

Do Consumers Value Price Transparency?*

CURRENT VERSION: NOVEMBER 2016

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Abstract

We examine the role of price transparency in consumer preferences and demand. We assemble a detailed dataset on the driving school industry in Portugal to quantify how firms present the price of the course of instruction, and its individual components, to potential students. Our unique data allows us to estimate a structural model of school choice and measure the impact of varying levels of price information on demand. The results show that consumers are willing to pay a significant amount for price transparency, on average 11 percent of the service price, and that consumer demographics drive heterogeneous preferences for transparency.

Keywords: pricing, transparency, information, consumer valuation

JEL Classification: D43, D83, L13, L15, L84

*We thank Susana Paulino at Instituto da Mobilidade e dos Transportes for access to the data and information about the industry. Ana Isabel Horta provided excellent research assistance, and Susana Belo assisted with local data collection. We thank Elisabeth Honka, JF Houde, and Yi-Lin Tsai for fruitful conversations throughout the writing of this paper. We also thank the seminar participants at the Alfred Lerner College of Business and Economics (The University of Delaware), Carlson School of Management (University of Minnesota), Foster School of Business (University of Washington), LeBow College of Business (Drexel University), Sauder School of Business (University of British Columbia), Stern School of Business (New York University), and Wharton School (University of Pennsylvania). We gratefully acknowledge support from the Grant-in-Aid Program (GIA) at the University of Minnesota and the Global Initiatives Research Program at the University of Pennsylvania. All errors are our own.

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1 Introduction

Regulatory efforts around pricing frequently focus on price transparency: ensuring that firms provide price information that allows consumers to readily understand what they are purchasing from the firm and how that compares to competitors' offerings. Such requirements arise out of concerns about the increasing role of secondary fees in generating significant and potentially unexpected expenses for consumers in a wide variety of product markets.¹ Regulations geared at increasing price transparency include the Credit Card Accountability Responsibility and Disclosure Act of 2009 that requires, among other things, disclosures on the number of months until balance payoff under minimum monthly payments.² Price transparency is also at the center of the Federal Communication Commission's ongoing efforts to inject competition into the market for cable boxes by requiring internet service providers and cable companies to list fees for equipment separately from other charges.³

At the same time, critics point to downsides of such highly detailed pricing in that it is not indicative of the total amount owed and, thus, less customer friendly than all-inclusive pricing, which provides a single price total to the customer. As a result, the U.K. Office of Fair Trading ranked "complex [price] offers" third in its 2010 report on potentially misleading pricing practices.⁴ Accordingly, price transparency considerations are especially relevant in contexts in which products involve multiple components and in which consumers are inexperienced in purchasing such products. Benefits to less complex, all-inclusive pricing might furthermore disproportionately accrue to certain consumer groups, motivating, for example, regulatory conditions imposed on Charter Communication in its 2016 purchase of Time Warner Cable and Bright House Networks to introduce a stand-alone broadband internet service plan for qualified low-income consumers that had to be marketed using all-inclusive prices.⁵

A key input to evaluating the likely impact of increasing price transparency is its role in consumer preferences and demand. Owing in part to the difficulty of measuring price transparency empirically, the majority of the literature on price formats or "frames" is experimental (for a meta-analysis of experimental research on the effects of price frames, see Krishna et al. 2002) and theoretical (e.g., Carlin 2009, Piccione and Spiegler 2012, Chioveanu and Zhou 2013). In this paper, we extend the earlier work by measuring the importance of price transparency for demand empirically.

We study the provision of price information by Portuguese driving schools. There are several

¹Contexts range from financial product markets such as commercial banking to the travel sector including airline tickets and hotel accommodations and public utilities subject to various regulatory fees.

²See Consumer Financial Protection Action (2013) "CARD Act Report," available at www.consumerfinance.gov/f/201309_cfpb_card-act-report.pdf and accessed on October 30, 2016.

³See, for instance, <http://arstechnica.com/information-technology/2016/09/charter-fights-fccs-attempt-to-uncover-hidden-cable-modem-fees/>, accessed on October 30, 2016.

⁴See <http://webarchive.nationalarchives.gov.uk/20140402142426/http://www.oft.gov.uk/OFTwork/markets-work/advertising-prices/>, accessed on October 30, 2016.

⁵See footnote 3 and https://apps.fcc.gov/edocs_public/attachmatch/FCC-16-59A1.pdf, accessed on October 30, 2016.

advantages to using this context to study price transparency. First, we observe significant variation in the way firms present prices, which, together with a large data set on demand, allows us to measure the effects of different price frames on school preferences. Second, schools offer a standardized product at a fixed price; as a result there is no service customization or bargaining. Third, the consumer – here the student – has to pay for all components, described below, of the price quote in order to acquire the service (driving instruction); the student cannot purchase them independently from each other. This feature distinguishes our setting from contexts in which firms practice mixed bundling strategies, allowing us to measure the effect on demand of different ways of presenting prices and the degree of transparency without needing to evaluate the substitution patterns between components that drive bundling considerations. Finally, consumers largely are inexperienced when buying the service as it is typically the first, and only, time they purchase it; this allows us to abstract from learning or state dependence in preferences that is usually associated with repeat purchases.

