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

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Abstract

This article empirically examines the “drip” pricing behavior of firms, where consumers purchase a base product and may later buy an add-on, often without anticipating the need for it. A loss leader pricing strategy emerges, with firms pricing the base product below, and the add-on above, standalone levels. Using data from the Portuguese driving instruction market, we find that base course prices decrease with competition, while prices for add-on repeat courses do not. A survey reveals that at least 25% of students are inattentive to repeat fees, driven by underestimating failure rates and being unaware of repeat test costs.

Keywords: add-on pricing, market structure, loss-leader pricing, inattentive consumers

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1 Introduction

In many industries, sellers charge 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. This pricing strategy is commonly referred to as "drip-pricing." According to the Federal Trade Commission, "Drip pricing is a pricing technique in which firms advertise only part of a product's price and reveal other charges later as the customer goes through the buying process. The additional charges can be mandatory charges, such as hotel resort fees, or fees for optional upgrades and add-ons. Drip pricing is used by many types of firms, including internet sellers, automobile dealers, financial institutions, and rental car companies."[1]

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. Gabaix and Laibson (2006) and subsequent extensions (e.g., Bordalo et al. 2013; Heidhues et al. 2016) formalize another explanation for high markups in add-on markets: they may be optimal when some consumers are unaware of the contingent charge for the unadvertised add-on product, or its likely magnitude.[2] 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.[3]

Recent attempts by the US federal administration to curb "junk fees" highlight the prevalence of drip pricing. Regulatory efforts in this space include the Federal Trade Commission (FTC)'s 2023 proposal to prohibit "unfair or deceptive practices relating to fees for goods or services" broadly, the Consumer Financial Protection Bureau's increased supervision of bank fees since 2022, and the introduction in 2024 of Broadband Consumer Labels by the Federal Communications Commission.[4] Similarly, at the state level, California's Senate Bill 478 from 2023 prohibits drip pricing. Outside the US, Canada has recognized drip pricing as a deceptive marketing practice since 2022, and the UK's Digital Markets, Competition and Consumers Bill, which includes measures to combat drip

[1] See `https://www.ftc.gov/news-events/events-calendar/2012/05/economics-drip-pricing`.

[2] Armstrong and Vickers (2012) define a contingent charge to be one that applies "only if particular contingencies arise and that often catch customers unaware, either because they did not know of the fee and/or that the triggering event would happen."

[3] Other work on the role of consumer belief biases in pricing practices includes Jin and Leslie (2003), DellaVigna and Malmendier (2004), Oster and Scott Morton (2005), DellaVigna and Malmendier (2006), Köszegi and Rabin (2006), Spiegler (2006), Grubb (2009), and Heidhues and Köszegi (2010).

[4] See `https://www.whitehouse.gov/cea/written-materials/2023/03/21/how-junk-fees-distort-competition/` for the federal call for a Junk Fee Prevention Act, and `https://www.ftc.gov/system/files/ftc_gov/pdf/r207011unfairjunkfeesnprmfinal.pdf` and `https://www.fcc.gov/broadbandlabels` for FTC and FCC actions.

pricing, is expected to come into effect in late 2024. Drip pricing has also been the subject of legal actions, including numerous lawsuits that question the legality of Ticketmaster's order processing fees.

To what extent are the theoretical predictions about add-on pricing borne out in practice? The empirical literature on add-on pricing is scant. Some work provides evidence on the incidence of add-on charges and documents high prices in tied aftermarkets consistent with the predictions of theoretical models of add-on pricing. For example, 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 post tax-inclusive prices (i.e., disclose surcharges) for personal care products. Hossain and Morgan (2006) and Brown et al. (2010) demonstrate that raising shipping charges increases revenues in eBay auctions. In the context of retail banking, Armstrong and Vickers (2012) provide evidence and a behavioral model of the incidence of overdraft fees and consumer inattention in the UK, and Stango and Zinman (2009, 2014) document the incidence and magnitude of overdraft fees in the US, together with estimates of the share of such fees that could have been avoided had customers paid greater attention to their finances. Stango and Zinman (2014) and Alan et al. (2015) find that providing information about overdraft costs reduces overdraft usage, thus suggesting the possibility of regulatory intervention to decrease consumer inattention.

Although some of this work provides evidence of add-on pricing in the spirit of Gabaix and Laibson (2006) by documenting a response in the size of the add-on market to a reduction in consumer inattention or naivete, there is no quantification of the role of the competitive environment in affecting upfront and add-on prices and profit margins, and of the division of firm profit between the two product markets. In this article, we complement the existing literature in studying add-on pricing in a consumer service setting where we observe a variety of market structures across different localities, ranging from highly concentrated markets to ones with numbers of competitors that earlier work found to be more than sufficient to yield near perfectly competitive margins for similar local services (see, e.g., Bresnahan and Reiss 1991 and Asplund and Sandin 1999). This allows us to investigate whether the conclusion of the theory literature that supranormal prices and markups can prevail for the add-on, but not the base, product in competitive markets is borne out in our setting, relative to the benchmark provided by prices in the more concentrated subset of markets.

A challenge that our observational data shares with other work is that it is difficult to disentangle sources of consumer naivete using consumption behavior alone. Some work has therefore investigated different explanations for consumers' limited responses to add-on charges using survey evidence (e.g., Armstrong and Vickers 2012, Chetty et al. 2009). There is, however, no empirical evidence validating the sources of consumer naivete with actual demand responses. To fill this gap, we conduct a consumer survey and link consumers' survey responses to their later add-on consumption, which allows us to compare their own expectations of use and their actual use of the add-on.

We investigate add-on pricing 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 written and a road test. Should the student fail either test, new fees accrue for additional lessons and a repeat test, the add-on service in this context. There are a number of reasons why students' attention to repeat fees may be limited. First, although schools are required to keep a full schedule of their repeat fees on site, they are not required to inform students about their pricing structure at the time of registration. Second, as with professional testing and certification markets more generally, we show using our newly collected survey evidence that consumers systematically underestimate their probability of failing the tests and, thus, their demand for the add-on.[5] This is despite the fact that test repetition, i.e., add-on usage, is common; 44.2 percent of students fail either the written or the road test the first time.

A unique feature of our setting is that we rely on novel administrative data for the universe of Portuguese driving school students over a three-year period, including information on the school they attend, the sequence of their driving test 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 the theory and the on-road repeat courses. We also exploit the simplicity of the firms' cost structure, together with data on school-specific cost shifters, to estimate the per-student cost to the school for the basic and repeat courses and profit margins for schools' upfront and add-on services. Taken together, these data allow us to trace the entire sequence of purchases that students make, the prices they pay for each purchase, and the role of the competitive environment in pricing and markups.

Beyond the availability of highly detailed consumer data, our setting has a number of distinct advantages for studying the prevalence and pricing of add-on purchases. First, in most settings, it is

[5] 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).

difficult to disentangle ex-ante planned add-on consumption from unexpected, surprise purchases.[6] In our setting, in contrast, the consumer – the student – does not derive independent utility from the repeat course; it is reasonable to assume all students would prefer to pass the driving test at first try and would not purchase the add-on if they did. Ex-ante purchase intentions for the add-on are thus likely non-existent. Second, regulatory restrictions on transferring already completed lessons across schools result in high switching costs and very infrequent school switches. The repeat course of instruction is thus a classic example of a tied aftermarket where the student purchases the repeat course from his existing school. At the same time, the schools do not use bundling strategies to sell the two products or negotiate over prices with students. Third, the fact that obtaining a driver's license is a one-time event means that students cannot rely on repeat purchases to learn about pricing or their individual likelihood of failing a test. Demand does not exhibit state dependence. Last, investigating the role of market structure on pricing strategies is challenging in observational studies because market structure is an endogenous equilibrium outcome. We exploit the availability of measures of cost and ease of market entry as instruments to identify the effect of the number of competitors on price.

To study firms' pricing, we set up a model that builds on the Gabaix and Laibson (2006) model of add-on pricing with naive 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 horizontally differentiated firms. 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. Naive consumers, conversely, do not account for the add-on and their likelihood of requiring it when choosing their school. We show that a typical loss-leader pricing strategy emerges in which firms sell the upfront product below competitive profit margins and simultaneously price the add-on at monopoly levels.

As in Gabaix and Laibson, the assumption of differentiated 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 naive consumers, who unexpectedly (to them) participate and generate profit in the add-on market, depresses the upfront product's price. Second, an increase in the probability with which consumers require the add-on product similarly raises profitability, offset by a lower upfront product

[6] For example, with observational data on airline purchases it is impossible to separate which consumers had planned to pay for baggage fees from those who were surprised by such fees once they arrive at the airport. The same applies to mini-bar purchases made at a hotel.

price and markup.

We test several of these predictions in the driving school setting. First, we establish that exam failures are the source of significant revenue and estimated profit to schools; our data indicate that 16.7 percent of revenue and an estimated 32.3 percent of variable profit derive from repeat courses for the median school.

Second, the percent markup for the base course averages 28.0 percent, but the corresponding figures for the add-on market are significantly higher: 86.6 and 57.8 percent in the theory and on-road add-on markets, respectively. Schools' upfront prices and markups also strongly correlate with the number of schools in their municipality, pointing to the standard downward pressure on prices of additional competition. On the other hand, schools' repeat fees and markups do not correlate significantly with the number of competitors, as predicted by the theoretical model.

Our theoretical model is agnostic regarding the reasons behind consumers' limited foresight. Similarly, our administrative 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 driving tests. We therefore conduct a survey of a representative sample of students as part of their written test session at a select testing center. Our survey-based analysis is novel in that it provides us with the ex-ante expectations of add-on consumption that would affect the initial provider choice, rather than inquiring about determinants of such consumption after it has occurred. We rely on the survey to provide evidence on the prevalence of price unawareness and, by linking the solicited ex-ante expectations with the students' ex-post test performance, over-optimism. Further, the survey provides us with a measure of effort that allows us to test whether sophisticated consumers engage in more effort than naive ones, as predicted by the theory model.

The survey evidence suggests that naivete is a plausible explanation for the fee structure in the industry: we identify a sizable group of students – 22 percent – who either believe they do not need to or do not know whether they need to pay for retaking a driving test. The survey evidence also suggests that students' expectations of their exam outcomes are biased upward. Such misaligned expectations, as well as price unawareness, are two reasons why students would not respond to the price of the add-on at the time of their school choice, thus suggesting that the share of naive students in the market exceeds 22 percent. The survey also shows that informed students engage in more effort to prepare for the driving test, thereby reducing the probability of having to purchase the add-on service, consistent with the theoretical model.

That naive students constitute a nontrivial subset of the student population has important distributional consequences. If sophisticated students can reduce their demand in the add-on market, they reap the benefits of low prices in the upfront market. Thus, naive students – whose business in both markets comprises a significant portion of schools' profits – effectively subsidize the remaining students with lower prices in the upfront market. Such distributional effects would be particularly concerning if naive students are comprised of demographically vulnerable population segments. Even though we do not formally evaluate these welfare implications, our evidence points to a number of potential avenues for regulation to combat students' naivete, including improving consumer understanding of pass rates via pass rate disclosures and enforcing that schools post up-to-date, easy to compare, complete pricing menus. Beyond the particular market we study, understanding add-on pricing is important for a variety of policy questions, ranging from consumer protection measures to tax incidence and optimal taxation, to antitrust questions, assessing, for example, whether add-on pricing facilitates tacit collusion on the price of the add-on.

The article proceeds as follows. Section 2 presents a model of add-on pricing with naive consumers. Section 3 introduces the data and the institutional setting of the Portuguese driving schools. Sections 4 and 5 provide evidence to support some of the assumptions and predictions of the model based on observational and survey data, and Section 6 discusses alternative interpretations and robustness checks. Section 7 concludes.

2 A Model of Add-on Pricing with Naive Students

We present a stylized 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 ignore their demand for the add-on product. We develop the model for our empirical setting of driving instruction, but the model can be reinterpreted for other contexts in which consumers purchase an upfront and add-on products and some consumers ignore their demand for the add-on products.

Because our setting does not map directly into the existing theoretical add-on models, we adapt the theory of Gabaix and Laibson to allow us to test the model's predictions in our empirical context. There are two main differences between our model and the model in Gabaix and Laibson (2006). First, we model the add-on consumption as a probabilistic outcome. Second, we follow Armstrong and Vickers (2012) in assuming that firms do not make an explicit "shrouding" decision. In our empirical setting, add-on charges are not prominently advertised, but also not hidden. Similarly, in the context of contingent overdraft charges studied by Armstrong and Vickers (2012), charges are not hidden but not prominently displayed in the banks' marketing materials.

Consider 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 test – and an add-on service a – a make-up course for test re-takers. 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. We assume that the add-on price takes the form of a surcharge: students who fail the test 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.[7] 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.[8] As in Gabaix and Laibson (2006), the add-on price p^a is bounded above by $\overline{p}^a$. For example, if a student is forced to pay an excessively high repeat-course price, he might choose not to continue with driving instruction or lodge a complaint with the regulatory body, the Instituto da Mobilidade e dos Transportes (IMT). Although the IMT does not regulate the price of repeat courses, its oversight likely limits the fees that schools can charge. In period 2, students learn whether or not they need to buy the add-on at its set price depending on their test results from period 1. Students have a strictly positive, identical probability of $\overline{\lambda} \in (0, 1]$ of failing the initial driving test.

