student type to enter the estimation. For the segment sizes of the unobserved student types to be identified, we need to observe in the data students who bypass schools, both with low base prices but high add-on prices, that are strongly preferred by other students.

Thus, the choice probability in (9) can be re-written as

$$P_{ij} = \pi_m P_{ij|\{h=m\}} + \left(1 - \pi_m\right) P_{ij|\{h=s\}}, \tag{11}$$

where

$$P_{ij|\{h=m\}} = \frac{\exp\left\{\mathbf{X}_j'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ij}\right) - \alpha p_j^u + \xi_j\right\}}{\sum_{k=1}^{J} \exp\left\{\mathbf{X}_k'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ik}\right) - \alpha p_k^u + \xi_k\right\}} \tag{12}$$

and

$$P_{ij|\{h=s\}} = \frac{\exp\left\{\mathbf{X}_j'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ij}\right) - \alpha\left(p_j^u + \lambda_{ij} p_j^a\right) + \xi_j\right\}}{\sum_{k=1}^{J} \exp\left\{\mathbf{X}_k'\beta_X + \mathbf{Z}_i'\beta_Z + f\left(D_{ik}\right) - \alpha\left(p_k^u + \lambda_{ik} p_k^a\right) + \xi_k\right\}} \tag{13}$$

Hence, the likelihood function is given by

$$L \equiv \prod_{i=1}^{N}\left[\pi_m\left(\prod_{j=1}^{J_M} P_{ij|\{h=m\}}^{y_{ij}}\right)+\pi_s\left(\prod_{j=1}^{J_M} P_{ij|\{h=s\}}^{y_{ij}}\right)\right], \tag{14}$$

where $y_{ij} = 1$ if student i chooses school j and zero otherwise; and J_M is the number of alternative schools for a given market M.

6.4 Parameter Identification

So far, we have established that there are consumers who make their school choice with limited account of the add-on's price. The survey evidence in Section 5 suggests that this could be for several reasons, including underestimating either the price of the add-on or the probability of failing. The objective of the empirical model is not to identify the underlying causes of myopia present in the data (which is difficult with observational data only), but rather to estimate the proportion of myopic consumers. Here, we discuss how the empirical choice model is able to identify two segments of consumers (sophisticates and myopes) with distinct preferences.

First, consider only myopic consumers (i.e. $\lambda = 0$) who base their school choice purely on each school's upfront price. The cost of a course of driving instruction then varies only across firms, but not by student at a given school. With no variation in prices across students, we rely on the variation in prices across schools and markets illustrated in Table 2 in order to estimate the students' price responsiveness.

Now consider the case with heterogeneity in consumers' decision processes such that myopic students choose schools based on base prices alone, and sophisticated students select based on the total price. If student types were observed, we could account for such differential choice processes by varying the utility across students, with some students ignoring the add-on price. Since this is not the case in our data, we use a modeling approach akin to the commonly used mixed logit models with a discrete mixture of types (also known as latent class choice models). There are a few differences in our approach that are worth noting.

In common latent class approaches, a probabilistic model is used to allocate consumers to segments that represent different unobserved tastes in the sample. In our case, we furthermore allow students' decision criteria to differ across segments. That is, the probabilistic "allocation model" assigns consumers to each class based on whether they are more likely to choose between schools by taking into account the upfront price only or both the upfront and add-on prices. The use of this setup is intuitively appealing given that our economic model has two types (or classes) of consumers making decisions according to different decision processes.

What type of variation is then needed in the data in order to achieve identification of the shares of sophisticates and myopes? Intuitively, this problem reduces to understanding what kind of variation would allow estimation of the share of consumers who make choices that are more consistent with the upfront price, instead of the expected add-on price.

A basic requirement for differentiating between upfront and total expected prices as drivers of school choice would thus be observing variation in expected add-on prices within each student's municipality that is not perfectly correlated with upfront prices. Note that variation in expected add-on prices reflects both variation in add-on prices per se, which we demonstrate in Table 2, and variation in students' fail probabilities across schools. Identification of the share coefficient thus stems in part from choices made by individuals who have sufficiently high probabilities of failing such that they prefer to bypass schools with low upfront prices (which are preferred by myopic students), in favor of schools that have lower expected total prices, all else equal. The results in Table 7 suggest that fail probabilities vary with student attributes such as gender and age; we further reject that the included school fixed effects are jointly insignificant in explaining exam outcomes in either of the specifications. For the chosen schools, the coefficient of variation in predicted fail probabilities based on the estimated models in Table 7 is 0.43 and 0.33 for the incidence of failing the theory and practice exams, respectively, and rises to 0.54 and 0.49, respectively, once we include predicted fail probabilities for those schools in the student's municipality that the student ultimately did not choose. These two sources of variation introduce variation in expected add-on prices across students and schools.

To investigate correlation between upfront and add-on prices, we compare the ranking of all schools in a student's municipality based on upfront prices and based on total prices. For over 25% of the students in the data, there is no significant statistical association (measured by the Spearman correlation coefficient) between the ranks of a school's upfront and total prices.

The estimated segment-share coefficient then represents the extent to which such variation between upfront and total prices translates into variation in choices. Descriptively, such variation is present in the data; 34.5% of students choose the school that is the lowest priced in its market based on either the upfront or the total price; of these 29.7% choose a school that is lowest in upfront, but not total, price; 16.9% choose a school that is lowest in total, but not upfront, price; and 53.5% choose a school that has both the lowest upfront and total price. Apart from price, the most important determinant of school choice is distance to the school; 37.3% of students choose the closest school, which is also the lowest priced along either of the price dimensions for 35.2% of those students. We investigate the separate explanatory power of upfront and total prices further in single-type school choice models below.

6.5 Results and Discussion

We display the results of the empirical model for a particular market in Table 9. Before we analyze the specification that captures the empirical model derived above – the last column in Table 9 – we discuss several alternative specifications of the school choice model.

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Insert Table 9 about here

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In specifications (i) and (ii) we investigate how different components of the student's price affect his school choice. We decompose each student's expected price into his upfront price and expected repeat fees and enter these two prices separately into the utility function. This separation addresses the possibility that the observed price patterns in the data purely reflect differences in the students' price sensitivities across the two services, but not differences in foresight across student types.

Since we include the upfront price, a school-level covariate, we cannot include school fixed effects to control for unobserved heterogeneity across schools that might be correlated with prices. Instead, we include pertinent school attributes. The specification school attributes only, including total expected prices instead of the two components, is similar to the one with school fixed effects [specifications (i) and (iii)], suggesting that much of the heterogeneity is observed.

The results for the first two specifications allow two conclusions: First, while slightly larger in absolute value, the effect of add-on prices on utility is not statistically significantly different from the effect of the upfront price; thus, price responsiveness is not more pronounced for repeat fees than it is for base prices. Second, the estimated coefficients remain largely unchanged, both for price and for the remaining school choice determinants, when we combine the two price components into a single expected price [specification (i)].

A downside to the single-type specifications is that we do not allow for unobserved heterogeneity in the estimated coefficients. We, therefore, now turn to specifications (iv) through (vi), which estimate discrete mixture models with two consumer types. The displayed specifications allow for heterogeneity in the price coefficient only. We also estimated alternative specifications that, in addition, allowed for heterogneity in both the distance covariates and the school fixed effects. The random coefficients on prices are robust to the addition of heterogeneity in other variables – that is, the result that myopes are more price sensitive than sophisticates obtains when we allow for heterogeneity in other covariates. Moreover, we learn that sophisticates are more sensitive to distance than myopes; they are less likely to choose a school that is farther away and are more likely to choose the closest school to their homes relative to myopes.

Similar to specifications (i) through (iii), the two-type models differ in the way price enters into the utility function. Specifications (iv) and (v) assume that utility depends only on expected prices for both market segments, but differ in that specification (iv) includes school controls while specification (v) includes school fixed effects. These specifications thus assume that all consumers in the market are sophisticated, but differ in their price sensitivities, which we find to be the case for the two-type specifications.