The full price of a course of driving instruction covers a large number of components, including theory and on-road lessons, registration and exam fees, etc. We operationalize price transparency as a firm-specific attribute that captures how much information schools provide to a potential student about price. We record whether the school provided all-inclusive pricing only, or was willing to offer information on components covered by the all-inclusive price, as well as breakdown of the total into component prices. Such information is helpful in comparing service offers from different schools, on an apples-to-apples basis, and in estimating possible additional charges due to, for example, taking additional driving lessons beyond the required minimum number. Our price transparency measures, thus, represent the value of providing detailed information in any form, rather than, for instance, a standardized price disclosure mechanism. To the extent that we capture whether or not prices are itemized, work on price partitioning operationalizes price frames in the most similar way to ours.⁶

We use hand-collected data on prices and transparency for the universe of approximately 1,000 driving schools in Portugal and individual choice data spanning all driving school students over a three-year period to estimate a structural model of demand. The model allows us to measure consumers’ heterogeneous responsiveness to prices and price transparency while controlling for other student and school characteristics, including distance from the school, age of the school’s driving fleet, and instructors’ experience.

We find that, all else equal, consumers are willing to pay a significant amount for price transparency. Valuations for price detail are positive across demographic groups, delineated by age, gender, and the degree of urbanization of the student’s residence, albeit with significant heterogeneity, with younger and male students in urban areas valuing price detail significantly more than

⁶Greenleaf et al. 2016 define partitioned pricing as “a strategy that divides a product’s price into a base price, charged for the product itself, and a mandatory surcharge(s) for products, services, fees, or taxes associated with purchasing or using the product” and all-inclusive or combined pricing as the pricing practice that “involves the use of single, all-inclusive price that covers all costs.” The main focus of research on partitioned pricing is to study the psychological processes by which partitioned pricing influences consumers’ product evaluations and their choices through the use of experiments.

other demographic groups. In the sample, estimated valuations of attending a school that provides additional information on components beyond the all-inclusive price range from €36.5 to €83.4, with a mean of €76.5 and a median of €80. These are economically meaningful magnitudes, given that the average school charges €695.3 for its base course of driving instruction.

Our results are consistent with the experimental literature on partitioned pricing, which posits that providing more detailed price information increases demand relative to offering all-inclusive prices. Work by Morwitz, Greenleaf, and Johnson 1998, Lee and Han 2002, and Kim 2006 highlights consumers' low motivation for processing price information in calculating all-inclusive prices, resulting in undue focus on the price of the product's primary component, thereby driving demand.⁷ Similar evidence has also been provided in the context of field experiments (Hossain and Morgan, 2006) in investigating the role that the timing of the display of shipping and tax information has on online retail demand. Interestingly, because schools quote the total price in addition to the price of components in our setting, when they choose to provide this information, our results suggest the positive effects of price partitioning extend beyond possible price miscalculations by consumers.⁸

A number of channels can give rise to the estimated contribution of price detail to demand. The provision of additional price information can result in a reduction in search costs and increased ease of comparing prices (Carlin 2009, Wilson 2010, Ellison and Wolitzky 2012). Providing detailed price information has also been found to increase store trustworthiness and perceived value (cf. Xia and Monroe 2004 and Bertini and Wathieu 2008). Lastly, transparency might also function as a quality signal through its informational effect (Völkner, Rühle, and Spann, 2012), similar to the role that advertising at times plays in enhancing consumer knowledge of the advertised product, in particular for experience goods like the one we study.⁹

The paper proceeds as follows. Section 2 provides a brief overview of driving instruction in Portugal and introduces the data. Section 3 develops a discrete choice model of the student's school choice that allows an investigation of the role that price information plays in consumer demand and discusses various challenges to operationalizing such a model in our setting. Section 4 summarizes the estimates of the school choice model and investigates the heterogeneity in consumer responses by demographic group. Section 5 concludes and offers directions for future research.

⁷Students' resulting underestimation of the total cost of the product, stirring demand to the firm using the partitioned pricing strategy, supports the regulatory concerns about highly detailed pricing being potentially misleading.

⁸To the best of our knowledge, Xia and Monroe (2004) and Carlson and Weathers (2008) are the only papers in the experimental partitioned pricing literature that present subjects with a total price in the partitioned price condition. Xia and Monroe (2004) compare the likelihood of purchase and perceptions of fairness and seller trustworthiness under partitioned pricing and all-inclusive pricing when total price is presented. Carlson and Weathers (2008) study how purchase intentions change with the number of price components and presentation of total price under different levels of seller trustworthiness.

⁹See, for example, Nelson (1974), Kihlstrom and Riordan (1984), Paul Milgrom (1986), and Akerberg (2003) for models of the informative effects of advertising.