We assume that there are two student types in the market: a share of $\pi \in (0, 1)$ sophisticated types s and $(1 - \pi)$ naive types m. In period one, the naive types disregard the add-on service; they only become aware of it ex post when they fail the test and are forced to purchase it. This assumption may reflect that naive students are unaware that there are fees for repeat courses. Naive students may also underestimate their probability of failing the test – for example, because these students suffer from over-optimism – or they may have a high discount rate and thus put less

[7] We discuss below that we observe a negligible share of school transfers by students in our data, which motivates the lock-in assumed here.

[8] We model firms' pricing as a single contract offered to all students, reflecting what is practiced in our empirical context. Firms may avoid mixed bundling, metering, or other menu pricing strategies that could induce self-selection, to minimize consumer attention to add-on prices and potential regulatory scrutiny.

weight on fees they have to pay in the future.

Our definition of naivete aligns with Armstrong and Vickers's (2012) who attribute inattentiveness either to a lack of knowledge about add-on fees or an incorrect assessment of the likelihood of incurring them.[9]

In contrast, sophisticated students recognize the possibility of having to retake the test. We assume they form rational expectations over their probability of failing the test, assessing it correctly at λ, and consider the add-on service when making their school choice in the first period. Sophisticated students can engage in costly effort to reduce their probability of failing from $\overline{\lambda}$ to $\underline{\lambda} > 0$, and hence their expected repeat fees, at an effort cost e. For simplicity, we abstract from the fact that the add-on price is only paid in the future and the expected total price of the course is the discounted sum of expected payments over time.[10, 11] The student types are thus differentiated by their perceived benefit from effort; naive consumers do not perceive any such benefit and hence do not engage in effort to reduce their probability of failing.

In line with our empirical setting, we follow Gabaix and Laibson (2006) in assuming that students make a discrete school choice, allowing for heterogeneous valuations of each school. We assume that 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

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

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

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

[9]In Armstrong and Vickers's (2012) case of bank overdraft services, this may involve unawareness of the charges or their exact amounts (possibly due to low salience of information), underestimating the charges or the likelihood of overdrawing, being aware of the charges but not expecting to have to pay them, or imperfect balance tracking.

[10]For example, they might study more for the written test or try harder at their on-road lessons to minimize their probability of failing and the likelihood they will be required to purchase the add-on service.

[11]For simplicity, we assume that all students have the same ex-ante fail probability $\overline{\lambda}$. The model predictions are robust to allowing for heterogeneity in ex-ante fail probabilities across students provided the cost of effort incurred by sophisticated students is less than the expected savings in repeat fees for all sophisticated students.

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. Because students are locked in to their school upon failing the initial test, the school acts as a monopolist over its demand and optimally charges the highest possible price, $\overline{p}^a$.

Now consider the pricing of the base service. In the Appendix we show that there is a unique symmetric equilibrium characterized by the following pricing strategies:

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

provided effort costs e are at most equal to $(\overline{\lambda} - \underline{\lambda})\overline{p}^a$.

In equilibrium, firms follow a loss-leader pricing strategy in which the upfront service is sold below competitive profit margins and the add-on service is priced at monopoly levels. The equilibrium pricing strategies reflect that the upfront service's price is increasing in the fraction of sophisticated types, or

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

Alternatively, as the size of the naive segment increases, the upfront price decreases to reflect that schools anticipate larger profits from the add-on service; schools want to attract more naive types upfront and recoup these losses in the add-on market.[12]

The equilibrium pricing strategies in (3), together with these observations, yield the following testable predictions:

Prediction P1. Prices in the upfront market decline as the number of firms increases. With large n and a sizable add-on market, 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.

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

Prediction P2. The price of the upfront service is monotonically decreasing in student types' average probability of failing the test, $\left[(1-\pi)\overline{\lambda}+\pi\underline{\lambda}\right]$. The greater the number of students schools can attract in the add-on market, the lower the price they charge in the upfront market to entice students to sign up with them.

Prediction P3. Prices for add-on services do not decline as the number of firms in the market increases.

Prediction P4. The add-on price does not depend on students' probability of failing.

Prediction P5. Sophisticated students engage in costly effort to reduce their exposure to the add-on market. Such effort reduces their probability of failing from $\overline{\lambda}$ to $\underline{\lambda}$ (i.e., to a level below that of a naive student).

In Sections 4 and 5 we assess the plausibility of some of the model assumptions and test Predictions P1-P5 using the market for driving instruction. In Section 6, we also consider price discrimination as an alternative, rational expectations based mechanism for the presence of add-on pricing. Other rational explanations put forth in the literature do not map closely into our institutional setting. In our context, as we describe below, upfront prices are as easily observable as add-on prices, and hence search costs are unlikely to be more pronounced for add-on than upfront prices, the source of divergent markups between the two types of products in Lal and Matutes (1994) and Ellison (2005). Further, switching costs would require firms to be unable to commit to add-on prices at the time of selling the upfront service (e.g., Shapiro 1995, Farrell and Klemperer 2007); by regulation, driving schools are required to commit to an add-on price (and to post it at the school location). We first describe the market for driving instruction in Portugal and summarize our sources of data.

3 Background and Data

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 IMT as the regulatory agency that oversees driving instruction.

To obtain a driver's license, any individual aged 18 years or older must first enroll in an IMTauthorized driving school.[13] There, candidates must complete 28 theory lessons, the curriculum of which is set by the IMT, and a minimum of 32 on-road driving lessons; students cannot legally practice driving without the presence of an instructor and outside of a lesson paid to a driving school. After completing the required theory lessons, students take a computerized written test. Subsequently, they perform a road (driving) test. Firms typically charge a single fee for the base course of instruction, covering classroom time, materials, practice written tests, on-road driving lessons, and the test administration by the testing center.[14]

If a candidate fails either the written or the road test, he must pay a fee to retake the test and, in the case of the road test, to complete five additional driving lessons. Both tests are administered at one of 35 testing centers, and the IMT charges schools a testing fee for each student taking the test. The fact that the school pays the fee and does not need to inform the student of its magnitude is one reason why schools are able to mark up the price of repeat courses. Twenty-two testing centers are managed by the IMT, and private organizations operate the remainder. The computerized written tests that are administered at both public and private centers are based on IMT-proprietary software that ensures tests are controlled tightly. An IMT certified examiner oversees the road test.

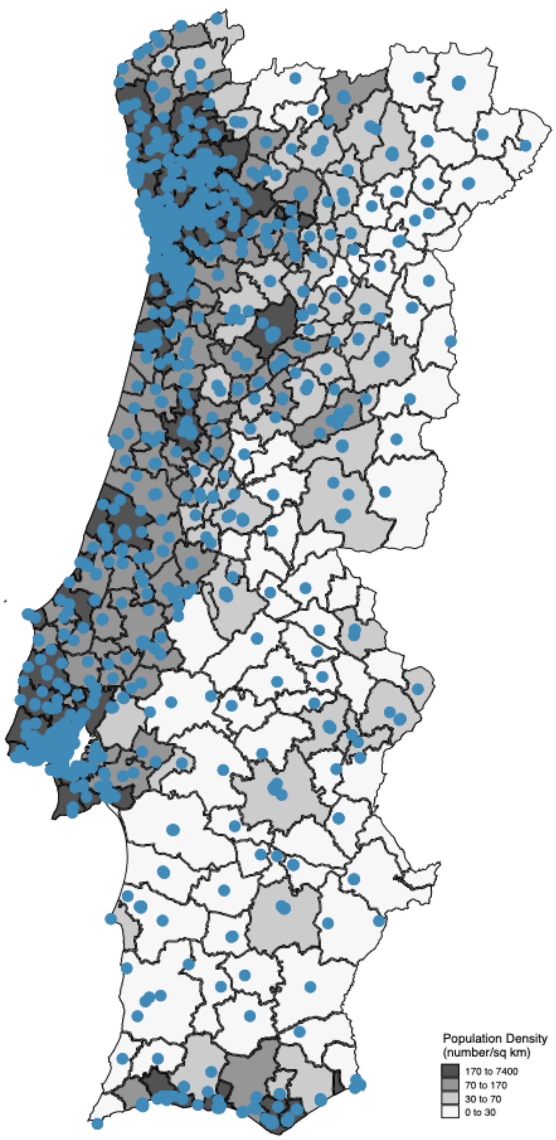
As of 2010, there were 1,141 driving schools in mainland Portugal. Since 1998, the number of firms in the industry has more than doubled. Entry resulted from significant liberalization efforts that lifted restrictions tying the maximum number of schools serving each municipality to population. A number of regulatory restraints remains in place, including that new entrants need to be located at a distance of at least 500 meters from existing schools. Regulations also govern the sharing of resources between schools, which 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. Panel (a) in Figure 1 plots the locations of all driving schools in mainland Portugal by municipality population density.

[13]Licensing by the IMT 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 IMT standards.

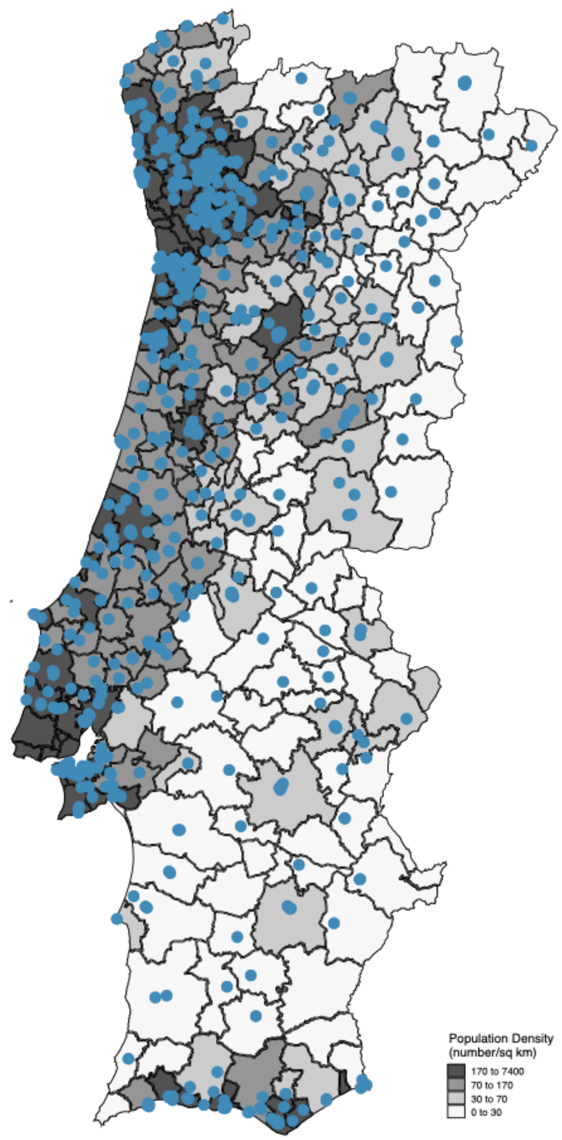
[14] Firms differ in the extent to which they present consumers with a detailed price breakdown for the base driving course. In Seim et al. (2017), we study how much consumers value this transparency about the contribution of individual components to the total base price, but abstract from the role of add-on fees in school choice.

Figure 1: Driving Schools by Municipality, Mainland Portugal

(a) All municipalities



(b) Available sample of municipalities



Data

Our empirical analysis combines a number of data sets at the school, student, and municipality level. First, from the IMT, we obtained data on school characteristics related to instructors and driving fleet. These data originate from the school's licensing application and are updated periodically. We geocoded school addresses using GIS software and added hand-collected prices and estimated costs. Second, the IMT provided information on individual-level school enrollment and driving tests for the entire population of students who enrolled in a school between 2008 and 2010. For the primary analysis, we focus on students who obtained their driver's license anytime in 2009 or 2010. In supplementary analyses, we rely on the subset of students who did not complete their license by the end of 2010 after a period of at least one year of not recording testing activity. We obtained demographic and other data at the level of the parish or municipality from the market research company Grupo Marktest, the Ministério do Trabalho e da Solidariedade Social, the Direcção Geral do Território (DGT), and Statistics Portugal. Finally, night-time light intensity data came from the Earth Observation Group (EOG) at NOAA/NCEI, which collects and processes nighttime satellite imagery.

We focus on applicants for a category-B passenger-vehicle license (the most common type of driver's license which excludes trucks and other specialty vehicles), resulting in a loss of 16.3 percent of candidates. Further, we restrict the sample to candidates for whom we have a complete history profile from enrollment at a school to completion of the road test, which eliminates 2.1 percent of category-B students who took the written test prior to 2008 (we only have access to written test data from 2008 onwards).

Our empirical analysis treats a municipality as the relevant market area within which firms compete and students choose schools. Because the districts of Lisbon and Porto are large and densely populated, the assumption of an individual municipality comprising an independent market is less reasonable for parts of those districts. Consequently, we exclude those municipalities in Lisbon and Porto that have a population density above 1,000 people per square kilometer, or approximately the 90^{th} percentile of the distribution of municipality population density. We verify visually that the 34 municipalities that we drop comprise densely populated contiguous areas within these two districts. Eliminating the students residing in these municipalities reduces the number of category-B applicants by 25 percent. We further restrict our sample to municipalities where complete price information is available for all schools in the municipality; there are 31 municipalities with incomplete price information for at least one school in the municipality.