Specification (vi) then replaces the expected price with the base price, as in the model of myopic consumer behavior in Section 2. Interestingly, we estimate a larger price coefficient in absolute value for the myopic segment, suggesting that myopes are more price sensitive despite considering only the base price – rather than the higher expected price – at the time of their initial school choice. The estimated share parameter implies that approximately one quarter of students fall into the first (myopic) market segment. The size of the segment we estimate is similar in size to the smaller segment in specifications (iv) and (v) (there we estimate the smaller segment's size to be slightly higher at approximately 30 percent), which is similarly the more price responsive. Lastly, note that model (vi) has the lowest likelihood value across specifications. The results thus suggest that observed consumer responses to the firm's chosen upfront and add-on prices is consistent with a sizable number of students who do not base their school choice on a comparison of their full expected fees at the different schools, but only on a comparison of the initial upfront payment.

7 Conclusion

In this paper, we have modeled a market in which firms take advantage of locked-in myopic consumers by charging high surcharges in unavoidable add-on markets. When consumers have limited foresight about their future demand for a product and face high switching costs, firms have the dual incentive to set as high a price as the add-on market can support and to charge a correspondingly low price in the upfront market to entice consumers to their firm in the first place. The model, hence, predicts upfront (add-on) markups that (do not) vary with the market structure a firm faces. The model also implies that all markups – both upfront and add-on – depend on the proportion of consumer types in the market and the type-specific probability of requiring the unavoidable add-on.

We present evidence of these phenomena in the context of Portuguese driving schools. With data on prices and constructed marginal costs, we demonstrate that schools not only face a strong profit motive for setting high surcharges in the add-on market, but also earn relatively high, monopoly-like markups in the add-on markets while earning lower markups in the upfront market. The evidence corroborates the model predictions that the latter vary with the level of competition whereas the former do not.

Our research benefits from a highly detailed data snapshot of the driving school industry, which gives us the ability to address additional questions of interest, most notably who the typical myopic consumer is and which consumer type participates most in the add-on market, implicitly cross-subsidizing the other. We specify a two-type mixture model of demand that empirically pins down the proportion of student types that is consistent with the observed school choices under schools' chosen base and add-on prices. That about one-quarter of students is myopic points to schools' strategic exploitation of this subset of students who do not anticipate their need for the add-on at their initial purchase occasion. As a next step, we plan to estimate the student fail probabilities jointly with the choice probabilities as well as to estimate a version of the model using concomitant variables, whereby we correlate the implied type share parameter with student attributes.

Evidence that speaks to the question of who subsidizes whom in a market such as ours is of significant normative policy interest to regulators of firm pricing behavior. In the case of policies under consideration by the IMTT, possible regulations range from requiring schools to inform students about typical propensities of failing the different exams to directly or indirectly regulating prices in the add-on market. As a next step, hence, we plan to analyze the attributes of schools whose market shares are specifically increased by the presence of myopic students. By using the estimates of our empirical model to compare the case in which only some student consider the add-on to the case in which all students consider the add-on, we will be able to draw conclusions about those schools that benefit from having myopic students in the market. Another avenue for future research is to implement an empirical pricing model in our setting, allowing us to compare counterfactual price predictions under varying assumptions about the student types in the market.

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Figures and Tables

Figure 1: Driving Schools by Municipality, Mainland Portugal

(a) All municipalities

(b) Available sample of municipalities

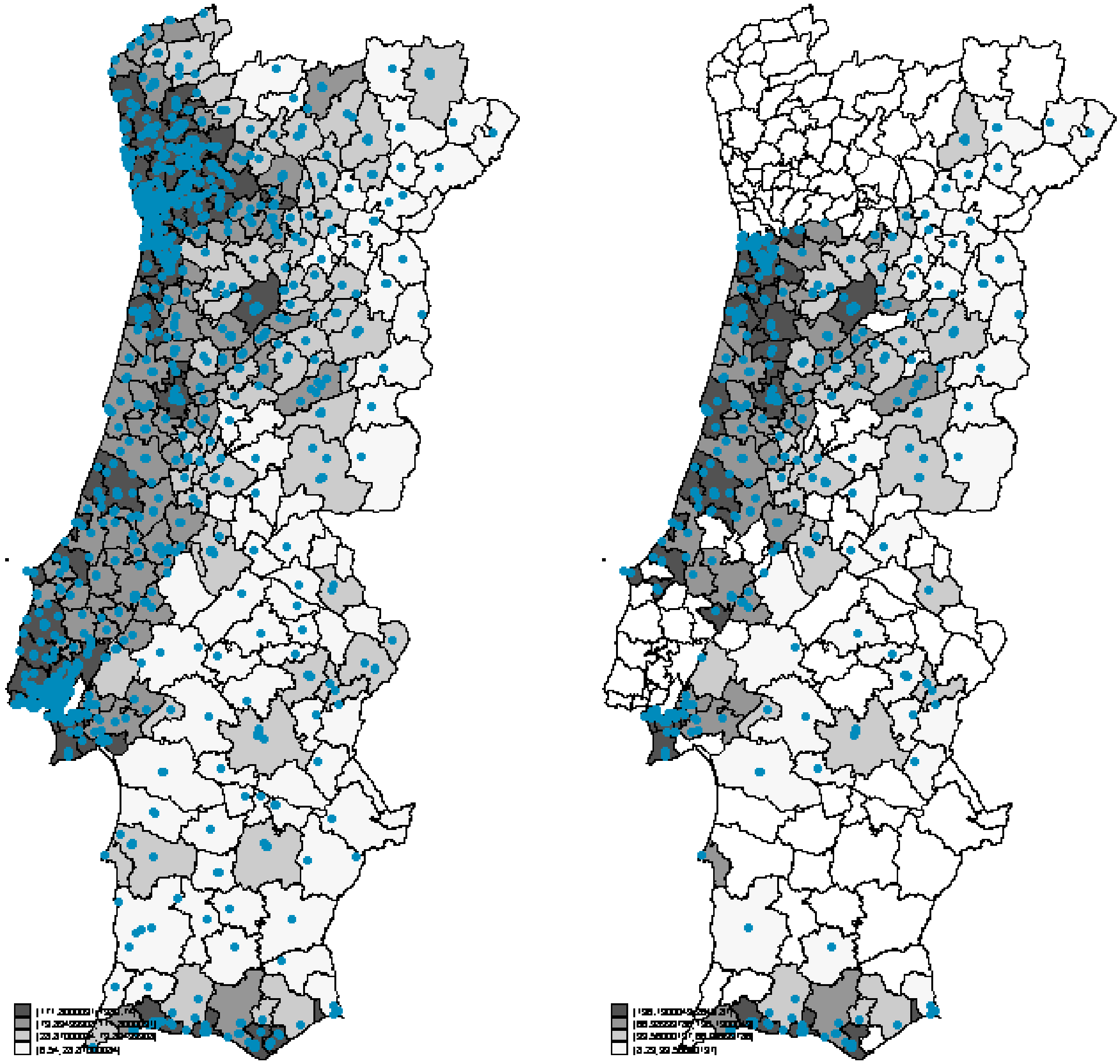

Figure 2: Number of Practice and Theory Exams Taken, by Student

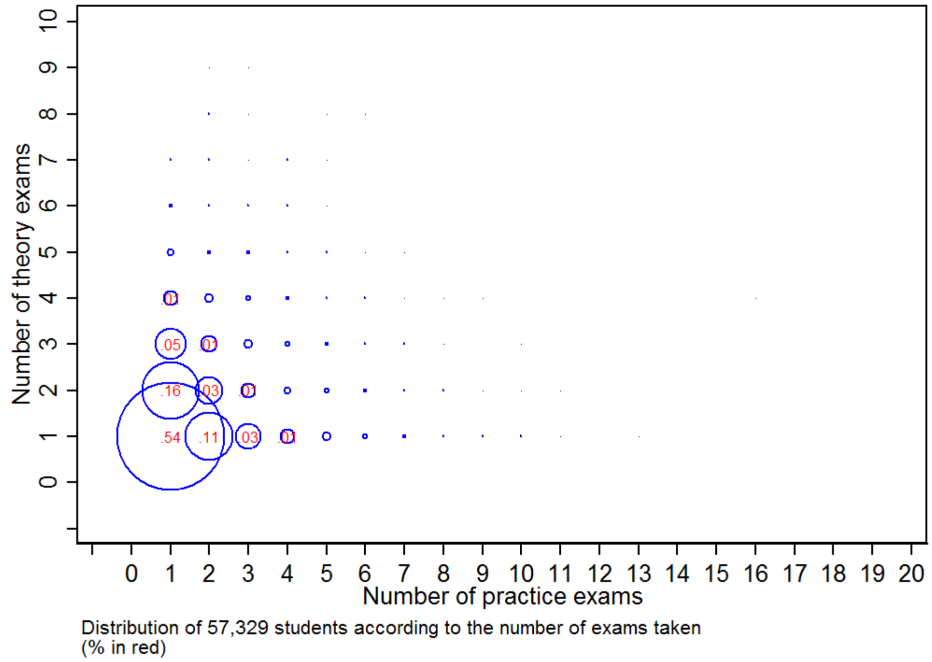

Figure 3: Distribution of Lerner Indices in Upfront and Add-on Markets, by School (%)