2 Empirical Setting and Data

To obtain a driver’s license in Portugal, any individual aged 18 years or older must first enroll in a driving school licensed by the regulatory agency that oversees the industry, the Instituto da Mobilidade e dos Transportes (IMT).¹⁰ Candidates must complete 28 theory lessons, the curriculum of which is set by the IMT, and a minimum of 32 on-road driving lessons. After completing the required theory lessons, students take a computerized theory exam. Subsequently, they perform an on-road driving test. The computerized theory exams are administered at a set of public and private test centers and are based on IMT-proprietary software to ensure tight control over exam content and conditions. An IMT certified examiner oversees the on-road driving test. Retaking either exam upon failing is possible for a fixed number of tries.¹¹

An institutional feature of particular relevance to our school-choice model described in Section 3.1 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, so that students are de-facto locked into the school by their initial choice.¹² As a result, we associate attending a given school with that school’s price for a complete course of driving instruction.

We rely on a number of data sources at the school, student, and municipality level. The IMT collects a number of school characteristics in the process of initially licensing and subsequently overseeing schools. The IMT also maintains individual-level school enrollment and driving exam records, and provided us with information on the universe of students who obtained their driver license in 2009 or 2010 and enrolled in a school as early as January 1, 2008. We complement the IMT data with data from several secondary sources and with primary, hand-collected data described below.

2.1 Sample Selection

We begin by describing our sample selection process. We focus on category-B passenger vehicle licenses as this the most common type of driver’s license, with 85 percent of licenses issued belonging to this category. We limit our sample of students to applicants who registered at an accredited driving school in mainland Portugal. We thus drop registrants living in the islands of Azores and Madeira due to limited demographic data availability for the archipelagos. We further drop 107 out of a total of 1,108 schools that operated in mainland Portugal at the end of 2010. The regulator indicated that these schools were in only limited operation over the period of the sample, having less than 10 students per year on average, and we were also unable to collect complete price information

¹⁰Licensing by the IMT requires, among other things, proof that the applicant has at least five years of experience in driving instruction, that the school is financially viable, and that the fleet and facilities satisfy certain minimum standards.

¹¹We study the incidence and pricing of exam retakes in Seim, Vitorino, and Muir (2016).

¹²In the data, we observe students switching schools rarely. Only 1.8 and 0.1 percent of all students transfer schools during the theory and on-road exam phases, respectively, while only 0.7 percent transfer in between the theory and on-road exam phases. The majority of these, or 64.5 percent, transfer to schools outside their original school’s municipality, suggesting that exogenous reasons such as moving explain a significant share of transfers (statistics not tabulated).

for 38 of these schools. The 107 schools serve only 3 percent of the total student population, which we drop from the sample.

A key determinant of student school choice is distance to the school. As noted above, the driving course, even if completed successfully at the first try of taking exams, comes with a large lesson requirement that necessitates frequent trips to the school by a population who, by definition, do not drive themselves. Information on school addresses, together with the students’ place of residence at the 7-digit postal code level – roughly the size of a city block – allows us to calculate the straight-line distance between the centroid of students’ postal code locations and their chosen school’s street address. Consistent with the importance of distance, the median student in our final sample chooses a school that entails traveling only 2.1 kilometers to the school and 40.2 percent of students choose the school closest to home.

The distribution of the distance to the school exhibits a long tail, however, with the maximum distance amounting to 546 kilometers. Such large distances are suggestive of inaccuracies in the students’ postal code; their postal code may be outdated or may not reflect their true location relative to their school because they live or complete their drivers’ education course elsewhere, for example, while on vacation. To minimize the role of such measurement error in the distance to the school, we drop students from the sample who travel more than 20 kilometers to their chosen school, corresponding to the 92nd percentile of the distance distribution. We further drop 2,664, or less than one percent of students, who only have a single school within a 20 kilometer radius and thus do not make an active school choice.

Our final sample contains 142,913 students enrolled at a total of 1,001 schools, which corresponds to 83 percent of students and 90 percent of schools in the complete data set. The sample driving schools operate in 254 out of 278 mainland municipalities, and Figure 1 plots their location by municipality population density. As expected, entry of driving schools is significantly more pronounced in the two urban centers of the country, Lisbon and Porto, while some of the interior municipalities are served by, at times, a single school. The map suggests that both the number of schools among which students are choosing from and the maximum distance students may be willing to travel to attend school likely differ significantly across areas with varying population densities, and we address this point in constructing students’ school choice sets in Section 4.

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2.2 School Characteristics

The IMT-provided school data set contains information on a number of attributes that affect student utility from attending a given school, most notably its location, its age as a proxy for reputation, and its instructors’ experience as one measure of school quality. The data was initially collected as

part of each school’s licensing process, and the IMT updates the information periodically. In Table 1 we provide descriptive statistics of the variables we include in the demand model.