The final sample contains 105,944 students residing in one of 235 municipalities with a total of 746 schools. These are displayed in panel (b) of Figure 1.

Sample Markets Table 1 describes the characteristics of the sample of markets. The average (median) municipality contains 3.5 (2) driving schools, ranging from 1 to 22 schools. Such a wide range facilitates assessing how prices change when we move from a monopoly to a near perfectly competitive environment. Municipalities range in population from 2,952 to 181,474 residents, with an average population of 29,523

Table 1: Summary Statistics, Municipality Characteristics, Sample Markets ($N = 235$)

	Mean	Std Dev	Min	Med	Max
Number of schools	3.536	3.453	1.000	2.000	22.000
Number of students	450.826	557.691	30.000	248.000	3353.000
Population (000)	29.523	32.903	2.952	16.851	181.474
Population in urban parishes (%)	81.941	21.135	15.489	89.704	100.000
Mean per-capita income (€)	854.689	116.622	616.600	863.600	1519.400
Population with higher education (%)	12.331	5.084	4.028	10.966	29.105
Number of parishes in muni	24.468	19.729	1.000	19.000	89.000
Number of car repair shops	61.822	51.700	0.000	50.000	214.000
Average monthly rent (€)	136.552	30.094	47.000	139.000	257.250
Non-residential buildings (%)	9.009	3.049	3.260	8.800	27.740
Number of grocery stores	12.405	10.987	0.000	10.000	53.000
Developed land (000 ha)	3.032	1.941	0.098	2.751	8.641
Night-time light intensity (%)	77.891	23.239	12.289	85.231	100.000

Note: Mean income is monthly wage income of full-time employees. Night-time light intensity measured as a share of all pixels within the municipality.

people living in one of 24.5 parishes; on average, there are 450.8 driving school students during our data period in a given municipality.

We rely on market demographics, which are available both at the municipality and parish level, as demand shifters. Eighty two percent of residents live in a parish that is either moderately or predominantly urban. Monthly wages amount to €854.69. Thirteen percent of residents have completed some level of post-secondary education.

Similarly, we use select market attributes as shifters of school fixed costs. These include the average monthly rent (€136.55 across municipalities, on average), the share of non-residential buildings (9.0 percent on average), the number of grocery stores (12.40 on average), the area being used for commercial or residential development (3,032 hectares on average), and the share of pixels with positive night-time light intensity (78 percent of the average municipality's pixels are illuminated).[15] [16]

School Characteristics Here, we summarize school characteristics, the size of the schools' student body, and market shares. See Table 2. For the average school, 142.0 students began and completed their course during our sample period.[17] There is significant variation in enrollment figures across schools, however; the interquartile range of enrollment spans from 86 to 176 students.

[15] Land usage data was obtained by the DGT using high-resolution satellite imagery, classified according to the United Nations' Land Cover Classification System (LCCS).

[16] Night-time light intensity data is available for a grid of 0.025-square-mile pixels across Portugal, which we map to each municipality to calculate the share of pixels with positive light intensity in each municipality. For a discussion and examples on the use of night-time light intensity data, see Gibson et al. 2021.

[17] Note that the student body of the typical school is significantly larger due to the fact that we restrict the sample to students who began and completed their course in our sample period. In total, over the three year period, the average school enrolled 425.9 students.

Table 2: Summary Statistics, School and Examiner Characteristics

	Mean	Std Dev	Q25	Med	Q75
Price, base course	701.554	107.706	625.000	699.000	771.000
Price, theory course repeat	129.399	25.326	115.000	130.000	150.000
Price, on-road course repeat	275.309	48.199	250.000	278.000	305.000
Marginal cost, base course	494.180	39.206	465.122	488.700	519.761
Marginal cost, theory course repeat	16.330	1.765	15.000	15.525	17.000
Marginal cost, on-road course repeat	112.779	10.169	104.796	111.835	119.005
Number of students	142.016	82.576	86.000	121.500	176.000
Age (yrs in 2010)	20.010	15.923	8.361	10.407	28.871
Number of instructors	5.576	3.602	3.000	5.000	7.000
Instructor experience (years)	8.003	5.337	4.202	6.444	10.139
Number of vehicles	3.756	2.254	3.000	3.000	4.000
Median weight of fleet cars (000 kg)	1.193	0.105	1.125	1.185	1.257
Distance to testing center (km)	20.485	17.146	6.362	17.331	28.538
Distance to IMTT office (km)	24.588	16.897	12.182	22.730	36.410
Distance to IMTT headquarters (km)	209.694	107.416	117.957	237.068	301.976

Note: Observations: 746 schools, 32 exam centers, and 190 examiners. All statistics are student weighted.

The average school employs 5.6 instructors who have worked in the firm for eight years. The median school has a driving fleet consisting of three passenger vehicles, for which we observe characteristics such as displacement, age, and weight. We calculate the straight-line distance from the school to the nearest district-wide IMT office, to the main IMT office which is located in Lisbon, and to its most frequently used testing center to proxy for costs of interacting with the IMT and of transporting students to the testing center. The average school is 24.6 kilometers from the closest IMT office, 209.7 kilometers from the main IMT office, and 20.5 kilometers from its most commonly used testing center.

The IMT does not collect price information. We complement the IMT data with hand-collected, detailed prices. We employed a team of 14 mystery shoppers who visited each school in person between November 2011 and March 2012 with an identical script to obtain information on base prices and repeat fees.[18] The top panel of Table 2 summarizes the distribution of prices across schools and markets. The median school charges €699 for its base driving course, with an interquartile range of €625 to €771. Thus, there is significant variation in prices, likely due to cost and demand differences across municipalities. Accordingly, the between-municipality standard deviation is 2.2 times the within-municipality standard deviation in upfront prices. The average on-road repeat course fee of €275.3 is more than double that of the theory repeat course fee, €129.4, mostly due to the on-road repeat course including five additional driving lessons.

[18]The distribution and level of prices are stable over time. Comparing 2010/2011 upfront prices to those from a 2009/2010 pilot phone survey of 298 schools – the period corresponding to the administrative student data – we find Pearson and Spearman rank correlations above 0.96, identical median prices, and average prices differing only by €3.

Marginal Costs To assess the profitability of each of the services, we estimate schools' marginal costs. We also use the marginal cost estimates to rule out alternative explanations for the results found in Section 4 (see Section 6). We benefit from the simplicity of the service offered and exploit information contained in a template that the industry association Associação Nacional dos Industriais do Ensino da Condução Automóvel (ANIECA) provides to members to estimate annual operating costs, including both total and unit costs.

According to the cost template, the base course marginal cost per student consists of: (i) fees paid to the testing center for the administration of one written test and one road test ; (ii) the cost of instructional materials for the theory lessons; (iii) the instructor wages for 32 driving lessons and for the final road test (which the instructor needs to attend); and (iv) the vehicle operating costs of driving one of the school's vehicles during the practice lessons and the test (cost of gasoline, depreciation expenses, maintenance and repairs, tolls and other road fees and taxes, and other expenses). The school's cost of the theory repeat course is limited to the student's written test fee, which is identical to the fee it pays to the testing center the first time the student takes the test. For the on-road repeat course, the school incurs test administration fees, as well as labor and vehicle maintenance costs equivalent to five driving lessons plus driving to the testing center.

We use information on testing center fees, municipality-level wages, local gasoline prices, the estimated distance in kilometers covered during a 32-lesson and a five-lesson course of instruction, and the annual usage in kilometers of each school's fleet of cars to derive marginal cost estimates (see Appendix A.2 for details). Per student, we estimate that the average school pays €53.45 in testing fees to cover the cost of one written and one road test (see Table A.2.1 in the Appendix). The cost of instructional materials is minimal and standardized, amounting to €10 per student. We estimate that instructor wages amount to €228.4 and €41.5 for 32 and five on-road lessons at the average school, respectively, capturing cost-of-living differences reflected in municipality-level incomes across municipalities. Vehicle operating costs – the costs of gasoline, depreciation, and maintenance and repairs – amount to €0.28 per kilometer.[19] When scaled by the 722.9 kilometers the average student covers during the driving course and test itself, the vehicle operating cost for the base and on-road repeat courses amount to €202.4 and €34.1 on average.

In total, the average school incurs an estimated marginal cost of €494.2 per student in the base course, with a standard deviation of €39.2. The add-on services generate estimated marginal costs of €16.3 and €112.8 for the theory and on-road repeat courses, respectively. We verified the reliability of our cost estimates in interviews with driving school owners and using feasibility studies that potential entrants prepare for the IMT as part of the licensing process. Our cost estimates are comparable to the new entrants' own cost estimates for a country-wide sample of schools.

[19]This compares to estimates of vehicle operating and ownership costs provided by the Automóvel Club de Portugal ACP.

Table 3: Summary Statistics, Student Attributes ($N = 105,944$)

	Mean	Std Dev	Q25	Med	Q75
Age at time of theory exam (years)	21.871	6.759	18.341	19.050	21.793
Gender (1=F, 0=M)	0.513	0.500	0.000	1.000	1.000
Distance to city center (km)	4.671	3.773	1.555	3.914	6.840
Distance to school (km)	4.660	5.759	0.995	2.796	5.967
Theory exams taken (number)	1.374	0.820	1.000	1.000	1.000
On-road exams taken (number)	1.353	0.680	1.000	1.000	2.000
Fail rate, first theory exam (%)	24.126	42.785	0.000	0.000	0.000
Fail rate, first on-road exam (%)	26.311	44.032	0.000	0.000	100.000
Fail rate, both first theory and on-road exams (%), school-level (N=746)	7.017	4.102	4.110	6.590	9.375
Time to completion (days)	247.208	150.213	140.000	208.000	312.000
Choice is closest school (1=Y, 0=N)	0.485	0.500	0.000	0.000	1.000

Student Attributes The IMT student records contain the date on which the student obtained his learner's permit and the category of the permit, the dates, times, testing centers and outcomes of each test, the issue date of the license, as well as the candidate's age, gender, and the seven-digit postal code of his residence, which approximately designates a city block.

Table 3 shows that the average (median) student in our sample is 21.9 years (19.1 years) old. There is an even split of male and female students: 51.3 percent of our sample is female.

We assume that each student lives at the centroid of his postal code area to compute the straight-line distance to his chosen school. Not only are a majority of students located less than three kilometers from their schools (median distance of 2.8 kilometers), but 48.5 percent of students choose the school closest to home. Clearly, spatial differentiation is an important dimension of pricing.

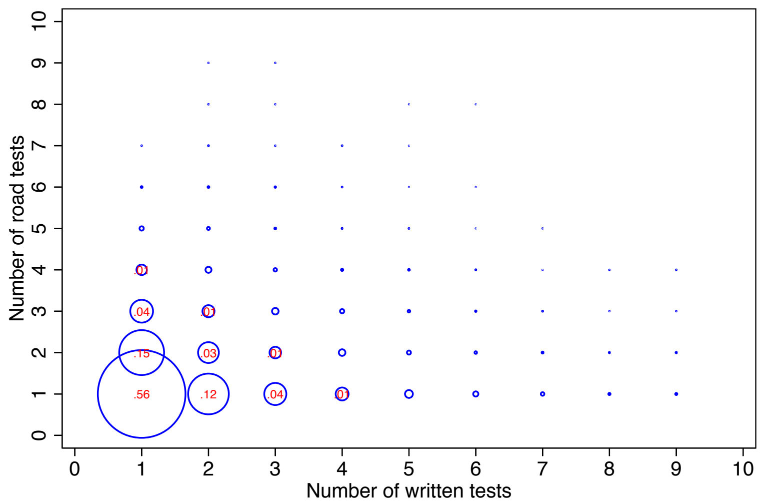
4 Pricing in the Upfront and Add-on Markets

In this section, we investigate the extent to which prices conform to Predictions P1-P4 of the theoretical model presented in Section 2 (we test the remaining Prediction P5 in the next section), establish the plausibility of the model assumptions, and describe the economic relevance of the retake markets more generally. We begin by summarizing students' test outcomes, school pass rates, and thus the size of the repeat market.

Incidence of Test Repetitions

Figure 2 and Table 3 suggest that the add-on market is sizable. Only 75.9 and 73.7 percent of students pass the written and road tests on the first attempt, respectively. The two tests' outcomes are largely independent because only 56.0 percent pass both tests on the first attempt. The average student takes the written and road tests approximately 1.37 and 1.35 times, respectively. This results in the driving school process being lengthy; the median student takes seven months from start to finish.

Figure 2: Number of Written and Road Tests Taken, by Student



The data also provide evidence to support our model assumption that students are de-facto locked into the school by their initial choice and rarely switch schools. Only 1.5 percent of all students transfer schools before passing the written test, 0.5 percent transfer after passing the written test but before taking the on-road test, and 0.1 percent transfer after having taken the on-road test and failed at least once. The majority of transfer events, or 67 percent, is between municipalities, suggesting that exogenous reasons such as moving explain a significant share of transfers. The primary switching cost is that, by regulation, lessons taken at one school do not transfer to another school; switching schools requires restarting the base course from the beginning. This is costly, both in terms of time and fees: given each student's current school choice, the cheapest base course of instruction at a different school in the municipality has a price equal to 5.3 times the current school's written-test repeat fee and 2.4 times its road-test repeat fee, on average.