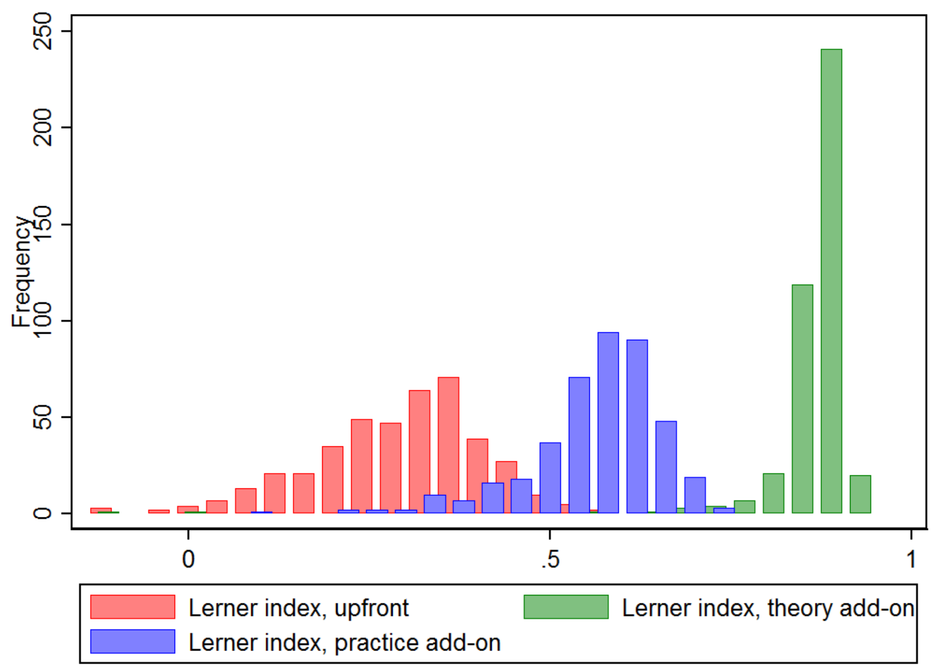

Figure 4: Variable Profit from Upfront and Add-on Services

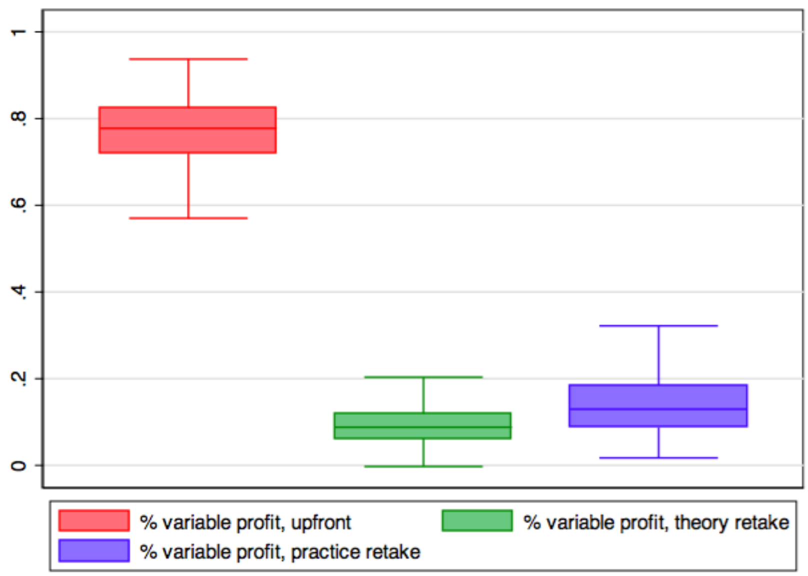

Figure 5: Student Questionnaire

QUESTIONÁRIO QUESTIONNAIRE

No âmbito de um estudo sobre ensino e exames de condução agradecemos que preencha o seguinte questionário. We are conducting a study concerning drivers' education and testing and would appreciate if you could answer the following questions

Preencha o que for necessário ou assinale com um (X) a opção adequada
Please fill in the blank spaces or mark your selection with an X

1. Foi a primeira vez que fez exame teórico de condução? ☐Sim ☐Não
Was this the first time you took the theory exam? Yes No

2. O exame foi mais difícil do que esperava? ☐Sim ☐Não
Was the exam harder than you were expecting it to be?

3. Acha que vai passar no exame teórico que acabou de realizar? ☐Sim ☐Não
Do you think you will pass the exam you just took?

4. Caso reprove, vai ter de pagar à sua escola de condução para repetir o exame teórico?
In case you fail, will you have to pay your school to retake the theory exam?
☐Não Sei ☐Sim ☐Não
Don't know Yes No

A) Aproximadamente quanto? (se não souber deixe em branco) ________ Euros
Approximately how much? (If you don't know please leave it blank)

Sei quanto é porque: ☐ Perguntei na escola ☐ A escola informou-me ☐ Outro: ________
I know how much it is because: I asked the school The school informed me Other

B) Quanto acha que você *devia* ter de pagar para poder repetir o exame? ________ Euros
How much do you think you would have to pay to be retake the exam?

5. Assinale com um (X) se cada situação descrita é VERDADEIRA ou FALSA
Mark with an (X) whether each of the following situations is True or False.

	VERDADE True	**FALSO** False
Fiz mais de 50 testes no computador como preparação para hoje As a preparation for today I did more than 50 computer (at home) tests	☐	☐
Fui fazendo testes à medida que ía assistindo às aulas teóricas I did practice tests during the entire time I was taking theory lessons	☐	☐
Usei o livro de código para perceber melhor os meus erros nos testes I used the "Rules of the Road" book to better understand my mistakes on those tests	☐	☐
Fui a mais aulas teóricas do que o mínimo exigido I attended more theory lessons than the minimum required	☐	☐
Preparei a matéria das aulas teóricas *antes* de ir assistir às aulas I prepared the lessons' material before attending the lessons	☐	☐
Tirei apontamentos nas aulas teóricas I took notes during the theory lessons	☐	☐
Tirei dúvidas com o instrutor várias vezes I asked the instructor for clarification several times	☐	☐
Acho que não é preciso estudar muito para o exame teórico I don't think one needs to study very hard for the theory exam	☐	☐

6. Quantas aulas práticas (de condução) já completou até à data de hoje? ________ Aulas
How many practice lessons (on-the-road) have you completed before today? Lessons

7. Acha que vai passar à primeira no exame prático (de condução)? ☐Sim ☐Não
Do you think you will pass the driving exam at first try?

8. Data de nascimento: ____/____/____ **9. Sexo:** ☐Feminino ☐Masculino
Date of birth Gender

10. (OPCIONAL) Caso não se importe de ser contactado posteriormente para perguntas adicionais referentes ao exame por favor indique o seu endereço de email
(OPTIONAL) Please provide your email address if we could contact you with additional questions regarding the exam.
E-mail: ____________________

Obrigado pela sua colaboração!
Thank you very much!