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We use information on the number of cars in each school’s fleet as a proxy for school size, ease of scheduling on-road lessons, and advertising because schools use their driving school cars as moving advertisements, prominently displaying school information on the sides of the cars. We also hand-collect information on whether each school maintains a website and use it to construct the indicator variable “WebPresence” as an alternate means of disseminating information and advertising school services; approximately 40 percent of schools operate a website at the time of our data.

The indicator “SecondarySchoolWithin500m” is one measure for the attractiveness of the school’s location in terms of being located near – within 500 meters – a secondary school, as 28 percent of sample schools are.¹³ “InstructorExperience” measures the average number of years that a given school’s instructors have been working as driving-school instructors; the interquartile range of 3.9 to 9.9 years suggests that most instructors remain in the profession long term and possess significant experience. The mean school has a driving fleet consisting of 3.6 passenger vehicles (“NumberPassengerVehicles”), with an average age of 5.7 years (“AgePassengerVehicles”).

While these attributes capture the school’s attractiveness to the student, we also include two cost shifters that we ultimately use as instruments for price. “DistanceToExamCenter” is the straight-line distance to the most frequently used exam center for each school. Both exams are administered at one of 35 primarily publicly run exam centers; 79.2 percent of schools use a single exam center for at least 90 percent of their student body (not tabulated). The distance to the exam center captures the travel and opportunity cost of taking students to and from the center to take their on-road driving exam. At the same time, since nearby schools use the same exam center and the student is likely unaware of the exam center’s exact location, a given school’s distance to the center is unlikely to be a determinant of the student’s school choice. The average school is 19.9 kilometers from its exam center with an interquartile range of 6.3 to 27.8 kilometers. The second cost shifter we employ is a proxy for vehicle operating costs, which comprise an estimated 40 percent of school variable costs.¹⁴ We employ the cost of fuel; since most instruction vehicles use diesel fuel, we use the lowest price per liter of diesel fuel (obtained from the Direção Geral de Energia e Geologia on December 12, 2012) available in the school’s municipality.

¹³To construct the indicator “SecondarySchoolWithin500m” we first geocoded street addresses for all secondary schools in Portugal (obtained from the Gabinete de Estatística e Planeamento da Educação do Ministério da Educação on December 6, 2011), and then calculated straight-line distances from each secondary school to each of the driving schools in the sample.

¹⁴The industry association Associação Nacional dos Industriais do Ensino da Condução Automóvel (ANIECA) provides estimates of annual operating costs to its members; the data is as of 2012.

As the IMT’s registration process centers on quality of instruction and roadworthiness of instruction vehicles, it neither collects schools’ prices nor information on how schools communicate such prices to students. Schools also typically do not provide price information on their websites (less than 2 percent of school websites contain price information – not tabulated).¹⁵ We therefore hand-collect school price information.

We employed a team of 14 mystery shoppers who visited each of 1,070 schools in person between November 2011 and March 2012; initial trials suggested that querying schools by phone was unlikely to yield systematic information due to some schools’ hesitancy to release information about the course on the phone. Each shopper followed an identical script displayed in Appendix A to query the personnel for price information. The mystery shoppers gathered data on all fees for services, the availability of preprinted materials detailing fees, and the ability and willingness of the school to provide a detailed breakdown of all price components, rather than the total price only. Schools use pre-determined, fixed prices. The mystery shoppers reported, for example, that none of the schools tried to engage in price negotiations; for a subsample of 80 schools across the country, two different mystery shoppers visited the schools on different days, but collected the same prices in all instances. The shoppers also noted whether schools followed the single IMT regulation concerning price transparency: to display a price schedule in a pertinent location in the school’s office. Only 79.1 percent of schools do so, and we do not find any evidence that schools that follow the IMT regulation benefit in the form of higher demand, suggesting that either the way the schedule is displayed is not focal to potential students, that the information is outdated, or both.¹⁶

We use the information collected by the mystery shoppers to construct a standardized price for the basic course of driving instruction for each school. The price covers a large number of components, including an initial school registration fee, a fee to issue a learner’s permit, the required minimum of 28 theory lessons and 32 on-road driving lessons, fees to take a single, computerized theory exam and a single on-road driving exam, administered at an IMT-accredited exam center, and, lastly, transportation to and from the exam center for the purposes of taking the on-road driving exam.¹⁷

Interviews with select schools and the IMT regulator suggest that most students pay for the driving course in installments, as they complete the course (usually a lengthy process – 255 days on average, see Table 2), rather than paying the entire cost upfront, and our price measure reflects this payment choice.

Table 1 includes information on the distribution of prices across schools. The median school charges €695 for its basic driving course, with a standard deviation of €108.3. Hedonic regression

¹⁵As a result, there are no website aggregators that post the prices for different schools. Our focus, therefore, is not on the increased transparency that arises from publicly posting prices, as in Rossi and Chintagunta (2016), for example, but on the amount of price information provided by each school.

¹⁶The mystery shoppers recorded prices from the price table for a subset of sampled schools; in 90 percent of cases, the prices listed on the price schedule differed from the prices the school official quoted the mystery shoppers during the same visit.