The theoretical model also suggests 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, similar to switching, abandoning a course after failing a driving test is rare: less than 1 percent of such students quit.[20] Second, 94% of these students quit after failing the road test. For the subsample of all students who fail the road test, we find in an unreported conditional logit model of the student's decision to quit that, controlling for other student, school, and municipality attributes, the

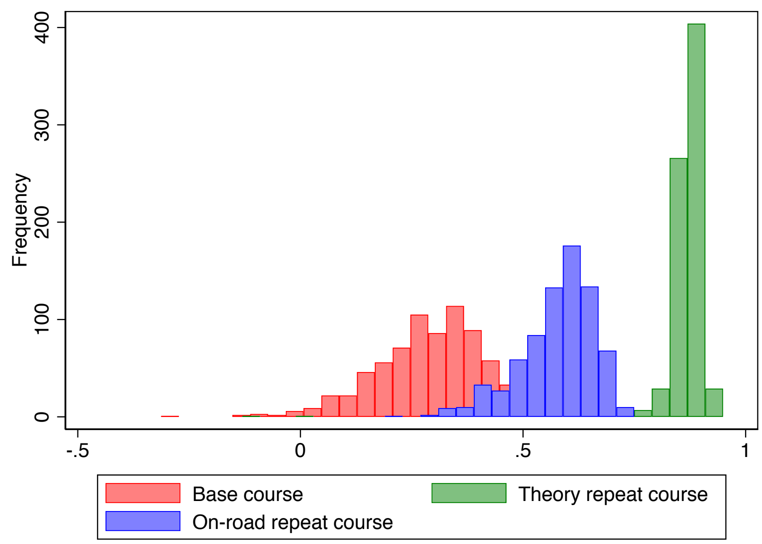
[20] For the purposes of this analysis, we define quitters as students who begin their course and fail at least one test before 2010 – thus incurring an add-on fee – but do not retake the test between their last failure and the end of 2010, allowing at least one year to pass since the last failed test.

propensity of quitting increases in the on-road test's repeat fee. Taken together, this thus suggests that quitters are sensitive to add-on prices, but add-on prices are not sufficiently high to induce large amounts of quitting. [21]

Markups

To assess the profitability of offering the three services (that is, the base course and each of the two repeat tests), we consider estimated price-cost margins and the percentage markup (ratio of markup to price). Table 4 summarizes both. In addition, Figure 3 shows the distributions of the percentage markups.

Figure 3: Distribution of Lerner Indices in Base and Repeat Course Markets, by School (%)



Based on our estimated marginal costs, the average percentage markup for the upfront service is 28.0 percent. In contrast, the percentage markups in the add-on markets are significantly higher, averaging 86.6 percent and 57.8 percent in the theory and on-road add-on markets, respectively. Markups being higher in the repeat than the base markets is corroborated by the fact that, in total, repeat fees amount to 58.8 percent of base prices for the average school, despite the written test retake requiring no additional lessons and the road test retake requiring only five (i.e., less than 20 percent of the base course's requirement) additional lessons. The on-road markups are based on marginal costs that include the cost of labor for the one-on-one on-road lessons because instructors are likely capacity constrained; one of the top five complaints students raise with the IMT about their driving school experience is the limited availability of on-road lesson slots. If we treat instructor wages as a fixed cost instead, average markups for the upfront service and the on-road

[21] The theory model treats the add-on price as the common walk-away price. In a richer model with downward sloping add-on demand, the myopes' quitting decision would inform optimal prices. Studying such optimal pricing empirically would require a larger survey sample of myopic students.

Table 4: Relative Prices and Estimated Markups for Base and Repeat Courses

	Mean	Std Dev	Q25	Med	Q75
Ratio, repeat to base fees	0.588	0.114	0.507	0.589	0.667
Markup, base course	207.373	107.619	131.737	201.303	281.446
Markup, theory course repeat	113.069	25.184	99.000	113.036	133.000
Markup, on-road course repeat	162.530	47.117	132.367	164.840	194.543
Effective markup	307.967	119.733	216.065	304.268	390.226
Percent markup, base course	0.280	0.118	0.205	0.287	0.363
Percent markup, theory course repeat	0.866	0.064	0.853	0.875	0.889
Percent markup, on-road course repeat	0.578	0.081	0.535	0.592	0.635
Percent effective markup	0.335	0.101	0.277	0.343	0.407

Note: The effective markup is the average total markup across a school's students.

add-on are 61.3 percent and 73.4 percent, respectively. Additionally, the distributions of the percentage markups exhibit a similar pattern as shown in Figure 3. For the theory add-on, marginal cost does not include wages and thus the markup remains unaffected.

Thirteen schools, or 1.7 percent of the sample, have negative markups in the upfront market, pricing below estimated cost. All but two of these schools earn positive total profit from the three services, however.[22] Schools 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. A school earns €308.0, or 32.7 percent of fees paid, on the average student.

Together the markups and test repeat incidences imply that a significant portion of schools' variable profits derive from add-on fees, consistent with the properties of the loss-leader equilibrium described in Section 2. The median school derives 32.3 percent of profit overall from repeats broken down into 13.3 and 18.9 percent from the written and road test add-on services, respectively. At the same time, schools earn a smaller share of total revenues from add-on services: the median school derives 4.9 and 11.8 percent of revenue from the two add-on services for a total of 16.8 percent of revenue. Thus, more revenue is passed on as variable profits to schools in the add-on market.

Determinants of Prices

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 explore whether the observed prices for the upfront and retake services are consistent with the predictions of the model from Section 2. We test whether

[22] We estimate that the two school outliers have negative markups per student of −€21.0 on average across the three services. We are unable to determine whether this is because of measurement error in cost or recorded prices or because these schools truly incur a loss.

prices for the base course of instruction, but not repeat fees, vary with the number of competitors in the market (Predictions P1 and P3), and with the students' probability of failing the driving tests (Predictions P2 and P4).

Figure 4 first summarizes the raw price patterns in the data showing a box plot of mean municipality upfront and repeat fees by number of competitors in the municipality. The plot is supportive of Predictions P1 and P3: upfront prices appear to decline in the number of competitors, but add-on prices do not. Empirically, there is also only a weak correlation of the base course and the theory repeat course prices (0.10), or the base course and the on-road repeat course prices (0.11), but a stronger correlation between the two add-on prices (0.34). Both of these sets of correlations provide initial evidence that factors affecting the setting of schools' upfront prices differ from those affecting their add-on prices.

Figure 4 does not control for other potentially confounding school and municipality characteristics. We therefore test the above predictions more formally in regression models of prices on market structure and the students' probability of failing, controlling for heterogeneity in demand and cost conditions across schools and municipalities. We employ both OLS and instrumental variables techniques to control for the possibility that the number of competitors is endogenous to school prices; for example, both entry and prices might be higher in markets with unobservably high demand, biasing the estimated coefficient on market structure upward.

To address such potential endogeneity, we employ shifters of the school's fixed cost. We include the average distance from the school to both the local IMT office and the central IMT office in Lisbon, capturing the cost of doing business with the IMT. The average rent in the municipality captures the contribution to fixed cost of the school's facilities. Lastly, we rely on four proxies for the availability of commercial properties: the proportion of nonresidential buildings, the number of grocery stores, the total size (in hectares) of developed land, and the share of pixels with positive night-time light intensity in a municipality. These variables correlate with the potential number of school locations in a market and thus serve as a proxy for ease of entry given the regulatory constraints on the distance between schools that we discuss in Section 3. To the extent that they may also correlate with the value of a driver's license, our parameter estimates represent upper bounds on the effect of market structure on prices.

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 5. The first-stage F-statistics and partial R-squared statistics for the instrumental variables regressions imply strong instruments at conventional levels, and the 2SLS results in column (3) enhance the negative effect of competition, relative to the OLS results, as expected. For every school added to the market, the upfront price decreases by approximately €12.02 (€11.77 under the OLS specification), corresponding to two percent of the average upfront price.

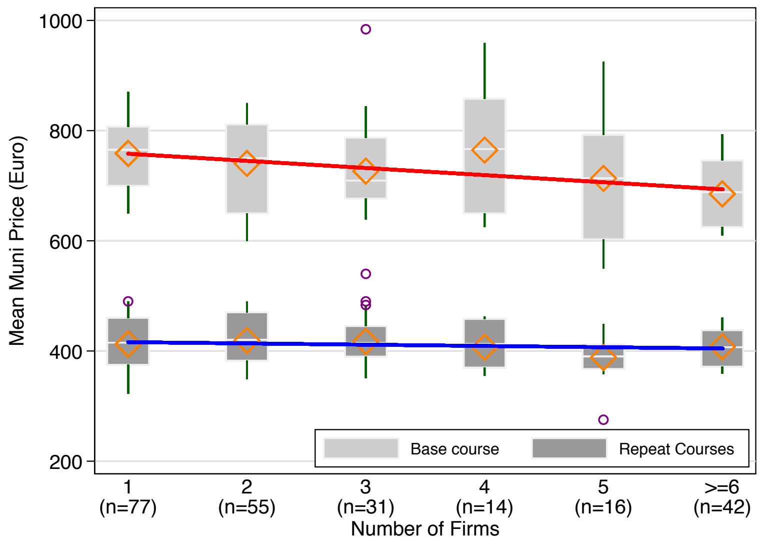
Relaxing the linearity assumption of competition on price underlying specification (1) by including market structure dummies for each observed firm configuration suggests that the decline in prices is more pronounced in going from monopoly to duopoly markets, when prices drop by €37.6 in the OLS specification

Table 5: Regression Models of Base Course Prices

	OLS		IV	
	(1)	(2)	(3)	(4)
Number of firms (N)	−11.774***		−12.024*	
	(3.643)		(6.252)	
($N = 2$) Y/N		−37.572**		−35.143*
		(15.569)		(20.734)
($N = 3$) Y/N		−42.848**		−42.292
		(19.201)		(29.257)
($N = 4$) Y/N		−59.399**		−58.036
		(27.076)		(39.055)
($N = 5$) Y/N		−90.993***		−78.110**
		(29.067)		(37.359)
($N \geq 6$) Y/N		−112.673***		−109.112*
		(26.700)		(55.847)
% fail both tests	−2.362**	−2.223**	−2.366**	−1.629**
	(1.002)	(0.985)	(0.976)	(0.792)
Number of instructors	1.872*	3.166***	1.845*	2.428*
	(1.124)	(1.092)	(1.083)	(1.325)
Median weight of fleet cars (kg)	−0.021	−0.005	−0.021	0.010
	(0.031)	(0.030)	(0.030)	(0.027)
Distance to testing center (km)	−0.392	−0.651**	−0.392	−0.451*
	(0.307)	(0.321)	(0.303)	(0.266)
School within 100m of high school Y/N	45.158	47.470	45.175	39.424
	(42.547)	(42.407)	(41.937)	(36.871)
School distance to city center	2.959**	3.696***	2.963***	2.325***
	(1.140)	(1.179)	(1.115)	(0.683)
% of population in urban parishes	−0.755***	−0.834***	−0.754***	−0.893
	(0.221)	(0.220)	(0.216)	(0.581)
Majority of parishes urban Y/N	−14.156	−2.984	−14.063	−3.288
	(14.994)	(14.132)	(15.099)	(16.782)
Per-capita income (€)	0.162**	0.210***	0.161**	0.141**
	(0.070)	(0.065)	(0.073)	(0.048)
Number of car repair shops	−0.692***	−0.736***	−0.687**	−0.768
	(0.247)	(0.279)	(0.268)	(0.824)
Population (000)	1.251***	0.672**	1.270**	0.955
	(0.375)	(0.336)	(0.516)	(1.054)
Adjusted R^2	0.353	0.371	0.353	
1^{st} stage partial R^2			0.397	
1^{st} stage F statistic			12.786	
Observations	746	746	746	746

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Municipality-level clustered standard errors in parentheses. Specifications include region fixed effects and additional, statistically insignificant, controls (instructor experience and its square, and a coastal area indicator). Models (3) and (4) use average distance to the closest IMT office, average distance to main IMT office, number of grocery stores, total size of developed land, share of pixels with positive night-time light intensity, average rent and commercial building share as instruments.

Figure 4: Average Municipality Prices by Number of Schools



Note: Interquartile range of municipality prices conditional on number of schools. Diamonds indicate mean price level.

(see column (2)). The largest markets with six or more competitors have prices that are on average €112.7 lower than monopoly markets. To address endogeneity concerns in the nonlinear specification, we account for the fact that the endogenous variables are discrete market structure outcomes by modeling them as an ordered probit model, allowing entry to shift with municipality characteristics that are shared by the price model as well as the excluded instruments. To capture the source of endogeneity concerns, we introduce an unobserved market-level error in the price equation that is correlated with the error that drives aggregate entry decisions. We estimate the resulting two-equation model using full information maximum likelihood (FIML) and derive the likelihood in Appendix A.3. The results for this specification are reported in column (4). Overall, our results are consistent with Prediction P1 that prices in the upfront market decline as the number of firms increases.

Across specifications, prices also respond to the share of students who fail both tests, our proxy for the add-on market size, as suggested by Prediction P2. A one standard deviation increase in the share of students who fail both tests (3.9 percentage points) is associated with a decline in price of between €6.37 to €9.26 across models, which is consistent with the model prediction of shifting profit from the upfront to the add-on market. The magnitude of this effect is similar to that predicted by the up-front pricing equation (Equation 3). If the type-weighted probability of failing across naive and sophisticated students increased by 3.9 percentage points, upfront prices should increase by €10.75, given an average add-on markup of €275.6 (see Table 2).