Table 1: Summary Statistics, Municipality Characteristics, Sample Markets

	Mean	StdDev	Q25	Med	Q75
Number of schools	3.06	2.72	1	2	4
Population (ppl)	26,355.56	28,506.56	8,871	15,938	31,482
Population aged 15-24 (%)	13.83	1.08	13.26	13.98	14.64
Population density (ppl/km)	576.28	1050.53	48.23	114.33	470.42
Mean resident age (yr)	40.30	2.73	38.66	40.03	41.85
Mean per-capita income (€)	888.74	115.98	820.20	882.70	944.20
Unemployment rate (%)	6.62	2.01	5.30	6.40	8.20
Secondary education completed (%)	35.29	9.79	28.41	35.47	40.53
Illiteracy rate (%)	10.49	4.43	7.19	9.73	12.42
Daily vehicle usage (%)	52.59	7.76	47.03	54.22	58.43
Mean commute time (min)	19.57	7.22	15.17	16.31	22.30
Vehicles sold (no/1000 ppl)	15.16	6.35	10.62	14.56	19.15
Gasoline price (€/L)	1.42	0.04	1.39	1.41	1.44

Note: Population density is a weighted average across parishes in a given municipality. Statistics other than number of schools and population are population weighted. Mean income refers to the average monthly wage income of full-time employees.

Table 2: Summary Statistics, School Characteristics

	Sample Schools ($N = 420$)					All Schools ($N = 1,136$)				
	Mean	StdDev	Q25	Med	Q75	Mean	StdDev	Q25	Med	Q75
(a) Prices										
Upfront	727.24	107.42	650	726	795					
Theory add-on	133.90	28.88	120	140	150					
Practice add-on	275.44	46.08	250	279	300					
(b) Marginal Cost										
Upfront	507.78	42.26	476.85	507.38	537.66					
Theory add-on	16.66	2.06	15	16	17					
Practice add-on	116.06	10.80	108.26	115.56	123.95					
(c) Other Characteristics										
Number of students (3yr)	449.74	288.43	270	374	563	491.73	345.27	280	417	606
Market share (%)	34.43	29.97	11.74	23.71	45.06	23.81	26.90	6.12	12.77	30.34
Age (yrs in 2010)	21.26	16.16	8.10	10.63	30.16	20.25	16.06	8.29	10.41	29.46
Website? (1=Y,0=N)	0.26	0.44	0	0	1	0.27	0.45	0	0	1
Number of instructors	5.32	3.42	3	4	7	4.89	3.29	3	4	6
Instructor experience (yr)	7.83	5.65	3.84	6.07	10.08	7.70	5.60	3.88	6.11	9.89
Number of vehicles	3.44	1.84	2	3	4	3.55	2.38	2	3	4
Mean vehicle age (yr)	5.25	3.47	2.44	4.34	7.56	5.87	3.59	3.00	5.11	8.58
Median vehicle displacement (L)	1.47	0.15	1.38	1.46	1.49	1.49	0.17	1.37	1.46	1.53
Distance to exam center (km)	25.16	20.18	8.17	21.52	35.86	20.22	18.66	6.36	15.32	28.28
Private center option? (1=Y,0=N)	0.67	0.47	0	1	1	0.72	0.45	0	1	1
Distance to IMTT office (km)	28.16	18.06	14.78	27.23	43.42	23.45	17.82	8.61	20.29	35.67

Table 3: Summary Statistics, Student Attributes ($N = 57,329$)

	Mean	StdDev	Distribution				
			Min	Q25	Med	Q75	Max
Age at theory exam (yr)	21.77	6.45	17.67	18.38	19.12	21.86	76.45
Gender (1=F,0=M)	0.51	0.50	0	0	1	1	1
Distance to school (km)	4.89	6.05	0	0.94	2.81	6.41	39.98
Theory exam taken (no)	1.35	0.76	1	1	1	1	16
Practice exam taken (no)	1.41	0.74	1	1	1	2	9
Pass rate, first theory exam (%)	0.77	0.42	0	1	1	1	1
Pass rate, first practice exam (%)	0.71	0.46	0	0	1	1	1
Time to completion (days)	262.32	152.82	16	153	224	332	1,081
Is choice closest school? (1=Y,0=N)	0.44	0.50	0	0	0	1	1

Table 4: Markups for Upfront and Add-on services

Markups (€)							
			Distribution				
Service	Mean	StdDev	Min	Q25	Med	Q75	Max
Upfront	219.19	110.79	−77.18	142.94	220.38	289.37	667.82
Theory add-on	117.25	28.85	−16.97	104.95	122.08	134.16	229.00
Practice add-on	159.33	46.44	10.14	133.62	161.45	187.77	314.86
Effective, all services	329.95	127.74	−18.07	236.87	328.98	418.73	723.23
Percentage Markup (%)							
Upfront	28.71	11.62	−14.03	21.76	30.55	36.45	57.26
Theory add-on	86.53	7.61	−13.06	85.83	87.98	89.29	92.68
Practice add-on	56.57	8.95	8.11	53.05	58.03	62.48	74.04
Effective, all services	34.19	10.21	−3.93	28.10	35.38	41.13	58.28

Note: The row labeled "Effective, all services" refers to the effective markup the firm earns across the upfront and add-on markets, as defined in the text.

Table 5: Regression Models of Upfront Price Markups

	Dependent Variable: Upfront Price Markups (€) ($N = 420$)			
	OLS		IV	
Variable	(i)	(ii)	(iii)	(iv)
Number of competitors	−18.4683***		−23.0808***	
	(5.2550)		(6.1360)	
% fail on both exams	−184.5350**	−183.6603**	−189.3607**	−171.5962*
	(93.4410)	(93.5556)	(94.3611)	(93.4676)
$\mathbb{I}_{\{N=2\}}$		−28.5762		−40.3790*
		(19.9820)		(20.6764)
$\mathbb{I}_{\{N=3\}}$		−39.7401*		−43.8096**
		(23.7688)		(21.3104)
$\mathbb{I}_{\{N=4\}}$		−68.7008**		−99.5305***
		(29.7309)		(28.7627)
$\mathbb{I}_{\{N=5\}}$		−84.1256***		−101.5145***
		(31.6220)		(26.3010)
$\mathbb{I}_{\{N\geq 6\}}$		−89.2456***		−137.2428***
		(28.2628)		(26.2572)
Controls				
Is nearest competitor 5-10 km?	27.6504**	27.9863**	28.4179**	29.5196**
	(12.5631)	(12.5848)	(12.6694)	(12.7653)
Is nearest competitor >10 km?	39.9621**	40.9140**	40.4819**	38.3595**
	(17.9588)	(18.0094)	(18.1022)	(17.7052)
Purchasing power index	20.7315	18.7855	44.6362	51.1269
	(43.8217)	(43.9977)	(47.3713)	(31.2216)
Purchasing power index, high season	76.6222***	76.8508***	76.3612***	93.5307***
	(12.7894)	(13.0203)	(13.0662)	(11.3552)
Adjusted R^2	0.2290	0.2270	——	——
1st Stage Partial R^2	——	——	0.7907	——
1st Stage F-Statistic	——	——	532.1709	——
Log-Likelihood (FIML)	——	——	——	2,520.74
Instrument(s)	——	——	Pre-deregulation n° schools	Pre-deregulation n° schools

Note: The purchasing power index is seasonally adjusted, while the high-season purchasing power index captures irregular fluctuations in purchasing power during the summer months relative to the remainder of the year. We include as additional controls the median age of the school's driving fleet and parish-level mean rental rates, both of which are statistically insignificant in explaining upfront markups.