¹⁷The school remits part, but typically not all, of the exam fees to the exam center to register the student for the theory and on-road exams.

models of log-prices suggest the observed price dispersion is due in part to differences between municipalities and districts (e.g., related to demographics), but also reflects variation in the schools' attributes (see Appendix B).

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In addition to substantial price dispersion, we also find that schools vary considerably in how they provide price information. Even though the mystery shoppers elicited an “all-inclusive” price as well as the individual prices for the different components included in the course, some schools chose not to provide a breakdown or, alternatively, to provide only partial information on the pricing for the individual components. In those cases, the mystery shoppers verified verbally that no additional charges would accrue on the student’s first try at completing the licensing process.

We use the price information collected by the mystery shoppers to describe how schools provide price information along several dimensions including: first, whether or not the school provided any written information – as opposed to a verbal description – regarding the price, and, if so, provided a detailed price component list or price breakdown; second, whether the school provided pre-printed materials describing the price, typically as part of a broader description of the driving course and schedules; third, a classification of the degree of transparency of the price information conveyed. Our analysis below focuses on the latter transparency scale. Consideration of the other two price provision attributes is nevertheless useful in understanding what the transparency scale captures.

We employ a “transparency scale” based on the level of price detail provided and classify schools into the following three categories:

Price detail level “0” (not transparent): The school provides an “all-inclusive” price only, without information on which components are included in the price or component prices.

Price detail level “1”: The school provides the total price and lists some of the components included in the price.

Price detail level “2” (transparent): The school provides the total price and lists *all* included components and some or all component prices.

Figures 2 through 4 provide illustrations for the price detail measure, using representative examples of the pricing materials the mystery shoppers obtained from the schools. These figures highlight a wide variation in schools’ provision of price information, with some providing minimal information despite the relative high price of the driving course. The figures also illustrate there is variation within each of the transparency levels in the way schools provide the price information. Our transparency scale focuses purely on how much information schools provide about price, but not on the format in which they provide it. For example, Figure 2 shows we classify two schools as offering little pricing transparency because they only provide a single price figure, even though one

offered a pre-printed flyer summarizing details of the registration process and school hours, while the other simply gave the mystery shopper a post-it note with the price.

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Such differences between how schools provide information are instead captured by the remaining price provision attributes of written information or pre-printed information. Seventy-four percent of schools provide some – potentially minimal – written information about prices, including 27 percent of schools where the official wrote down only the total price but gave more information verbally and another 36 percent of schools where the verbal and written information was identical. In addition, 25 percent of schools offer pre-printed materials with price information (not tabulated).

Our focus on the amount of information included in the price quote stems from its role in the student’s ability to understand prices and assess the value of different components of the service being offered. More detailed information can facilitate price comparison across schools, much like the role that Carlin (2009)’s theoretical work attributes to price transparency.¹⁸ In our context, improved comparison shopping could result from being aware of the various components that are included in the price, so that an apples-to-apples comparison may be made across schools, or from being able to compare the cost of additional charges that a student might choose or be required to pay down the road, such as additional driving lessons taken beyond the state-required 32 lesson minimum or taken because of failing the driving exam. Since our measure of price detail represents, in part, whether or not prices are itemized, it relates to work on price partitioning that operationalizes price frames in a similar way. There are two distinctions between the way

¹⁸The literature defines price transparency either at the firm- or market-level. Carlin (2009) is an example of the former and, thus, closest to our formulation. In this paper, each firm’s choice of price transparency increases its customers’ ease of evaluating the firm’s own price disclosure and comparing its prices in the market, but does not affect the customers’ ability to evaluate the disclosures of competing firms. Examples of the latter include the theoretical work by Piccione and Spiegler (2012) and Chioveanu and Zhou (2013), who investigate the implications of firms choosing different – but not necessarily more or less transparent – price formats on the functioning of the market as a whole, and lab work by Lynch and Ariely (2000) who show that increasing the ease of cross-store price comparisons among two virtual wine retailers increases consumers’ price responsiveness.

firms present prices in our context, relative to the typical experimental setting in the partitioned pricing literature, however. First, the typical school’s offering covers significantly more than the two components typically considered in experiments, and several price components are comparable in cost, rather than consisting of one large component, the base product, and one smaller component. Second, the experimental setting typically presents partitioned prices without separately tabulating a total. Among driving schools, in contrast, all schools quote a total price.

Table 1 summarizes the distribution of price detail provided: 11.8 percent of schools do not have transparent prices, 48.4 percent of schools have somewhat transparent prices, and 39.9 percent have transparent prices. We also use an alternative binary classification to check the robustness of our empirical analyses that classifies schools as transparent (“PriceDetail”=1) or not transparent (“PriceDetail”=0) by grouping the price detail levels “1” and “2” into the same category.