Table 6 shows the results for the equivalent regressions of add-on prices on the number of market competitors and the size of the add-on market. We collapse repeat fees into a single sum of the two, which we employ as our dependent variable. As with the upfront price regressions, the results are robust to instrumenting for the number of firms and introducing school- and municipality-level controls. For all models, the number of schools in the municipality is statistically insignificant in affecting the repeat fee. The results, thus, suggest that even in competitive local markets, where prices for the base course of instruction are significantly lower than in more concentrated ones, firms are able to maintain high prices for add-ons.[23]

Similarly, the size of the add-on market - the share of students failing both tests - does not have a significant association with repeat fees. These results lend support to Predictions P3 and P4. They also suggest that the share of failing students does not simply proxy for school quality, which would be an alternative explanation for why prices for the base course might be lower for schools with higher fail rates. If firms were simply differentiating on quality in their pricing, we would expect better schools (with lower pass rates) to charge higher prices for both the upfront course and the repeat course, which we do not find to be the case. We also employ a rich set of school characteristics, such as the age of the instruction vehicles or the experience of the instructors, to control for the role that vertical differentiation might play in pricing.

As a robustness check, we replicate the analyses in Tables 5 and 6 using the Herfindahl-Hirschman Index ("HHI") as a measure of competition that reflects both the number and size of the competitors in a market. The results obtained using three alternative HHI measures, which we depict in Appendix B.1, are consistent with the ones from our primary specification based on the number of firms as a measure of competition.

5 Survey Evidence

The evidence presented so far supports the model's predictions related to firms' pricing strategies in the upfront and add-on markets. Because the administrative data do not provide information on students' expectations regarding test outcomes, the costs associated with failing, or students' effort, we developed and conducted a survey in collaboration with the IMT. This survey allows us to compare students' expectations about enrolling in repeat courses (add-on demand) with their actual enrollment and assess their awareness of potential add-on fees. Consequently, we can disentangle factors influencing inattentiveness to contingent add-on fees, whether due to misperceptions of the likelihood of failing or the repeat fee itself.[24] Additionally, the survey enables us to investigate whether more sophisticated students exhibit greater effort compared to their less sophisticated peers, potentially as a strategy to mitigate exposure to the add-on market, as hypothesized in Prediction P5.

The IMT administered the survey at the public testing center in the Setúbal district. This testing center is large, covering a significant share of students, schools, and municipalities with a range of market structures.

[23]Earlier work on assessing the competitiveness of local markets as a function of the number of competitors (Bresnahan and Reiss 1991, Asplund and Sandin 1999) finds that, in professional services settings, including driving schools, market conduct often reaches competitive levels with as few as four competitors in the market.

[24]Another source of inattention could be high discount rates, leading students to discount future payments and potentially neglect to inquire about add-on fees. Although our survey provides some evidence of over-optimism and a lack of knowledge about repeat fees, it does not allow us to estimate students' discount rates.

Table 6: Regression Models of Repeat Course Prices

	OLS		IV	
	(1)	(2)	(3)	(4)
Number of firms (N)	−1.926		−1.059	
	(1.974)		(2.420)	
($N = 2$) Y/N		1.329		9.157
		(10.304)		(10.949)
($N = 3$) Y/N		−1.332		10.804
		(12.074)		(14.586)
($N = 4$) Y/N		−4.538		6.572
		(16.183)		(19.361)
($N = 5$) Y/N		−21.022		−6.651
		(14.194)		(18.326)
($N \geq 6$) Y/N		1.795		19.538
		(14.488)		(22.943)
% fail both tests	−0.059	−0.047	−0.045	0.574
	(0.532)	(0.534)	(0.528)	(0.643)
Number of instructors	3.809***	4.097***	3.903***	2.797***
	(0.844)	(0.840)	(0.881)	(0.739)
Median weight of fleet cars (kg)	0.081***	0.078***	0.081***	0.055***
	(0.020)	(0.020)	(0.020)	(0.021)
Distance to testing center (km)	0.032	0.005	0.032	−0.074
	(0.183)	(0.181)	(0.179)	(0.168)
School within 100m of high school Y/N	57.762***	55.578**	57.703***	51.004*
	(21.224)	(21.670)	(20.961)	(28.890)
School distance to city center	1.397*	1.644**	1.380*	0.685
	(0.792)	(0.828)	(0.777)	(0.620)
% of population in urban parishes	−0.437**	−0.424**	−0.441***	−0.504**
	(0.168)	(0.164)	(0.167)	(0.210)
Majority of parishes urban Y/N	−25.051***	−23.229***	−25.374***	−26.642***
	(8.155)	(8.201)	(8.118)	(8.834)
Per-capita income (€)	0.032	0.045	0.036	−0.004
	(0.037)	(0.036)	(0.037)	(0.040)
Number of car repair shops	0.286*	0.254	0.269*	0.116
	(0.150)	(0.156)	(0.155)	(0.310)
Population (000)	−0.084	−0.297	−0.151	−0.135
	(0.254)	(0.198)	(0.259)	(0.355)
Adjusted R^2	0.141	0.144	0.141	
1^{st} stage partial R^2			0.397	
1^{st} stage F statistic			12.786	
Observations	746	746	746	746

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. See notes to Table 5.

In our administrative sample data, the testing center administered 3.5% of all tests, ranking 11th out of 33 centers, and served 12 municipalities with 1 to 14 schools each, totaling 41 out of 746 schools. On average, the schools charged €699 for the base course and €110 and €270 for the theory and on-road repeat courses, respectively.

The survey was offered to all students who took the written test during December 2012 and January 2013, immediately following the test and before receiving their results. Participation in the survey was voluntary; the examiner administering the test presented it as part of a general study on driver education and testing. Figure 5 depicts the survey. The IMT shared the anonymized survey responses with us, along with information on the students' performance on the written test and on the road test taken at a later date. The survey is thus unique in allowing us to examine ex-ante expectations of failing, rather than perceptions stated after the test outcome is known, and to link those ex-ante expectations to ex-post behavior.

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 written test? Yes No

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

3. Acha que vai passar no exame teórico que acabou de realizar? ☐Sim ☐Não
Do you think you will pass the test 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 written test?
☐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 should have to pay to retake this test?

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 written test	☐	☐

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

7. Acha que vai passar à primeira no exame prático (de condução)? ☐Sim ☐Não
Do you think you will pass the road test 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 can contact you with additional questions regarding the test.
E-mail: ____________________

Obrigado pela sua colaboração!
Thank you very much!

Table 7: Expectations of Financial Repercussions of Failing Written Test, Survey Respondents

	Share of Respondents		
	All	Female	Male
No	4.091	3.070	5.189
Do not know	17.500	14.912	20.283
Yes, but do not know how much	26.364	25.439	27.358
Yes, and know how much	52.045	56.579	47.170**

Note: Breakdown of responses of 440 survey participants to question "In case you fail, will you have to pay your school to retake the written test?". P-values for test of equality of male and female shares of respondents indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In total, 797 students took the written test in Setúbal during the two-month survey period, and 782 students participated in the survey, resulting in a 98 percent response rate. In the following analyses, we focus on first-time written-test takers of the passenger vehicle (category B) license test only, resulting in a sample of 440 respondents. This sample sample is representative of the main sample: 51.8 percent are female; the mean (median) age at the time of the written test is 22.6 (19.7) years with a standard deviation of 7.1 years.

To assess student awareness of potential add-on fees, we asked whether they would need to pay to retake the written test if they failed (see Question 4 in Figure 5). Table 7 summarizes the responses to this question. Among surveyed students, 4.1 percent stated they would not have to pay anything; 17.5 percent said they did not know; and 78.4 percent said they would have to pay some amount. Of these students, 26.4 percent stated that they asked the school whether they would have to pay, and 43.3 percent stated that the school informed them directly that additional fees would accrue. However, only 66.4 percent of the students who expected to pay for a retake, or 52.0 percent in aggregate, stated that they knew the amount they would have to pay. This share is higher among female students, 56.6 percent of whom stated knowledge of the amount of the retake fees. The students who answered that they knew the retake fees were close to correct, underestimating the retake fees by only 4.1 percent on average (not tabulated).

To simplify our subsequent analysis, we categorize students as "informed" or "uninformed" regarding repeat fees based on their responses to Question 4. Those who answered "yes" to needing to pay an additional fee are classified as "informed." The other students are classified as "uninformed." Importantly, although all uninformed students are considered naive (per the model) due to their unawareness of add-on fees, the informed group likely includes both naive and sophisticated students. Some informed students might be overly optimistic about their test performance and place little to no weight on add-on prices at the time of school choice. Thus, the 22 percent of uninformed students in the survey likely underestimates the total proportion of naive students in the market.

We assess potential over-optimism by comparing students' pre-test expectations of passing both the written and road tests, as obtained in the survey, to their actual outcomes.[25] Note that if over-optimism about test performance is present, it is likely to be more salient for the road test than for the written test, as students have different levels of knowledge about their likelihood of passing each test. Students complete the survey immediately after taking the written test, so their answers reflect their ability to judge their performance. At that time, on-road training has not yet begun for the average student, and the road test occurs approximately three months later. Thus, students' assessment of their likelihood of passing the road test is not influenced by first-hand test experience, similar to their initial assessment when signing up for a driving course.[26]

Table 8 compares the expected and actual test outcomes for different types of respondents (informed vs. uninformed and male vs. female). Similar to the nationwide sample, failing a driving test is common among survey respondents: only 72.5 percent pass the written test on the first try, and 76.6 percent pass the subsequent road test on the first try. In aggregate, students have nearly correct expectations regarding the likelihood of passing the written test, with 69.1 percent expecting to pass. The only demographic group for whom there is a statistically significant difference between the expected and the actual pass rates is female students, whose expectation falls short of the actual test outcomes by eight percentage points. The lack of a statistically significant divergence between expected and actual outcomes in aggregate, among male students, and for the informed and uninformed subgroups, however, suggests that once the written test has been taken, the average student has an accurate understanding of their performance relative to the passing standard.

At the same time, there is evidence of over-optimism in passing the future road test, with 86.6 percent of students predicting success compared to the actual 76.6 percent pass rate. Differences between expectations and outcomes persist across the different subgroups, with male and uninformed students having the largest gaps. For example, the percentage of students who expect to pass exceeds the actual pass rate by 14.3 percentage points for uninformed students and 8.9 percentage points for informed students.[27]

Finally, we use the survey to gain insight into the students' test preparation (as a measure of "effort") to test Prediction P5 that sophisticates are able to decrease their ex-ante probability of failing by engaging in effort. Because students may differ in what they consider to be significant effort, the survey asked them specific questions regarding the number of practice tests taken, use of the textbook, additional theory lessons taken, preparation of the lessons' material before class, note taking, and interactions with the instructor (see Question 5 in Figure 5).[28] We developed this list after interviewing several driving school instructors,

[25] Although we cannot label students individually as over-optimistic as we do for informed or uninformed – because we only ask if they expect to pass and do not elicit their estimated chances of passing – we can evaluate overall optimism by comparing aggregate expected pass rates to actual pass rates.

[26] Unfortunately, the survey does not capture students' road-test performance expectations at school enrollment, which would best align with the theoretical model. However, the lack of correlation between written and road test outcomes suggests the written test does not offer significant additional insight into road test performance.

[27] Taking the survey may increase students' awareness of retake fees, leading them to exert more effort in preparing for the road test and thereby increasing their likelihood of passing. If that is the case, the differences we report between expected and actual road test results likely represent a lower bound for the true differences.

[28] The block of questions in the questionnaire related to effort includes one reverse-keyed question – the last –

Table 8: Comparison of Expected and Actual Test Outcomes, Survey Respondents

	Written		Road	
	Pass Rate	Mean Difference, Expectation less Incidence of Passing	Pass Rate	Mean Difference, Expectation less Incidence of Passing
Overall	0.725	−0.034	0.766	0.100***
Female	0.711	−0.083**	0.739	0.075*
Male	0.741	0.019	0.792	0.126***
Informed	0.733	−0.035	0.786	0.089***
Uninformed	0.695	−0.032	0.683	0.143**

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Informed students defined as: "Expect to pay for test retake = Y". The percent of female and informed students for the written (road) test comparison is 51.82% and 78.41% (50.31% and 80.31%). There is no statistically significant difference at the 5% level between female and male or informed and uninformed students' pass rates in the written test. Informed students have higher pass rates than uninformed students in the road test at the 5% level.

examiners, and students to understand what distinguishes well-prepared students. Because the students had not begun their preparation for the road test yet, these questions focus on their preparation for the written test.

As Table 9 shows, the evidence is suggestive that sophisticated students engage in more effort in their preparation for the test than naive students. For three out of the seven effort items in Question 5, the difference in effort between informed and uninformed students is significant and positive, and almost significant at the 10 percent level for a fourth item.[29]

As additional evidence that informed students prepare for their tests more than uninformed students, we analyze the behavior of repeat test takers relative to first-time test takers, treating repeaters as one group of informed students. Untabulated findings indicate that repeaters engage in more effort along all but one of the seven preparation categories than uninformed first-time test takers, with a statistically significantly higher level of effort for three categories. We also compare repeater students with the informed first-time test takers. There are no effort differences between repeaters and first timer informed students, except for the category "extra classes", where a larger share of repeater students has taken lessons, as commonly suggested by the schools to failing students.

allowing us to check for response bias from "straightlining." Only four respondents showed evidence of this behavior, and our results are robust to excluding them from the sample.