Table 6: Regression Models of Add-on Price Markups

	Dependent Variable: Add-on Prices Markups (€) ($N = 420$)			
	OLS		IV	
Variable	(i)	(ii)	(i)	(ii)
Number of competitors	4.1565		3.4867	
	(3.0982)		(3.6201)	
% fail on both exams	−15.4540	−38.7768	−13.9462	−54.5195
	(72.0285)	(71.6858)	(72.1764)	(70.6029)
$\mathbb{I}_{\{N=2\}}$		12.0636		11.5478
		(11.7648)		(12.4975)
$\mathbb{I}_{\{N=3\}}$		−0.5614		−3.0023
		(13.6513)		(13.8752)
$\mathbb{I}_{\{N=4\}}$		−18.1971		−22.1511
		(16.2117)		(16.2830)
$\mathbb{I}_{\{N=5\}}$		−10.2672		−7.6106
		(17.1246)		(16.1419)
$\mathbb{I}_{\{N\geq 6\}}$		38.9382**		41.4553**
		(15.8491)		(17.2705)
Controls				
Is nearest competitor 5-10 km?	10.2601	10.5090	10.3378	10.6021
	(10.0134)	(9.9884)	(10.1166)	(9.8755)
Is nearest competitor >10 km?	22.9516	23.9333	22.9607	23.5487
	(14.1371)	(14.1032)	(14.2851)	(14.0330)
Purchasing power index	−95.0997***	−98.2149***	−91.8844***	−102.3040***
	(25.7563)	(24.3948)	(27.8984)	(22.7729)
Purchasing power index, high season	−3.6098	−2.3404	−3.6855	−1.7981
	(7.4164)	(7.1048)	(7.6184)	(7.1348)
% residents who use public transport	−1.7071**	−2.1601***	−1.6793**	−2.4054***
	(0.7519)	(0.7170)	(0.7745)	(0.6994)
Adjusted R^2	0.0961	0.1636	——	——
1st Stage Partial R^2	——	——	0.7984	——
1st Stage F-Statistic	——	——	597.4884	——
Log-Likelihood (FIML)	——	——	——	2,380.01
Instrument(s)	——	——	Pre-deregulation n^{o} schools	Pre-deregulation n^{o} schools

Table 7: Conditional Logit Model for Propensity of Failing Exams

Variable	Theory Exam	Practice Exam
Female	−0.3880***	0.0034
	(0.0613)	(0.0659)
Age	0.0165***	0.0101***
	(0.0021)	(0.0022)
Female*age	0.0126***	0.0301***
	(0.0026)	(0.0027)
Is parish suburban? [1=Y,0=N]	−0.0385	0.0097
	(0.0330)	(0.0419)
Is parish urban? [1=Y,0=N]	−0.0855*	0.1061**
	(0.0372)	(0.0369)
Female*suburban		0.1594***
		(0.0439)
Female*urban		0.0647
		(0.0450)
Parish-level illiteracy rate	0.5950*	
	(0.2834)	
Is exam center public? [1=Y,0=N]		0.6145***
		(0.0404)
Log Likelihood	−37,107.34	−37,108.78
N	57,329	57,329

Table 8: Students' Exam Outcome Expectations, by Ultimate Outcome

		Do you think you will pass the theory exam you just took? (%)					
		All		Female		Male	
Exam Result		No	Yes	No	Yes	No	Yes
Failed	27.7	49.2	50.8	55.2	44.8	41.8	58.2
Passed	72.3	23.8	76.2	30.0	70.0	17.9	82.1
Total	100.0	30.8	69.2	37.4	62.6	24.2	75.8

		Do you think you will pass the driving exam at your first try? (%)					
		All		Female		Male	
Exam Result		No	Yes	No	Yes	No	Yes
Failed	24.8	26.4	73.6	35.0	65.0	14.6	85.4
Passed	75.2	12.9	87.1	17.5	82.5	8.4	91.6
Total	100.0	16.2	83.8	21.2	78.8	9.6	90.4

Table 9: School Choice Model: Preliminary Results

	1-Type			2-Types		
Variables	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Share (π_1)	——	——	——	−0.7857*	−0.9531**	−1.0677***
				(0.4160)	(0.3869)	(0.3949)
Upfront price (α_1)		−30.0456***				−82.3891***
		(3.1796)				(12.1207)
Expected add-on price		−36.3258***	−37.3828***			
		(3.8932)	(4.6649)			
Expected price (α_1)	−30.3315***			−57.6572***	−70.8361***	
	(3.1514)			(8.0111)	(9.3543)	
Expected price (α_2)				−26.7551***	−39.4712***	−47.8560***
				(4.8583)	(5.8862)	(10.1984)
Distance	−10.0190***	−10.0513***	−9.8275***	−10.8074***	−10.6086***	−10.4420***
	(0.7741)	(0.7746)	(0.7775)	(0.6885)	(0.6881)	(0.5424)
Distance^2	14.1295***	14.2360***	13.8343***	16.5583***	16.1440***	15.8499***
	(2.4352)	(2.4345)	(2.3251)	(2.3152)	(2.2489)	(2.2464)
Distance*female	1.1431**	1.1499**	1.1763**	1.0848**	1.1727**	1.2497**
	(0.5038)	(0.5019)	(0.5056)	(0.5293)	(0.5293)	(0.5047)
School Controls						
Instructor experience	6.7250***	7.2213***		8.5484***		
	(0.7726)	(0.7920)		(1.1006)		
Number of specialty courses	0.1269***	0.0796***		0.1502***		
	(0.0256)	(0.0290)		(0.0310)		
Number of vehicles	0.2939***	0.2774***		0.3743***		
	(0.0438)	(0.0431)		(0.0545)		
Age of school	−4.6264***	−4.9081***		−5.6160***		
	(0.4643)	(0.4786)		(0.6549)		
Distance to nearest competitor	−0.5451***	−0.5933***		−0.6169***		
	(0.0686)	(0.0696)		(0.0596)		
Distance to IMTT office	1.2965***	1.2395***		1.4586***		
	(0.2281)	(0.2282)		(0.2251)		
Distance to nearest university	−2.0957***	−2.1876***		−2.3872***		
	(0.4113)	(0.4212)		(0.4617)		
School fixed effects	N	N	Y	N	Y	Y
Log Likelihood	1,749.72	1,744.76	1,737.54	1,739.80	1,728.12	1,725.46
N	1,804	1,804	1,804	1,804	1,804	1,804

Note: The segment 1 and segment 2 share parameters equal $\theta_1 = \frac{\exp\{\pi_1\}}{1+\exp\{\pi_1\}}$ and $\theta_2 = 1 - \theta_2$, respectively. The implied segment 1 share values for specifications (iv), (v), and (vi) are 31.3, 27.8, and 25.6 percent, respectively.

Appendix

A. Equilibrium in Illustrative Model in Section 2

In this Appendix we establish the equilibrium of the add-on pricing model in Section 2. Here, we assume that the full menu of prices is observable to consumers; myopic students simply choose not to take add-on prices into account when making their school choice. In the following section we establish that, in contrast to markets where the add-on is avoidable, there is no profit gain to the firm from shrouding add-on prices. Recall the properties of the equilibrium summarized in (3):

PROPOSITION
Suppose there are n schools that offer an upfront service for price p^u at cost c^u and an add-on service for price p^a at cost c^a, and that there are a continuum of students. Let the fraction of sophisticates in the student population be $\pi \in (0,1)$ and the fraction of students who fail the exam be $\overline{\lambda} \in (0,1]$. If students fail the exam, they must buy the add-on service in period 2. There is a unique symmetric Nash equilibrium in which sophisticates engage in effort to lower their probability of failing to $\underline{\lambda}$ and, in period 1, schools charge an upfront price of

$$(p^u)^* = c^u + \frac{\sigma n}{n-1} - \left[(1-\pi)\overline{\lambda} + \pi\underline{\lambda}\right](\overline{p}^a - c^a)$$

while, in period 2, they charge an add-on price of

$$(p^a)^* = \overline{p}^a > c^a.$$

Proof. Consider first the school's choice of add-on price, p^a. In the second period, school j sells the add-on service to π sophisticated and $(1-\pi)$ myopic students and earns profit of

$$\begin{aligned}\Pi_j \quad = \quad & \pi\left[p_j^u - c^u + \underline{\lambda}\left(p_j^a - c^a\right)\right] D^s\left(p_{-j}^u - p_j^u + \underline{\lambda}(p_{-j}^a - p_j^a)\right) + \\ & (1-\pi)\left[p_j^u - c^u + \overline{\lambda}\left(p_j^a - c^a\right)\right] D^m\left(p_{-j}^u - p_j^u\right),\end{aligned} \tag{A1}$$

where we express the school's demand, $\{D^m, D^s\}$, in (2) only as a function of the price arguments.