2.3 Student Attributes

The IMT student records contain some demographic information about the students – their age, gender, and place of residence – and details about the students’ course of study. The latter consists of dates of initial enrollment and exam registrations, as well as exam outcomes. Even though we focus primarily on the student’s initial school enrollment decision here, the data allow us to trace a student’s full exam history (including repeats) until completion.

Table 2 provides a summary of the student attributes. The average (median) student in our sample is 22.3 years (19.2 years) old. There is an even split of male and female students: 52 percent of our sample is female.

We use the students’ place of residence information to complement the IMT data with more aggregate demographic data for municipalities or their parish subdivisions from the market research company Grupo Marktest, the Ministério do Trabalho e da Solidariedade Social, and Statistics Portugal.

3 Measuring Consumer Preferences for Price Detail

3.1 Model of Consumer School Choice

Our goal lies in inferring the effect of providing consumers with detailed price information on consumers’ school choices. Consequently, we specify a model of consumer school choice and estimate consumer preferences using 2008-2010 data on school choices, prices, price detail, and other attributes. We then assess the importance of price detail on consumer choice behavior by comparing its effect to the effect of price, as the primary means of competition between schools.

We consider a discrete choice model of demand between horizontally and vertically differentiated driving schools. Following the literature, we assume that a potential student derives utility from pertinent characteristics of the school and that the utility differs systematically with the demographic attributes of the potential student and the municipality. In the analysis, we assume both firms and students observe all relevant school attributes.

Each student makes a choice based on a utility comparison among the schools in the student's choice set.¹⁹ Student i 's utility from attending school j is defined as

$$u_{ij} = \sum_{k=1}^K X_{j,k} \mathbf{Z}_i' \beta_{\cdot,k}^{xz} + p_j \mathbf{Z}_i' \alpha^z + f(D_{ij}) + \mathbf{X}_j' \beta^x - \alpha p_j + \xi_j + \varepsilon_{ij}, \quad (1)$$

where \mathbf{X}_j is a K vector of school characteristics; \mathbf{Z}_i is an N vector of student-specific attributes such as demographics; D_{ij} is the distance from student i 's location to the location of school j ; p_j is the price charged by each school; ξ_j denotes the quality of school j ; and ε_{ij} is an unobservable (to the econometrician) error term that we assume to be mean independent of the included right-hand side variables. Since, in estimation, we treat the level of price detail provided by a school like other school characteristics beyond price, we include price detail in the school attribute matrix \mathbf{X}_j . β^{xz} , α^z , and β^x are $N \times K$, $N \times 1$, and $K \times 1$ matrices of coefficients, respectively. The interactions between student attributes \mathbf{Z}_i and school characteristics \mathbf{X}_j and price p_j , account for observable individual heterogeneity in how different students value particular school characteristics and how sensitive they are to price.

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

$$f(D_{ij}) = \beta_{d1} D_{ij} + \beta_{d2} D_{ij}^2 + D_{ij} \mathbf{Z}_i' \beta_{d3} + \beta_{d4} D_{ij} \cdot \mathbb{I}_{\{j=\text{closest}\}}, \quad (2)$$

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

We use a two-step estimation method in the spirit of Berry, Levinsohn, and Pakes (2004) and employed by Gaynor and Vogt (2003) in the context of hospital choice. To obtain the estimating equations for each step, we express Equation (1) as a "mean" level of utility of school j , δ_j , and deviations from this mean. This results in the following two equations:

$$u_{ij} = \delta_j + \sum_{k=1}^K X_{j,k} \mathbf{Z}_i' \beta_{\cdot,k}^{xz} + p_j \mathbf{Z}_i' \alpha^z + f(D_{ij}) + \varepsilon_{ij}, \quad (3)$$

and

$$\delta_j = \mathbf{X}_j' \beta^x - \alpha p_j + \xi_j. \quad (4)$$

Assuming that ε_{ij} follows an i.i.d. type I extreme value distribution, the probability that student i

¹⁹Since the data only contain information on enrolled students, we are unable to model the choice of not obtaining a driver's license. We, therefore, may not assess the extent to which providing students with detailed price information may affect the size of the market, rather than substitution between available options.

chooses to attend school j , $ch_{ij} = 1$, may then be written as

$$\Pr(ch_{ij} = 1) = \frac{\exp \left\{ \delta_j + \sum_{k=1}^K X_{j,k} \mathbf{Z}'_i \beta_{\cdot,k}^{xz} + p_j \mathbf{Z}'_i \alpha^z + f(D_{ij}) \right\}}{\sum_{j'=1}^{J_i} \exp \left\{ \delta_{j'} + \sum_{k=1}^K X_{j',k} \mathbf{Z}'_i \beta_{\cdot,k}^{xz} + p_{j'} \mathbf{Z}'_i \alpha^z + f(D_{ij'}) \right\}}. \quad (5)$$

Given we observe multiple students choosing each school, we treat δ_j as a school fixed effect. We designate one school as the reference school and normalize its mean utility δ_j to zero. The remaining fixed effect estimates thus represent mean utility differences between a given school j and the reference school. Our identification of the fixed effects exploits the fact that, even though schools operate in very different parts of the country, they are connected indirectly through different students' choice sets that overlap and share common schools.