[29]Assuming the uninformed group is broadly representative of naive students, observed effort differences between informed and uninformed students (in the survey) give a lower bound for effort differences between sophisticated and naive students (in the model). Although all uninformed students are naive, the informed group includes both types.

Table 9: Test Preparation by Student Type, Survey Respondents

	Share of "Yes" Responses		
	Informed	Uninformed	p-Value
More than 50 practice exams taken	0.722	0.628	0.047
Practice tests taken consistently throughout course	0.764	0.779	0.612
Use of book to understand errors in practice tests	0.889	0.826	0.057
Sitting in extra lessons	0.605	0.631	0.668
Preparation of material prior to class	0.168	0.108	0.092
Note taking during class	0.709	0.643	0.122
Frequent engagement with instructor	0.807	0.845	0.784

Note: Items listed correspond to block of items in Question 5 concerning the extent of preparation for the written test (see questionnaire in Figure 5). P-values are for the tests of equality of preparation (shares of "Yes" responses) for informed and uninformed students versus the hypotheses that informed students engage in more preparation than uninformed students.

Recalling from Table 7 that pass rates are higher for informed students compared to uninformed students (albeit with a one-sided p-value of 0.23 in the case of the written test), this suggests that higher effort translates into a higher probability of passing. This is consistent with Prediction P5, which states that sophisticated students engage in effort to reduce their probability of failing and, consequently, their exposure to the add-on market.

6 Alternative Explanations and Robustness

Here we consider alternative explanations for the observed pricing patterns and conduct robustness checks on the above results. The fact that markups on add-ons significantly exceed those on base product prices may be the result of price discrimination, which our model rules out by assuming homogeneous price sensitivities ($\sigma_m = \sigma_s = \sigma$ in Equation 2). However, if students who are more likely to fail the tests are also less price-sensitive, indicating a correlation between students' add-on demand and their price sensitivity, high add-on prices could be an optimal strategy for schools, even with perfectly observable prices. Alternatively, if the less price-sensitive students are inattentive to add-on prices and hence have higher add-on demand, as in the model in Section 2, firms may exploit add-on prices to soften competition in the upfront market: steep add-on prices discourage firms from cutting the price of the upfront good because this attracts more price-sensitive consumers who are less likely to buy the add-on (Ellison 2005).[30]

To investigate this alternative explanation, we estimate outcome models in which the students' individual propensity to fail a test is modeled as a function of student and school characteristics, as well as proxies for the students' price sensitivity. Table 10 reports the results. We include two measures of price sensitivity. First, we construct a measure of revealed price sensitivity that classifies students who choose a school that

[30]We thank an anonymous reviewer for highlighting this adverse selection mechanism.

is not their closest, but charges the cheapest base course fee in the municipality. Second, empirical evidence and a sizable body of economic theory support that price sensitivity increases in the price of a product. Although students pay the same upfront price, they incur different travel costs and hence total costs of school attendance. We, therefore, rely on variation in travel cost to capture variation in price sensitivity. We proxy for travel costs using the students' distance from their chosen school and test whether add-on demand responds to distance. We focus on a subsample of students who reside in monopoly markets to remove the element of school choice. This is not possible for the first price sensitivity proxy, which relies directly on comparing the student's school choice to other alternatives. Neither measure of price sensitivity correlates significantly with the propensity of failing. We thus find little evidence in support of markup differentials between base and add-on fees resulting from price discrimination strategies on the part of firms; the latter would also not necessarily yield the prediction that add-on prices are invariant to market structure, as we find above.

A second concern is that the model assumes that firms are symmetric in costs. If instead, firms differed in cost, such cost differences may be responsible for the patterns in prices uncovered in Section 4. For example, an alternative explanation for the observed decline in upfront prices as a function of the number of competitors could be that marginal costs are lower in markets with more competitors. Such cost differences should also translate into add-on prices declining in the number of competitors. We nevertheless investigate this possibility, as well as other explanations related to cost differences across schools, by repeating the analyses in Tables 5 and 6 using markups as the dependent variables. The results in Appendix B.2, Tables B.2.1 and B.2.2, show economically similar and statistically stronger evidence that base markups, but not repeat course markups, decline in the number of competitors. These analyses also provide an additional robustness check for the estimated relationship between upfront and add-on prices and the share of test repeaters that was found in Section 4 in support of Predictions P2 and P4.

A third concern is that fail rates may be endogenous to upfront prices. Fail rates may be correlated with school attributes above and beyond the dimensions of school quality that we control for, as listed in Tables 5 and 6. Similarly, if naive students were more price sensitive than sophisticated students, they would be more likely to select lower-priced schools, potentially increasing those schools' fail rates. Both of these mechanisms would introduce a negative correlation between upfront prices and fail rates that is unrelated to the schools' strategic add-on pricing motive. We therefore conduct a robustness check in Appendix B.3 where we use individual test outcomes to identify the school contribution to the students' test outcomes as a fixed effect, controlling for student demographics such as age and gender and parish-level differences in propensities of passing. As in Chetty et al. (2014), we then remove the school contribution in predicting student fail probabilities and aggregate school fail rates. We use this alternative measure of fail rates in the school level price regressions. We also redid our analysis using market-level fail rates to exploit cross-market rather than cross-school variation in fail rates (not tabulated). The relationship between upfront and add-on prices and the level of competition in the municipality and fail rates remains robust in these analyses.

Table 10: Conditional Logit Model of Propensity of Failing Driving Tests

	Written Test			Road Test		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.470***	−0.457***	−0.388*	0.498***	0.448***	0.855***
	(0.063)	(0.067)	(0.220)	(0.077)	(0.080)	(0.289)
Age	0.016***	0.017***	0.023***	0.023***	0.023***	0.033***
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.008)
Female*Age	0.015***	0.015***	0.009	0.024***	0.025***	0.011
	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)	(0.009)
Share with higher education (parish)	−0.729***	−0.714***	−2.257*	0.214	0.241	−0.272
	(0.164)	(0.167)	(1.210)	(0.154)	(0.156)	(1.237)
Distance to city center	0.006**	0.005	0.003	0.004	0.004	0.034*
	(0.003)	(0.003)	(0.018)	(0.003)	(0.003)	(0.019)
Distance to city center*Age≥21	0.007**	0.007**	0.006	−0.004	−0.002	−0.033**
	(0.004)	(0.004)	(0.015)	(0.004)	(0.004)	(0.016)
Instructor experience*Female	0.006**	0.006*	0.008	−0.004	−0.005	−0.006
	(0.003)	(0.003)	(0.010)	(0.003)	(0.003)	(0.010)
Examiner experience				−0.005***	−0.006***	0.003
				(0.001)	(0.001)	(0.003)
Examiner experience*Female				−0.002***	−0.002***	−0.002
				(0.001)	(0.001)	(0.003)
Price Sensitive Y/N		0.022			0.008	
		(0.031)			(0.032)	
Distance to school			−0.002			−0.022
			(0.017)			(0.017)
Observations	105944	99959	5985.000	105944	99959	5985
Log-likelihood	−54975.882	−51726.354	−3094.623	−53933.652	−50756.741	−3031.186

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Price Sensitive Y/N indicates students whose chosen school is the lowest priced in the market, but not the closest to their home. School fixed effects included in all models.

7 Conclusion

In this article, we have presented a theoretical model in which firms take advantage of locked-in naive consumers by charging high fees in add-on markets. When consumers are inattentive to their demand for add-on products and services 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 that only upfront prices vary with the market structure a firm faces and depend on the distribution of consumer types in the market.

We present evidence of these phenomena in the context of Portuguese driving schools. We rely on detailed data of the driving school industry, together with student-level survey evidence. With data on prices and estimated marginal costs, we demonstrate that schools not only face a strong profit motive for setting high repeat fees, but also charge significantly higher markups in the add-on than in the upfront market, corroborating the model predictions. Survey evidence provides further support for the model's predictions in identifying a significant share of students as uninformed or over-optimistic, pointing to the possibility of schools' strategic exploitation of this subset of students.

Evidence that speaks to the extent of cross-subsidization, from consumers who are naive to those who are not, in a market such as ours is of significant normative policy interest to regulators. In the case of policies under consideration by the IMT, regulatory proposals range from requiring schools to inform students about typical propensities of failing the tests to releasing price information to directly or indirectly regulating prices in the add-on market. Policy makers' interest frequently stems from a concern that the naive consumer segment is more likely to be socially vulnerable. Investigating whether consumer inattention to add-on fees varies systematically with demographics is thus a valuable avenue for future research in informing public policy design.

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Appendix A: Model Derivations and Estimation Details

A.1 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; naive 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):

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 test be $\overline{\lambda} \in (0,1]$. If students fail the test, 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

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

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 $(1-\pi)$ naive students and earns profit of

$$\begin{aligned}\Pi_j = {} & \pi\left[p_j^u - c^u + \underline{\lambda}\left(p_j^a - c^a\right)\right] D^s\left(p_{-j}^u - p_j^u + \underline{\lambda}(p_{-j}^a - p_j^a)\right) + \\ & (1-\pi)\left[p_j^u - c^u + \overline{\lambda}\left(p_j^a - c^a\right)\right] D^m\left(p_{-j}^u - p_j^u\right),\end{aligned} \qquad \text{(A.1.1)}$$

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 naive 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 naive students through the decline in the upfront price and – provided $\overline{\lambda} > \underline{\lambda}$ – the revenue per naive student.[31]

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

The firm's upfront price p_u then maximizes:

$$\Pi_j = \left\{p_j^u - c^u + \left[\pi\underline{\lambda} + (1-\pi)\overline{\lambda}\right](\overline{p}_a - c^a)\right\} D^m \left(p_{-j}^u - p_j^u\right). \tag{A.1.2}$$

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 naive students' demand, D^m. Solving the first-order condition to the firm's upfront pricing problem results in equilibrium prices of:

$$(p^u)^* = c^u + \frac{\sigma n}{n-1} - \left[(1-\pi)\overline{\lambda} + \pi\underline{\lambda}\right](\overline{p}^a - c^a). \tag{A.1.3}$$

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

$$(p^u)^* = c^u + \frac{\sigma n}{n-1} - \overline{\lambda}(\overline{p}^a - c^a). \tag{A.1.4}$$

Equation (A.1.4) 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

$$(p^u)^* + \overline{\lambda}\overline{p}^a = c^u + \overline{\lambda}c^a + \frac{\sigma n}{n-1}. \tag{A.1.5}$$

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:

$$\Pi_j = \left[p_j^u + \overline{\lambda}p_j^a - \left(c^u + \overline{\lambda}c^a\right)\right] D^s\left(p_{-j}^u - p_j^u + \overline{\lambda}(p_{-j}^a - p_j^a)\right) \tag{A.1.6}$$

In the absence of naive 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 (A.1.5). Add-on pricing in the presence of naive 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 test repeaters.

A.2 Calculation of Marginal Costs

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

The base course marginal cost comprises five cost components: the fees paid to the testing center for the written and road tests (F^T and F^P, respectively), the cost of the instructional materials the school provides to the student (M), the instructor wages (W), and the cost of operating a fleet car (V) for a student's practice lessons. The theory repeat course generates as cost only the testing center fee. The on-road repeat course involves additional driving lessons with associated scaled-down wage and vehicle operating costs, in addition to the testing center's fee. Accordingly, we specify the marginal costs, MC^s, for service $s = \{U, T, P\}$ as:

$$MC^U = F^T + F^P + M + W + (700 + 2D)\,V \tag{A.2.1}$$

$$MC^T = F^T \tag{A.2.2}$$

$$MC^P = F^P + \frac{6}{33}W + \left(\frac{6}{33} \cdot 700 + 2D\right)V, \tag{A.2.3}$$

and compute each cost component as follows:

1. Test administration fees (F^T and F^P) The IMT provided us with information on each of the 25 testing centers' fees for administering the written and road tests. We use the administration fees of the testing center used by the school, or a weighted average of fees if the school uses multiple testing centers.

2. Instructional materials expenses (M) The IMT and ANIECA quote €10 for instructional materials (driver handbooks and CD-ROMs).

3. Instructor wages (W) Based on interviews with ANIECA and school representatives, an instructor's monthly wage ranges between €750 and €950. We assume that instructor wages are proportional to mean monthly earnings in the school's municipality across municipalities. We gross up the wages to include 23.75 percent social security tax and a €3.4 per diem stipend.

   Since each student's base and on-road repeat courses include 32 and five driving lessons, respectively, we convert the monthly wages figure to an hourly basis based on ANIECA's information on the typical 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. The resulting marginal labor cost averages to €235.63 and only €42.84 for the base and repeat courses, respectively.