Given that the add-on price, p^a, does not shift the demand of the myopic students, it is optimal for the firm to set it at the highest possible level, $\overline{p}^a$. A lower add-on price would not be profit-maximizing: for any combination of competitor prices, $\{p_{-j}^u, p_{-j}^a\}$, the firm could raise its add-on price by Δ and lower its upfront price by $\underline{\lambda}\Delta$. This would leave the demand and per-student revenue earned on sophisticated students unchanged. It would, however, increase both the demand from myopic students through the decline in the upfront price and – provided $\overline{\lambda} > \underline{\lambda}$ – the revenue per myopic student.[21]

The firm's upfront price p_u then maximizes:

$$\Pi_j = \left\{p_j^u - c^u + \left[\pi\underline{\lambda} + (1-\pi)\overline{\lambda}\right](\overline{p}_a - c^a)\right\} D^m\left(p_{-j}^u - p_j^u\right). \tag{A2}$$

Since schools are symmetric and charge the same add-on price in equilibrium, relative differences in add-on prices do not affect the sophisticated students' school choice. As a result, at the optimal add-on prices, their demand equals the myopic students' demand, D^m. Solving the first-order condition to the

[21] If $\overline{\lambda} < \underline{\lambda}$, a similar argument results from raising the add-on price by Δ and lowering the upfront price by $\overline{\lambda}\Delta$.

firm's upfront pricing problem results in equilibrium prices of:

$$(p^u)^* = c^u + \frac{\sigma n}{n-1} - \left[(1-\pi)\overline{\lambda} + \pi\underline{\lambda}\right](\overline{p}^a - c^a). \tag{A3}$$

This exposition assumes that sophisticated students find it in their best interest to engage in costly effort to reduce their probability of failing to $\underline{\lambda}$. They will do so provided the cost savings from engaging in effort, $(\overline{\lambda} - \underline{\lambda})\,\overline{p}^a$, exceed the cost of effort e. Otherwise, the optimal upfront price simplifies to:

$$(p^u)^* = c^u + \frac{\sigma n}{n-1} - \overline{\lambda}(\overline{p}^a - c^a). \tag{A4}$$

Equation (A4) also illustrates the profit-neutrality inherent in the add-on pricing model with symmetric types. In equilibrium, with equal probabilities of failing across types, the firm earns expected revenue per student of

$$(p^u)^* + \overline{\lambda}\overline{p}^a = c^u + \overline{\lambda}c^a + \frac{\sigma n}{n-1}. \tag{A5}$$

The same level of revenue would result in a pricing game where firms serve only sophisticated students who account for both the upfront and the add-on services in their school choice. Then, the firm's profit function would be:

$$\Pi_j = \left[p_j^u + \overline{\lambda}p_j^a - \left(c^u + \overline{\lambda}c^a\right)\right] D^s\left(p_{-j}^u - p_j^u + \overline{\lambda}(p_{-j}^a - p_j^a)\right) \tag{A6}$$

In the absence of myopic types, there is no unique solution to the firm's pricing problem to pin down $(p^u)^*$ and $(p^a)^*$ if firms commit to prices in the first period. Only the expected per-student revenue is uniquely identified; it equals the expected revenue in (A5). Add-on pricing in the presence of myopic students thus does not change the total amount of revenue a school earns from a student in expectation. It does, however, pin down how that revenue is distributed over the two services, placing a higher monetary burden on exam repeaters.

Note also that with unavoidable add-ons and no cost to unshrouding prices, it can be shown that the firm is indifferent between shrouding and unshrouding. This result differs from the equilibrium derived in Gabaix and Laibson (2006) for the case of avoidable add-ons;[22] here, since sophisticated consumers know that they cannot substitute away from the add-on for certain and expect the add-on's price to equal the walk-away price, there is no gain to shrouding. While the shrouded equilibrium would be the optimal choice if there were even a small cost to unshrouding and releasing the add-on price to sophisticated consumers, our exposition in Section 2 relies on the unshrouded equilibrium for simplicity.

B. Calculation of Marginal Costs

In this Appendix, we describe how we compute marginal costs for the schools' three services.

The marginal cost of the upfront service comprises five cost components: the fees for taking the theory and practice exams (F^T and F^P, respectively), the fee for purchasing the instructional materials the school provides to the student (M), the wages paid to the instructors (W), and the per kilometer cost of operating a fleet car (V), scaled by the number of kilometers a student drives during the instructional courses. The theory repeat course generates as cost only the fixed fee charged by the exam center for an examination.

[22] A number of authors, including Miao (2010), Kosfeld and Schüwer (2011), Heidhues et al. (2012), and Shulman and Geng (2012) have confirmed the results in Gabaix and Laibson (2006) in more general settings.

In contrast, the practice repeat course involves additional driving lessons with associated scaled-down wage and vehicle operating costs, in addition to the exam center's fee. Accordingly, we specify the marginal costs, MC^s, for service $s = \{U, T, P\}$ as:

$$\begin{aligned} MC^U &= F^T + F^P + M + W + (700 + 2D)\,V \\ MC^T &= F^T \\ MC^P &= F^P + \frac{6}{33}W + \left(\frac{6}{33} \cdot 700 + 2D\right)V, \end{aligned} \tag{B1}$$

and compute each cost component as follows:

1. Exam adminstration fees (F^T and F^P) The IMTT provided us with information on the fees that each of the 25 exam centers charges for administering the theory and practice exams. For a given school, we use the administration fees of the exam center used by the school, or a weighted average of fees if the school uses multiple exam centers.

2. Instructional materials expenses (M) Numerous sources quote €10 per student for instructional materials such as driver handbooks, CD-ROMs, and so on.

3. Instructor wages (W) The industry is subject to a non-binding price floor for instructor pay whereby the minimum pre-tax instructor salary is set at €683.05 per month; interviews with ANIECA and school representatives suggest a salary range between €750 and €950. We assume that instructor salaries fall within this range and are proportional to mean monthly earnings in the school's municipality across municipalities. Schools also pay a 23.75 percent social security tax and a €3.4 per diem stipend to its instructors, which we include to calculate schools' monthly, all-inclusive, labor cost per instructor.

   Since each student's base and practice repeat courses include 32 and five driving lessons, respectively, we convert the monthly salary figure to an hourly basis based on ANIECA information on length of working days and number of days worked per month. We assume that schools incur only fixed, and not marginal, costs for the student's classroom time since schools rarely operate at capacity. For the average school the all-inclusive marginal labor cost equals €236.94 per student for the upfront course, and only €43.08 for the repeat course on average.

4. Vehicle operating costs [$(700 + 2D)\,V$] The most sizable marginal cost component stems from the usage of the driving schools' fleet during driving lessons. We follow existing methodologies for computing a vehicle's user cost in Portugal, which is comprised of (i) fuel costs, (ii) depreciation costs, (iii) maintenance and repairs costs, and (iv) tire costs. From these four cost components we generate a cost per kilometer of operating a driving school vehicle, V, which we multiply by twice the return distance to the exam center plus the 700 kilometers that school owners state a student approximately covers during his base driving course in lessons plus; for the practice repeat course we scale this distance by 0.18 to 127.27 kilometers. The sources of data for the individual cost components are:

   - Fuel costs. We measure fuel costs as the price per liter of diesel fuel times fuel consumption in liters per kilometer. We obtained diesel gasoline price information from the Direcção-Geral de Energia e Geologia who provided us with a daily snapshot of prices for March 12, 2012, of all gasoline stations in each school's municipality, allowing us to capture cross-sectional, but not time-series, variation in fuel costs. For each school, we use the average of the five lowest fuel prices in the school's municipality. Based on interviews with school owners and ANIECA representatives, we use a consumption rate of 6.36 liters per 100 km, with some adjustments for variation in median horsepower of vehicles in the driving fleet across schools.