Estimation proceeds in two stages. In the first stage we estimate the parameters in Equation (3) by maximum likelihood, including school fixed effects and interactions of student attributes and school characteristics. In the second stage we project the estimated δ_j on price, price detail, and other controls, as in Equation (4) to obtain estimates of β^x and α .

Identifying consumer price responsiveness is informative both on its own, but also in providing a means of translating the remaining estimates into monetary units. A common challenge is identifying the contribution of price, as the primary strategic variable, independently of other, unobserved determinants of mean utility and, thus, school choice that may be correlated with price. We mitigate this concern in two ways. First, we control explicitly for the contribution of school characteristics and a case-mix adjusted school quality index, constructed as described in Section 4.2, on mean utility. Second, to address any potential unaccounted-for dimensions of quality that could continue to bias the price coefficient, we instrument for price using schools' variable cost shifters.

4 Demand Estimation Implementation and Results

Before turning to the estimates of the demand model outlined in Section 3, we discuss two aspects of the empirical implementation. We first describe how we define the set of schools among which each student chooses, followed by a description of how we construct a proxy for school quality.

4.1 Choice Set Definition

The demand model assumes that students make their school choices out of a relevant set of schools. Thus, we need to specify a choice set for each student that contains the schools among which she is likely to choose. While licensing restrictions require that each school conduct all lessons within the boundary of the municipality covered by the school's license, students are free to choose to attend any accredited school. To construct meaningful choice sets, we therefore follow earlier work (e.g., Gaynor and Vogt 2003) in defining each student's choice set as all schools that are within a

distance radius of that student’s zip code of residence. In line with our sample selection criteria, we limit the radius to a maximum of 20 kilometers.

The median student has 58 schools within a 20 kilometer radius of his residence, reflecting the density of schools in the Lisbon and Porto metropolitan areas. In contrast, a student at the 25th percentile has only 18. Few students with as many schools around them choose to attend one of the highest ranked schools based on distance: for the median student, the chosen school is the second closest to the student’s location, and 95 percent of students choose one of the 20 closest schools to their location. We, therefore, limit the choice set to contain at most 25 schools. To account for the fact that students’ preferences over the maximum distance they would be willing to travel to a school likely differ between urban and rural areas, we let each student’s choice-set radius be inversely proportional to the population density of the student’s parish, as in Zheng (2016).²⁰

A comparison of the resulting choice sets between students from highly urban districts of Lisbon and Porto and students from the less densely populated remainder of the country illustrates the effect that population density has on the radius of students’ choice sets. In the final sample the average student in Lisbon and Porto chooses among 24 schools within a radius of 8.7 kilometers, while the average student outside these two districts chooses among 17 schools within a radius of 14.9 kilometers.²¹

4.2 Case-Mix Adjusted School Quality

One potentially important dimension of school choice is the school’s quality of instruction. Our data contain various measures such as the experience of instructors and the characteristics of the fleet of training vehicles, which both summarize one dimension of school quality. As in other educational settings, student test scores – here pass rates – arguably proxy for a second dimension of school quality: the school’s success at preparing the students for the driving exams.

We account for variation along this second quality dimension by exploiting the student-level exam information. The students take two exams, yielding two possible measures to be exploited. We rely on students’ performance on the first theory exam they take since the theory exam is a more standardized, controlled test than the on-road exam, whose outcome is influenced by the examiner and other events on the day of the exam. Across schools over the three year period from 2008 to 2010, we observe 142,913 student theory exam outcomes; 76.2 percent of students pass the exam the first time they take it. At the level of the school, the average pass rate over the three-year period is 75.5 percent, just below the mean rate across students, reflecting some variation in the size of schools’ student bodies and correlation in outcomes at the school level. We isolate the school’s contribution to the student’s exam outcome by estimating a fixed-effects logistic regression

²⁰Student i ’s choice set is defined as all the schools within r_i kilometers of his home address, where r_i equals $\min\{10 \times [1 + (\text{median}(\text{“PopDens”}) - \text{“PopDens}_i\text{”}) / \text{median}(\text{“PopDens”})], 20\}$. The radius r_i takes on values between nine and 20 kilometers and equals 18 kilometers for the median student with respect to population density (not tabulated). The radius r_i increases as population density decreases.

²¹We also verified that, in the final sample, the students’ choice sets overlapped and effectively connected each school in the data with all remaining ones through student choice sets, thereby allowing us to identify all school fixed effects relative to a single reference school, as discussed in Section 3.1.

of the student’s likelihood of passing the exam, controlling for student and parish characteristics.²² The results in Table 3 suggest significant variation in passing propensities primarily by student age and gender; female students and younger students are more likely to pass the exam. There is little effect of the income of the student’s parish or whether the student lives in a rural or urban area, but students from parishes with a more highly educated population, captured by the share of the population that has completed compulsory education, are more likely to pass the exam. The logit results suggest significant variation in school fixed effects; Figure 5 contains the empirical distribution across schools. In the demand model, we employ the estimated school fixed effects as an index of school quality.