4. Vehicle operating costs $[(700 + 2D)\,V]$ We follow existing methodologies for computing a vehicle's user cost in Portugal, comprised of (i) fuel costs, (ii) depreciation costs, (iii) maintenance and repairs costs, and (iv) tire costs. For the base course, we scale this user cost per kilometer, V, by twice

the return distance to the testing center plus the 700 kilometers that school owners state are covered during lessons; for the repeat course, the latter amounts to only 127 kilometers. The sources of data for the individual cost components are:

- Fuel costs. We measure fuel costs as the average local price per liter of diesel fuel (obtained from the Direcção-Geral de Energia e Geologia on March 12, 2012 for each of the five lowest priced stations per municipality), times fuel consumption per kilometer. ANIECA and school owners state typical consumption rates of 6.36 liters per 100 km.
- Depreciation costs. We follow existing methodologies whereby a vehicle depreciates fully by 8.4 years and has a purchase price of €25,000, on average. This, together with information on the average distance traveled by a fleet car per year, yields an estimate of cost-per-kilometer driven.
- 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, and convert it to an estimate of cost per kilometer driven based on the annual distance traveled and a life of 8.4 years.
- Tire costs. We assume that the average car requires four new tires for every 40,000 kilometers at a cost of €70 per tire, which translates into an average tire cost of €.01 per kilometer

The vehicle operating cost requires an estimate of the annual distance covered per vehicle. We use each school's data on kilometers covered per vehicle-year, as reported to the IMT, as an input to calculate each school's marginal cost for its base and repeat courses as in Equation (A.2.1). Table A.2.1 summarizes the inputs into the cost calculation and the resulting totals.

As a robustness check in case of measurement error, we recalculate marginal costs and markups using the median distance covered across all fleet cars of 20,358 kilometers per vehicle-year for all schools. This alternative marginal cost measure averages to €493.55 for the upfront service and €112.42 for the on-road repeat course. The markup patterns in Figure 3 and regression results in Tables B.2.1 and B.2.2 are robust to using this alternative marginal cost.

Table A.2.1: Marginal Cost Components for All Services (€, $N = 746$)

	Mean	Std Dev	Q25	Med	Q75
Base Course					
Testing fees	53.453	8.679	45.000	53.205	59.000
Instructional materials	10.000	0.000	10.000	10.000	10.000
Instructor wages	228.356	15.116	215.665	229.916	236.650
Vehicle operating costs	202.372	32.050	178.274	197.824	223.100
Total	494.180	39.206	465.122	488.700	519.761
Theory Repeat Course					
Written test fee	16.330	1.765	15.000	15.525	17.000
On-road Repeat Course					
Road test fee	37.120	7.031	30.000	37.215	42.000
Instructor wages	41.519	2.748	39.212	41.803	43.027
Vehicle operating costs	34.140	5.873	29.920	33.651	37.318
Total	112.779	10.169	104.796	111.835	119.005

A.3 Nonlinear Specification Estimation Procedure

In this Appendix, we describe the full information maximum likelihood (FIML) procedure we use to control for the endogeneity of the discrete market structure indicators in the nonlinear price regressions describe in Section 4.

We assume that school i's price in market m is a function of observable market attributes, $\mathbf{X^1}$, market and school specific variables, $\mathbf{X^2}$, market structure indicators γ^P_{jm}, and a school and market specific unobservable, ξ:

$$p^P_{im} = \alpha^P + \beta^{P,1}\mathbf{X}^1_m + \beta^{P,2}\mathbf{X}^2_{im} + \sum_{j=2}^{6}\gamma^P_{jm}\mathbb{1}_{\{\Pi^E_m=j\}} + \xi^P_{im} = f^P(\mathbf{X}^1_m, \mathbf{X}^2_{im}, \beta^{\mathbf{P}}) \tag{A.3.1}$$

We assume the unobservable can be decomposed into $\xi^P_{im} = \varepsilon^P_m + \eta^P_{im}$, where ε^P_m is a common error component shared by all schools in market m and η^P_{im} is the school-specific error term with $\eta^P_{im} \sim N\left(0, \sigma^2_{\eta,P}\right)$.

We specify the number of schools in market m, which ranges from 1 to 6 in the data, as an ordered probit model:[32]

$$\Pi^E_m = \begin{cases} 1 & \text{if } \alpha^E + \beta^{E,1}\mathbf{X}^1_m + \beta^{E,2}\mathbf{Z}_m + \varepsilon^E_m < \zeta^E_1 \\ j & \text{if } \zeta^E_j < \alpha^E + \beta^{E,1}\mathbf{X}^1_m + \beta^{E,2}\mathbf{Z}_m + \varepsilon^E_m < \zeta^E_{j+1} \text{ for } j = 2,..,5 \\ 6 & \text{if } \alpha^E + \beta^{E,1}\mathbf{X}^1_m + \beta^{E,2}\mathbf{Z}_m + \varepsilon^E_m > \zeta^E_6, \end{cases} \tag{A.3.2}$$

where the parameter ζ^E_j implies a cutoff for the unobservable ε^E_m between $j-1$ and j schools and $\mathbf{Z}^E_m$ contains market-specific attributes that are excluded from the pricing equation.

We assume that ε^P_m and ε^E_m are distributed bivariate normal as follows:

$$\begin{pmatrix} \varepsilon^P_m \\ \varepsilon^E_m \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_P & \sigma_{EP} \\ \sigma_{EP} & 1 \end{pmatrix}\right) \tag{A.3.3}$$

The covariance terms allow for correlations in the market-level unobservables that give rise to endogeneity concerns, with σ_{EP} and σ_P parameters to be estimated.

In estimating the nonlinear system of equations, the contribution of the likelihood from market m equals:

$$L_m = \Pr\left(p^P_{im} = p_i \forall i, \Pi^E_m = j\right) = \Pr\left(\xi^P_{im} = p_i - f^P_i \forall i, \zeta^E_j - f^E < \varepsilon^E_m < \zeta^E_{j+1} - f^E\right) \tag{A.3.4}$$

where j is an index of the observed number of entrants, p_{im} is the observed price of school i, and $f^E(\mathbf{X}^1_m$, $\mathbf{Z}_{im}$, $\beta^{\mathbf{E}}$)= α^E+ $\beta^{E,1}\mathbf{X}^1_m$+ $\beta^{E,2}\mathbf{Z}_m$. This probability is given by the integral of the $2N+1$-dimensional normal distribution of ξ^P_{im} and ε^E_m with mean zero and variance-covariance matrix given by (where $\mathbf{I}$ is the

[32]We combine markets with six or more schools into the final category.

identity matrix and $\mathbf{\Xi}$ is a matrix of ones)

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_P^2 \mathbf{\Xi}_{2N\times 2N} + \mathbf{I}_{2N\times 2N} & \sigma_{EP}\mathbf{I}_{2N\times 1} \\ \sigma_{EP}\mathbf{I}_{1\times 2N} & 1 \end{bmatrix} \tag{A.3.5}$$

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 prices and the observed number of entrants, respectively. Note that $\mathbf{\Sigma}$ results from stacking the $2N$ price equation errors $\xi_{im}^P = \varepsilon_m^P + \eta_{im}^P$ and the single market-level error, ε_m^E. We integrate out η_{im}^P to yield:

$$L_m = \int_{\zeta_j^E - f^E}^{\zeta_{j+1}^E - f^E} \int_{-\infty}^{\infty} \left[\prod_{i=1}^{N} \phi\left(p_i - f_i^P - \varepsilon_m^P\right) \right] \phi\left(\varepsilon_m^P, \varepsilon_m^E\right) d\varepsilon_m^P d\varepsilon_m^E, \tag{A.3.6}$$

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 A.3.3.

Conditioning on ε_m^P and integrating over ε_m^E results in:

$$L_m = \int_{-\infty}^{\infty} \left[\prod_{i=1}^{N} g_i^P\left(\varepsilon_m^P\right) \right] \times \left[\Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_{j+1}^E - f^E\right) - \Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_j^E - f^E\right) \right] \phi\left(\varepsilon_m^P\right) d\varepsilon_m^P, \tag{A.3.7}$$

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 and use a numerical optimizer to maximize the full likelihood:

$$L = \prod_{m=1}^{M} \left\{ \int_{-\infty}^{\infty} \left[\prod_{i=1}^{N} \frac{1}{\sigma_{\eta,P}} \phi\left(\frac{p_i - f_i^P - \varepsilon_m^P}{\sigma_{\eta,P}} \right) \right] \times \left[\Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_{j+1}^E - f^E\right) - \Phi_{\varepsilon_m^E|\varepsilon_m^P}\left(\zeta_j^E - f^E\right) \right] \phi\left(\varepsilon_m^P\right) d\varepsilon_m^P \right\}. \tag{A.3.8}$$

Appendix B: Robustness Checks

B.1 Alternative Competition Measures

Here, we supplement the regression analysis in Section 4 with models that use the HHI as a measure of market concentration which recognizes size differences between competitors. We constructed three alternative HHI measures. The first HHI measure is a direct function of the firms' market share as measured by the number of unique students ("HHI students"). The two other measures are a function of the school's size or capacity as proxied by the share of instructors and training cars associated with the school in a given market ("HHI instructors" and "HHI cars", respectively).

Because the HHI captures the size of the competitors, in addition to their number, we supplement our original instruments used for the number of firms in specification (1) (the main specification in the paper) with additional instruments related to firm size. Specifically, we construct two instruments based on the distances between each student and every school in the market: the median distance and the median absolute deviation of the distances. Under the assumption that locations are predetermined, these instruments capture that some schools are more attractive than others in the same municipality.

Using the three new alternative HHI measures we re-ran the main regression models for the base course prices and for the repeat course prices. The results are in tables B.1.1 and B.1.2. In the first column of each of these tables, we report the IV results from our main Tables 5 and 6 (and that use the number of firms as a measure of competition) for comparison and the results using the three new alternative HHI measures in columns (2) through (4).

The results obtained using the alternative HHI measures are consistent with the ones that use the number of firms as a measure of competition. They also support of the theoretical model predictions that the prices for the base course of instruction, but not the repeat fees, vary with the level of competition in a market (Predictions P1 and P3) and with the students' probability of failing the driving tests (Predictions P2 and P4). Further, in terms of magnitude, the results are also consistent. For example, a one standard deviation increase in the HHI constructed based on the number of students (given by 0.28×195) has a similar effect as a one standard deviation decrease in the number of firms (given by 4.87×12).

Table B.1.1: Regression Models of Base Course Prices

	IV			
	(1)	(2)	(3)	(4)
Number of firms (N)	−12.024*			
	(6.252)			
HHI students		195.366***		
		(60.648)		
HHI instructors			185.931***	
			(58.391)	
HHI cars				181.710***
				(52.434)
% fail both tests	−2.366**	−2.466***	−2.266**	−2.196**
	(0.976)	(0.942)	(0.930)	(0.923)
Number of instructors	1.845*	2.901***	2.956***	2.955***
	(1.083)	(1.124)	(1.101)	(1.099)
Median weight of fleet cars (kg)	−0.021	0.020	0.019	0.016
	(0.030)	(0.031)	(0.031)	(0.030)
Distance to testing center (km)	−0.392	−0.855**	−0.829**	−0.829**
	(0.303)	(0.395)	(0.387)	(0.379)
School within 100m of high school Y/N	45.175	63.675	65.854	65.095
	(41.937)	(40.554)	(41.568)	(42.425)
School distance to city center	2.963***	4.244***	4.116***	4.113***
	(1.115)	(1.137)	(1.123)	(1.114)
% of population in urban parishes	−0.754***	−0.788***	−0.779***	−0.786***
	(0.216)	(0.229)	(0.226)	(0.227)
Majority of parishes urban Y/N	−14.063	4.695	4.976	2.742
	(15.099)	(16.786)	(16.643)	(15.959)
Per-capita income (€)	0.161**	0.190***	0.200***	0.198***
	(0.073)	(0.071)	(0.070)	(0.070)
Number of car repair shops	−0.687**	−0.693**	−0.691**	−0.682**
	(0.268)	(0.284)	(0.279)	(0.287)
Population (000)	1.270**	0.725**	0.690**	0.662*
	(0.516)	(0.364)	(0.351)	(0.360)
Adjusted R^2	0.353	0.339	0.347	0.346
1^{st} stage partial R^2	0.397	0.173	0.182	0.205
1^{st} stage F statistic	12.786	11.092	11.335	13.841

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. Specifications include region fixed effects and additional, statistically insignificant, controls (instructor experience and its square, and a coastal area indicator). Model (1) uses distance to the closest IMT office, distance to main IMT office, number of supermarkets, total size of artificial land, share of pixels with positive night-time light intensity, average rent and commercial building share as instruments. Models (2)–(4) use, in addition, instruments constructed based on the distances between the students and the schools in each market.

Table B.1.2: Regression Models of Repeat Course Price

	IV			
	(1)	(2)	(3)	(4)
Number of firms (N)	−1.059			
	(2.420)			
HHI students		−16.102		
		(39.019)		
HHI instructors			−15.420	
			(37.943)	
HHI cars				−14.049
				(35.110)
% fail both tests	−0.045	−0.004	−0.021	−0.027
	(0.528)	(0.529)	(0.528)	(0.529)
Number of instructors	3.903***	4.038***	4.034***	4.033***
	(0.881)	(0.868)	(0.871)	(0.869)
Median weight of fleet cars (kg)	0.081***	0.077***	0.077***	0.078***
	(0.020)	(0.020)	(0.020)	(0.020)
Distance to testing center (km)	0.032	0.072	0.070	0.067
	(0.179)	(0.219)	(0.218)	(0.214)
School within 100m of high school Y/N	57.703***	56.039***	55.848***	56.028***
	(20.961)	(20.171)	(20.252)	(20.282)
School distance to city center	1.380*	1.236	1.246	1.254
	(0.777)	(0.831)	(0.825)	(0.819)
% of population in urban parishes	−0.441***	−0.449***	−0.450***	−0.449***
	(0.167)	(0.168)	(0.169)	(0.168)
Majority of parishes urban Y/N	−25.374***	−27.683***	−27.718***	−27.413***
	(8.118)	(9.213)	(9.272)	(9.021)
Per-capita income (€)	0.036	0.042	0.042	0.042
	(0.037)	(0.034)	(0.034)	(0.034)
Number of car repair shops	0.269*	0.229	0.229	0.229
	(0.155)	(0.158)	(0.159)	(0.158)
Population (000)	−0.151	−0.263	−0.261	−0.257
	(0.259)	(0.192)	(0.192)	(0.190)
Adjusted R^2	0.141	0.134	0.134	0.134
1^{st} stage partial R^2	0.397	0.178	0.187	0.210
1^{st} stage F statistic	12.786	11.725	12.004	14.769

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. See notes to Table B.1.1.