- Depreciation costs. We follow existing methodologies for vehicle user costs and assume that each vehicle depreciates fully by 8.4 years and has a purchase price of €25,000, on average. Given information on the size of each school's fleet and student body, which allow us to construct a measure of the average distance traveled per car and year, we distribute the vehicle's value over its total lifetime and arrive at a cost-per-kilometer driven figure.
- Maintenance and repair costs. We use public estimates of an average maintenance and repair cost of €4,000 over the car's service life, which we adjust to reflect fleet characteristics relative to the average car in the sample. As with depreciation, we convert the total to a per kilometer basis by dividing by our estimate of the total number of kilometers each car covers per year.
- Tire costs. We assume that the average car requires four new tires for every 40,000 kilometers traveled at a cost of €70 per tire, which translates into an average tire cost of €.01 per kilometer

We use these inputs to calculate each school's marginal cost for its upfront and add-on services according to (B1). Table B-1 summarizes the inputs into the cost calculation and the resulting totals. The cost an additional student is €507.78 on average for the base course. The cost of providing the add-on services is not surprisingly much less; the average school incurs €16.66 in marginal costs for the theory add-on and €116.06 for the practice repeat course.

Since a number of cost inputs relied on the size and composition of each school's fleet, information that IMTT updates only periodically, we employ as a robustness check a "constant-usage" marginal cost that employs a constant (across schools) estimate of annual distance covered per vehicle; we employ the median of 20,358 kilometers per vehicle-year. This alternative marginal cost measure averages to €499.29 for the upfront service, but has a lower standard deviation of €18.70 than our primary marginal cost measure. The markup regressions above are robust to using the constant-usage marginal cost.

C. Nonlinear Specification Estimation Procedure

In this Appendix, we describe how we construct and estimate the likelihood for our nonlinear specification. We estimate a system of two nonlinear equations using full information maximum likelihood (FIML), which predicts schools' chosen markups (resulting from their choice of prices) while controlling for correlations in unobserved market attributes that render market entry endogenous. Our estimation accounts for the fact that the markup is continuous while the market structure is discrete.

We specify the choice of markups for school i in market m as a (continuous) random effects model:

$$p_{im}^{P} = f^{P}\left(\alpha^{P}, \beta^{P}, \gamma^{P}, \mathbf{X}_{im}^{P}\right) + \xi_{im}^{P} \qquad \text{(Markup Equation)}$$

Here, we define $f^{P}(\cdot)$ as

$$f^{P}\left(\alpha^{P}, \beta^{P}, \gamma^{P}, \mathbf{X}_{im}^{P}\right) \equiv \alpha^{P} + \beta^{P}\mathbf{X}_{im}^{P} + \sum_{j=2}^{6} \gamma_{jm}^{P} \mathbb{1}_{\{\Pi_m^E = j\}},$$

where $\mathbf{X}_{im}^{P}$ contains school- and market-specific attributes. We estimate the market structure random effect, γ_{jm}^{P}, for markets with at least two firms in order that we have repeated observations by market.

Table B-1: Marginal Cost Components for All Services (€)

Service	Mean	StdDev	Distribution Min	Q25	Med	Q75	Max
Upfront							
Exam administration fees	54.48	9.75	45	45	52.9	59	73
Instructional materials	10	10	10	10	10	10	10
Instructor wages	236.94	18.24	204.21	224.04	237.22	247.35	278.54
Vehicle operating costs	201.36	33.84	132.93	175.34	197.58	224.64	317.35
Total	507.78	42.26	411.76	476.85	507.38	537.66	629.68
Constant-usage, Total	499.29	18.70	457.25	484.04	500.94	513.70	544.24
Theory Add-On							
Theory exam fee	16.66	2.06	14	15	15.9	17	21
Practice Add-On							
Practice exam fee	37.82	7.76	30	30	36.7	42	52
Instructor wages	43.08	3.32	37.13	40.73	43.13	44.97	50.64
Vehicle operating costs	34.17	6.20	21.17	29.54	33.46	37.77	53.18
Total	116.06	10.80	94.87	108.26	115.56	123.95	147.11
Constant-usage, Total	114.68	8.16	100.17	107.67	114.77	120.05	135.51

As in our main specification, we control for the possibility of endogeneity of the number of competitors by instrumenting with the number of competitors prior to the industry's deregulation. We specify the number of schools (or entrants) in market m, which ranges from 1 to 6 in the data, as a (discrete) ordered probit model:[23]

$$\Pi_m^E = \begin{cases} 1 & \text{if } f^E\left(\alpha^E, \beta^E, \mathbf{Z}_m^E\right) + \varepsilon_m^E < \zeta_1^E \\ j & \text{if } \zeta_j^E < f^E\left(\alpha^E, \beta^E, \mathbf{Z}_m^E\right) + \varepsilon_m^E < \zeta_{j+1}^E \text{ for } j = 2, .., 5 \\ 6 & \text{if } f^E\left(\alpha^E, \beta^E, \mathbf{Z}_m^E\right) + \varepsilon_m^E > \zeta_6^E, \end{cases} \tag{Entry Equation}$$

where the parameter ζ_j^E implies a cutoff for the unobservable ε_m^E between $j-1$ and j schools in the market and we define $f^E(\cdot)$ as

$$f^E\left(\alpha^E, \beta^E, \mathbf{Z}_m^E\right) \equiv \alpha^E + \beta^E \mathbf{Z}_m^E,$$

where $\mathbf{Z}_m^E$ contains market-specific attributes as well as the pre-deregulation number of schools, which we use as an instrument for the potential endogeneity.

We assume the markup choice error term ξ_{im}^P can be decomposed into a market- and school-specific component with $\xi_{im}^P = \varepsilon_m^P + \eta_{im}^P$, where ε_m^P is the market-specific error term for markups and η_{im}^P is the school-specific error term for markups with $\eta_{im}^P \sim N\left(0, \sigma_{\eta,P}^2\right)$. ε_m^P and ε_m^E, unobservable, market-specific factors that affect the entry and markup decisions, respectively, are distributed bivariate normal as follows:

$$\begin{pmatrix} \varepsilon_m^P \\ \varepsilon_m^E \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_P^2 & \sigma_{PE} \\ \sigma_{EP} & 1 \end{pmatrix}\right) \tag{C1}$$

The covariance terms allow for correlations in the market-level unobservables that give rise to endogeneity concerns. In addition to the parameters of the markup equation and entry equation covariates, we thus

[23] We combine markets with six or more schools into the final cutoff value.

estimate three parameters related to the joint distribution of the unobservables, and five ordered probit cutoff estimates, ζ_j^E.

In estimating the nonlinear system of equations with schools' markups as our dependent variable, the contribution of the likelihood from market m is the likelihood function

$$L_m = \Pr\left(p_{im}^P = p_i \forall i, \Pi_m^E = j\right),$$

where j is an index of the observed number of entrants and p_{im} equals the observed markup of school i. Thus, this likelihood of observing schools' markup choices in market m equals the joint probability distribution given by

$$\Pr\left(\xi_{im}^P = p_i - f_i^P, \zeta_j^E - f^E < \varepsilon_m^E < \zeta_{j+1}^E - f^E\right),$$

where ζ_j^E is the cutoff for j entrants. This probability is given by the integral of the $2N+1$-dimensional normal distribution of ξ_{im}^P and ε_m^E with mean zero and variance-covariance matrix given by (where $\mathbf{I}$ is the identity matrix and $\mathbf{\Xi}$ is a matrix of ones)

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_P^2 \mathbf{\Xi}_{2N\times 2N} + \mathbf{I}_{2N\times 2N} & \sigma_{PE}\mathbf{I}_{2N\times 1} \\ \sigma_{EP}\mathbf{I}_{1\times 2N} & 1 \end{bmatrix}$$

over the surface defined by f^P; and f^E and the cutoffs ζ_2^E through ζ_6^E that are consistent with observed markups and the observed number of entrants, respectively. Note that $\mathbf{\Sigma}$ results from stacking the $2N$ markup decision errors $\xi_{im}^P = \varepsilon_m^P + \eta_{im}^P$ and the single market-level error, ε_m^E. The variance-covariance matrix allows for correlation in the unobservable market shifters of the markup and entry equations, and thus controls for the endogeneity of market structure across equations.

The assumption that $\xi_{im}^P = \varepsilon_m^P + \eta_{im}^P$ with $\eta_{im}^P \sim N\left(0, \sigma_{\eta,P}^2\right)$ allows us to simplify the likelihood by integrating out η_{im}^P, which results in the likelihood function being equal to

$$L_m = \int_{\zeta_j^E - f^E}^{\zeta_{j+1}^E - f^E} \int_{-\infty}^{\infty} \left[\prod_{i=1}^N g_i^P\left(\varepsilon_m^P\right)\right] \phi\left(\varepsilon_m^P, \varepsilon_m^E\right) d\varepsilon_m^P d\varepsilon_m^E,$$

where

$$g_i^P\left(\varepsilon_m^P\right) = \phi\left(p_i - f_i^P - \varepsilon_m^P\right)$$

is the standard normal pdf of η_{im}^P and $\phi\left(\varepsilon_m^P, \varepsilon_m^E\right)$ refers to the pdf of the bivariate normal distribution of $\left(\varepsilon_m^P, \varepsilon_m^E\right)$ given by C1.

We further integrate ε_m^E out of the likelihood, conditioning on the markup equation market error ε_m^P to obtain

$$L_m = \int_{-\infty}^{\infty} \left[\prod_{i=1}^N g_i^P\left(\varepsilon_m^P\right)\right] \times \left[\Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_{j+1}^E - f^E\right) - \Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_j^E - f^E\right)\right] \phi\left(\varepsilon_m^P\right) \varepsilon_m^P,$$

where $\Phi_{\varepsilon_m^E|\varepsilon_m^P}$ denotes the conditional cdf of ε_m^E, given realizations of ε_m^P.

For a given value of the parameters, we use simulation techniques to compute each market's contribution to the likelihood function by integrating numerically over the normal distribution of ε_m^P. This yields the continuous pdf of the markup distribution. We then use a numerical maximization routine to maximize the full likelihood equation

$$L \equiv \prod_{m=1}^{M} \left\{ \int_{-\infty}^{\infty} \left[\prod_{i=1}^{N} \frac{1}{\sigma_{\eta,P}} \phi \left(\frac{p_i - f_i^P - \varepsilon_m^P}{\sigma_{\eta,P}} \right) \right] \times \left[\Phi_{\varepsilon_m^E | \varepsilon_m^P} \left(\zeta_{j+1}^E - f^E \right) - \Phi_{\varepsilon_m^E | \varepsilon_m^P} \left(\zeta_j^E - f^E \right) \right] \phi \left(\varepsilon_m^P \right) d\varepsilon_m^P \right\}$$

and update the parameters until convergence.

D. Determinants of Prices

Here, we supplement the regression analysis in Section 4.4 with regression models of school prices. These regressions serve two purposes. First, they allow us to verify that our results are not driven by measurement error in our constructed marginal costs. Second, we investigate the model's prediction that add-on prices are set at monopoly levels, and don't vary with the number of competitors, but only the school's own characteristics and the value of a driving license in the market generally.

The results of the regressions of the upfront prices on the number of market competitors with school- and municipality-level controls are shown in Table D-1. The number of schools in the municipality maintains a strong and significantly negative impact on upfront prices. The controls continue to suggest that higher prices are associated with greater distances to the nearest competitor.

The results for the equivalent regressions of the add-on prices on the number of market competitors with school- and municipality-level controls are shown in Table D-2. The number of schools in a school's own municipality is statistically insignificant in affecting add-on prices, as it was with markups. At the same time, schools have lower add-on prices in municipalities where public transportation is more commonly used, our proxy of the value of a driver's license.

The regressions, which seek to understand the determinants of prices and markups, are robust to using either as the dependent variable. While measurement error certainly exists in our marginal cost proxies, it does not drive our regression results. Nor are the competitive outcomes solely cost based. The results from using either prices or markups as the dependent variables are consistent with several predictions from the theoretical model.

Table D-1: Regression Models of Upfront Prices

	Dependent Variable: Upfront Prices (€) ($N = 420$)			
	OLS		IV	
Variable	(i)	(ii)	(i)	(ii)
Number of competitors	-17.1767***		-21.1401***	
	(5.2221)		(6.1105)	
% fail on both exams	-192.4944**	-191.4743**	-196.6612**	-206.2241**
	(93.1296)	(93.2646)	(93.9746)	(91.4221)
$\mathbb{I}_{\{N=2\}}$		-20.0554		-22.8369
		(19.8740)		(20.9308)
$\mathbb{I}_{\{N=3\}}$		-31.2562		-31.2958
		(23.6374)		(22.4958)
$\mathbb{I}_{\{N=4\}}$		-56.7439*		-68.6305**
		(29.5578)		(34.8038)
$\mathbb{I}_{\{N=5\}}$		-80.1365**		-83.4298***
		(31.4373)		(30.6705)
$\mathbb{I}_{\{N\geq 6\}}$		-81.5072***		-55.1451**
		(28.1005)		(29.3517)
Controls				
Is nearest competitor 5-10 km?	27.5113**	27.4701**	28.1475**	27.6935**
	(12.5253)	(12.5478)	(12.6176)	(12.7526)
Is nearest competitor >10 km?	43.2928**	43.5990**	43.7330**	39.6426**
	(17.9002)	(17.9562)	(18.0281)	(17.7232)
Purchasing power	69.6517	68.7741	90.2115*	73.1101
	(43.5363)	(43.7374)	(47.1748)	(46.2771)
Dynamic relative purchasing power	77.8963***	77.8746***	77.6997***	83.7991***
	(12.7075)	(12.9450)	(13.0120)	(9.1024)
Adjusted R^2	0.2192	0.2180	——	——
1st Stage Partial R^2	——	——	0.7984	——
1st Stage F-Statistic	——	——	597.4884	——
Log-Likelihood (FIML)	——	——	——	2,518.92
Instrument(s)	——	——	Pre-deregulation n$^{\text{o}}$ schools	Pre-deregulation n$^{\text{o}}$ schools

Note: For a list of included controls, see footnote to Table 5.

Table D-2: Regression Models of Add-on Prices

Variable	**Dependent Variable: Add-on Prices (€)** ($N = 420$) OLS (i)	OLS (ii)	IV (i)	IV (ii)
Number of competitors	4.2732		3.1283	
	(3.6821)		(4.3304)	
% fail on both exams	−46.7093	−64.8902	−46.0995	−75.3946
	(87.3762)	(86.6235)	(88.2837)	(70.8155)
$\mathbb{I}_{\{N=2\}}$		24.0029*		18.2386
		(14.1997)		(12.5352)
$\mathbb{I}_{\{N=3\}}$		17.0952		2.2052
		(16.4018)		(13.7671)
$\mathbb{I}_{\{N=4\}}$		−12.7968		−16.3745
		(19.4073)		(16.0776)
$\mathbb{I}_{\{N=5\}}$		−10.3040		−6.3781
		(20.4776)		(16.4546)
$\mathbb{I}_{\{N\geq 6\}}$		45.7761**		42.7746**
		(18.9348)		(18.5690)
Controls				
Is nearest competitor 5-10 km?	19.8741	18.9416	19.9339	8.6434
	(12.3160)	(12.2641)	(12.4199)	(9.9109)
Is nearest competitor >10 km?	13.6870	13.8442	13.4288	26.4586
	(17.3943)	(17.3362)	(17.5271)	(14.0548)
Purchasing power	−91.3200***	−94.6637***	−85.7041***	−100.0871***
	(30.5038)	(29.1153)	(33.3277)	(23.4869)
Dynamic relative purchasing power	−1.8254	0.1702	−2.0187	0.7239
	(8.7909)	(8.4972)	(9.1003)	(7.0755)
% residents who use public transport	−2.0630**	−2.4520***	−2.0151**	−2.4094***
	(0.8898)	(0.8560)	(0.9242)	(0.7170)
Adjusted R^2	0.0840	0.1438	——	——
1st Stage Partial R^2	——	——	0.7984	——
1st Stage F-Statistic	——	——	597.4884	——
Log-Likelihood (FIML)	——	——	——	2,379.97
Instrument(s)	——	——	Pre-deregulation n° schools	Pre-deregulation n° schools

Note: For a list of included controls, see footnote to Table 5. Additionally, we include the municipality-level proportion of residents using public transportation.