B.2 Determinants of Markups

Here, we supplement the regression analysis in Section 4 with regression models of estimated school markups to verify that our primary results are not driven by cost differences between schools and across markets that are reflected in price. Table B.2.1 reports results for base course markups; Table B.2.2 for repeat course markups, with similar patterns to the effect of competition and fail rates as in Tables 5 and 6.

Table B.2.1: Regression Models of Base Course Markups

	OLS		IV	
	(1)	(2)	(3)	(4)
Number of firms (N)	−11.104***		−11.581*	
	(3.850)		(6.705)	
($N = 2$) Y/N		−51.045***		−50.431**
		(16.677)		(20.963)
($N = 3$) Y/N		−62.659***		−62.871**
		(19.286)		(29.411)
($N = 4$) Y/N		−85.896***		−84.781**
		(28.340)		(36.272)
($N = 5$) Y/N		−95.315***		−86.926**
		(29.092)		(34.738)
($N \geq 6$) Y/N		−123.301***		−128.586**
		(27.732)		(53.155)
% fail both tests	−2.426**	−2.362**	−2.434**	−1.854**
	(1.067)	(1.023)	(1.043)	(0.823)
Number of instructors	1.171	2.333*	1.120	2.027
	(1.237)	(1.188)	(1.182)	(1.368)
Median weight of fleet cars (kg)	−0.163***	−0.141***	−0.163***	−0.099***
	(0.033)	(0.033)	(0.033)	(0.031)
Distance to testing center (km)	−0.386	−0.674**	−0.387	−0.582**
	(0.314)	(0.317)	(0.310)	(0.293)
School within 100m of high school Y/N	41.428	49.287	41.461	39.245
	(37.178)	(36.548)	(36.662)	(38.049)
School distance to city center	2.851**	3.587***	2.860**	2.341***
	(1.162)	(1.201)	(1.135)	(0.782)
% of population in urban parishes	−0.693***	−0.761***	−0.691***	−0.812
	(0.221)	(0.219)	(0.218)	(0.570)
Majority of parishes urban Y/N	−12.560	0.471	−12.383	−0.015
	(15.845)	(15.004)	(16.024)	(16.674)
Per-capita income (€)	0.049	0.095	0.047	0.047
	(0.068)	(0.062)	(0.071)	(0.054)
Number of car repair shops	−0.562*	−0.590*	−0.553*	−0.604
	(0.287)	(0.323)	(0.308)	(0.703)
Population (000)	1.077**	0.525	1.114**	0.716
	(0.422)	(0.379)	(0.562)	(0.951)
Adjusted R^2	0.301	0.326	0.301	
1st stage partial R^2			0.397	
1st stage F statistic			12.786	
Observations	746	746	746	746

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Municipality-level clustered standard errors in parentheses. For a list of suppressed controls and instruments, see footnote to Table 5.

Table B.2.2: Regression Models of Repeat Course Markups

	OLS		IV	
	(1)	(2)	(3)	(4)
Number of firms (N)	−1.869		−1.622	
	(1.976)		(2.379)	
($N = 2$) Y/N		−5.090		1.140
		(10.089)		(10.964)
($N = 3$) Y/N		−9.817		0.044
		(12.151)		(13.757)
($N = 4$) Y/N		−12.823		−4.134
		(15.321)		(19.409)
($N = 5$) Y/N		−21.834		−10.360
		(14.164)		(17.436)
($N \geq 6$) Y/N		−1.220		12.240
		(14.005)		(22.460)
% fail both tests	−0.155	−0.161	−0.151	0.456
	(0.535)	(0.530)	(0.531)	(0.650)
Number of instructors	3.603***	3.878***	3.629***	2.742***
	(0.872)	(0.872)	(0.912)	(0.704)
Median weight of fleet cars (kg)	0.047**	0.047**	0.047**	0.032
	(0.020)	(0.020)	(0.020)	(0.022)
Distance to testing center (km)	−0.047	−0.078	−0.047	−0.164
	(0.174)	(0.170)	(0.171)	(0.177)
School within 100m of high school Y/N	59.864***	60.147***	59.847***	53.543*
	(21.450)	(21.852)	(21.145)	(30.073)
School distance to city center	1.162	1.377*	1.157	0.568
	(0.795)	(0.827)	(0.781)	(0.624)
% of population in urban parishes	−0.461***	−0.447***	−0.462***	−0.510**
	(0.169)	(0.168)	(0.168)	(0.200)
Majority of parishes urban Y/N	−21.696***	−19.508**	−21.788***	−22.492***
	(8.115)	(8.094)	(8.041)	(8.677)
Per-capita income (€)	0.020	0.033	0.021	−0.016
	(0.036)	(0.035)	(0.036)	(0.039)
Number of car repair shops	0.342**	0.309*	0.337**	0.192
	(0.153)	(0.161)	(0.156)	(0.297)
Population (000)	−0.106	−0.328	−0.125	−0.182
	(0.258)	(0.204)	(0.266)	(0.340)
Adjusted R^2	0.117	0.119		
1st stage partial R^2			0.397	
1st stage F statistic			12.786	
Observations	746	746	746	746

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Municipality-level clustered standard errors in parentheses. For a list of suppressed controls and instruments, see footnote to Table 5.

B.3 Endogeneity of Fail Rates

Here we report the results of a robustness check where we control for the potential endogeneity of schools' fail rates in our primary price models. We proceed as follows. First, we estimate a student-level logit model of the propensity of failing both driving tests, utilizing $81,472$ student outcomes and allowing the probability of failing both tests to depend on student demographics (such as gender and age), fixed effects for the student's parish – the most granular spatial designation available to us – and school fixed effects. In order to identify school and parish fixed effects separately, we focus on municipalities with multiple parishes. This reduces the set of schools included in this exercise from 746 schools in the main analysis to 650 schools. Second, as in Chetty et al. (2014), we predict the propensity of failing for each student, replacing their chosen school's fixed effect with the average estimated school fixed effect across schools, giving each student the treatment of the "average school" in their test outcome. Consequently, the variation in predicted propensities of failing represents exclusively the attributes of the students themselves – their demographics and parish fixed effect – rather than the school they attended. Third, we aggregate predicted fail probabilities across students to the level of the school and use the resulting predicted fail rate in place of the school's actual fail rate in our price models. We present the results of the final estimation in the second column of Tables B.3.1 and B.3.2, replicating in column (1) our primary specification, for comparison. The contributions of the number of firms and fail rates to both the upfront and add-on prices are robust.

Table B.3.1: Regression Models of Base Course Prices

	IV	
	(1)	(2)
Number of firms (N)	-12.024*	-11.370**
	(6.252)	(5.736)
% fail both tests	-2.366**	
	(0.976)	
% fail both tests (predicted)		-2.174***
		(0.784)
Number of instructors	1.845*	2.456**
	(1.083)	(1.056)
Median weight of fleet cars (kg)	-0.021	-0.026
	(0.030)	(0.031)
Distance to testing center (km)	-0.392	-0.551
	(0.303)	(0.345)
School within 100m from high school	45.175	19.420
	(41.937)	(38.383)
School distance to city center	2.963***	2.160**
	(1.115)	(1.084)
% of population in urban parishes	-0.754***	-0.920***
	(0.216)	(0.230)
Majority of parishes urban Y/N	-14.063	-16.344
	(15.099)	(15.036)
Per-capita income	0.161**	0.221***
	(0.073)	(0.071)
Number of car repair shops	-0.687**	-0.552**
	(0.268)	(0.277)
Population (000)	1.270**	1.178**
	(0.516)	(0.483)
N	746	650
Adjusted R^2	0.353	0.297
1^{st} stage partial R^2	0.397	0.428
1^{st} stage F statistic	12.786	16.224

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. Specifications include region fixed effects and additional, statistically insignificant, controls (instructor experience and its square, and a coastal area indicator). All models use average distance to the closest IMT office, average distance to main IMT office, number of grocery stores, total size of developed land, share of pixels with positive night-time light intensity, average rent and commercial building share to instrument for the number of firms. Specification (2) uses the predicted percent of students who fail both driving tests after removing the school contribution to the test outcome. See text for details.

Table B.3.2: Regression Models of Repeat Course Prices

	IV	
	(1)	(2)
Number of firms (N)	−1.059	−2.618
	(2.420)	(2.498)
% fail both tests	−0.045	
	(0.528)	
% fail both tests (predicted)		0.687
		(0.615)
Number of instructors	3.903***	3.288***
	(0.881)	(0.985)
Median weight of fleet cars (kg)	0.081***	0.088***
	(0.020)	(0.023)
Distance to testing center (km)	0.032	−0.104
	(0.179)	(0.221)
School within 100m from high school	57.703***	43.581**
	(20.961)	(21.424)
School distance to city center	1.380*	1.676**
	(0.777)	(0.846)
% of population in urban parishes	−0.441***	−0.400**
	(0.167)	(0.172)
Majority of parishes urban Y/N	−25.374***	−20.204**
	(8.118)	(8.761)
Per-capita income	0.036	0.041
	(0.037)	(0.046)
Number of car repair shops	0.269*	0.234
	(0.155)	(0.166)
Population (000)	−0.151	−0.016
	(0.259)	(0.273)
N	746	650
Adjusted R^2	0.141	0.150
1^{st} stage partial R^2	0.397	0.428
1^{st} stage F statistic	12.786	16.224

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. See notes to Table B.3.1.

B.4 Fail Rates' Definition

Here we report the results of a robustness check where we replace the schools' fail rates in our primary price models with the municipality level fail rates. The contributions of the number of firms and fail rates to both the upfront and add-on prices are robust.

Table B.4.1: Regression Models of Base Course Prices

	IV	
	(1)	(2)
Number of firms (N)	−12.024*	−12.397**
	(6.252)	(6.176)
% fail both exams (school)	−2.366**	
	(0.976)	
% fail both exams (muni)		−3.763*
		(1.997)
Number of instructors	1.845*	1.800*
	(1.083)	(1.075)
Median weight of fleet cars (kg)	−0.021	−0.021
	(0.030)	(0.030)
Distance to testing center (km)	−0.392	−0.371
	(0.303)	(0.297)
School within 100m from high school	45.175	48.312
	(41.937)	(42.713)
School distance to city center	2.963***	2.916***
	(1.115)	(1.096)
% of population in urban parishes	−0.754***	−0.747***
	(0.216)	(0.212)
Majority of parishes urban Y/N	−14.063	−14.250
	(15.099)	(15.287)
Per-capita income	0.161**	0.160**
	(0.073)	(0.073)
Number of car repair shops	−0.687**	−0.680***
	(0.268)	(0.263)
Population (000)	1.270**	1.281**
	(0.516)	(0.506)
N	746	746
Adjusted R^2	0.353	0.354
1^{st} stage partial R^2	0.397	0.396
1^{st} stage F statistic	12.786	12.730

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. Specifications include region fixed effects and additional, statistically insignificant, controls (instructor experience and its square, and a coastal area indicator). All models use average distance to the closest IMT office, average distance to main IMT office, number of grocery stores, total size of developed land, share of pixels with positive night-time light intensity, average rent and commercial building share to instrument for the number of firms.

Table B.4.2: Regression Models of Repeat Course Prices

	IV	
	(1)	(2)
Number of firms (N)	−1.059	−1.373
	(2.420)	(2.419)
% fail both exams (school)	−0.045	
	(0.528)	
% fail both exams (muni)		−1.370
		(1.005)
Number of instructors	3.903***	3.891***
	(0.881)	(0.868)
Median weight of fleet cars (kg)	0.081***	0.080***
	(0.020)	(0.020)
Distance to testing center (km)	0.032	0.051
	(0.179)	(0.177)
School within 100m from high school	57.703***	57.527***
	(20.961)	(20.121)
School distance to city center	1.380*	1.385*
	(0.777)	(0.777)
% of population in urban parishes	−0.441***	−0.434***
	(0.167)	(0.165)
Majority of parishes urban Y/N	−25.374***	−25.404***
	(8.118)	(7.985)
Per-capita income	0.036	0.034
	(0.037)	(0.037)
Number of car repair shops	0.269*	0.285*
	(0.155)	(0.151)
Population (000)	−0.151	−0.153
	(0.259)	(0.253)
N	746	746
Adjusted R^2	0.141	0.144
1^{st} stage partial R^2	0.397	0.396
1^{st} stage F statistic	12.786	12.730

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Municipality-level clustered standard errors in parentheses. See notes to Table B.4.1.