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 Insert Table 3 about here
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 Insert Figure 5 about here
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4.3 Estimation Results

Preference Heterogeneity. As discussed in Section 3, the estimation of the demand model of school choice is done in two stages. The results from the first stage are reported in Table 4 and include a set of interactions among school characteristics, including price and level of price detail, and student characteristics. These variables are summarized in Tables 1 and 2. In addition, the results include unreported estimates for a full set of school fixed effects (1,000 indicator variables for the 1,001 schools). We present the results for two specifications with different definitions of the price detail variable.

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 Insert Table 4 about here
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²²We interpret the estimated school fixed effect as the school’s contribution to passing, and, thus, as school quality. A second explanation for the within-school correlation in outcomes is sorting by students into schools based on ability. Swanson (2013) proposes an instrumental-variables based approach to correcting the estimated school quality for endogenous sorting in the hospital choice context. In our context we find that accounting for observable demographic determinants of sorting into schools results in a statistically significant improvement in model fit over a model that includes school fixed effects only (likelihood ratio test statistic of 1165.62; p -value of 0.0001). At the same time, adding student demographics does not significantly affect the estimated school fixed effects (i.e., the correlation between the school fixed effects based on models with and without demographics is 0.986). While this does not rule out a contamination of the estimated school quality by unobserved determinants of school sorting, it is suggestive that such effects might be limited in our setting.

The results in Table 4 are, for the most part, intuitive. Across the two specifications, and as expected, distance plays a large role in student decisions when choosing a driving school. Students who live in more urban areas are less sensitive to the distance to get to their driving school training. This could be because it is easier to travel (due to the availability of public transportation) in less rural areas. In addition, people who live in more urban areas are more price sensitive; we do not find significant differences in price sensitivity between students of differing ages or genders.

We include the same interactions of demographics with price detail. Our results suggest that younger students value price detail more, being more likely to choose a school that provides either detailed price information in total, or, in the second specification, relatively detailed price information (price detail level “1”) and, in particular, very detailed price information (price detail level “2”). The majority of the student population is made up of high-school students or recent high-school graduates, with the student age distribution exhibiting a relatively narrow interquartile range of 18.4 to 22.5 years of age at the time of the first theory exam. The distribution exhibits a long right tail, however, with the oldest student in the sample being 78 years of age and more than 10 percent of students being above the age of 30. This older portion of the student population likely differs significantly from their high-school counterparts in their preferences; the age effects that we observe in the response to price detail are one such indication. In both specifications, we also find that preference for price detail, and again price detail level “2”, is most pronounced among students in urban areas relative to students in less urban and rural areas. We interpret the magnitudes of the estimated price detail coefficients below, after having estimated mean price responsiveness.

Mean Utility. Turning to the estimates of mean utility levels in the second stage of the estimation, recall that we are estimating Equation (4), with the estimated school fixed effects from the first stage as our left-hand side variable. We report both OLS and 2SLS estimates; the two-stage least squares results rely on two school cost shifters – the average price of one liter of diesel gasoline in the municipality in which a given school is located and the distance from each school to the school’s most frequently used exam center – as instruments for price. The OLS estimates that correspond to Specifications (1) and (2) in Table 5 are reported in columns (OLS-1) and (OLS-2), respectively, while we denote the IV estimates as (2SLS-1) and (2SLS-2).

We include in our empirical specification of mean utility a number of school characteristics, such as the age of the cars in the school’s fleet or the experience of its instructors. Further, we include, as a proxy for school quality, the above described “case-mix” adjusted mean exam pass rate. The coefficients on the school characteristics indicate that students on average prefer schools with a web presence, located close to secondary schools (consistent with a significant share of students still completing high-school), with more experienced instructors, with more cars in their fleet, and with a larger student population (proxied by the number of cars and the number of license types offered). The case-mix adjusted quality variable is also of the expected sign, with students preferring schools with higher pass rates, suggesting that they are at least somewhat informed about differences in schools’ quality along this dimension.

Across specifications, we estimate a negative mean price responsiveness. In moving from the two OLS specifications to the two IV specifications, the price coefficient, in absolute value, almost doubles once we correct for price endogeneity, suggesting that price is indeed correlated with other hard-to-measure school attributes to which students assign positive value. The first-stage F -statistics in the notes to Table 5 suggest that our cost-based instruments are indeed good predictors of price.

Turning to the main variable of interest, the level of price detail, the estimates suggest on average that students prefer more price information to less: schools that provide less price information are less likely to be chosen by a student. Consistent with this interpretation, we find in Specification (2) of the OLS and 2SLS models that students prefer schools providing very detailed price information over schools providing somewhat detailed price information.

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Insert Table 5 about here
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Monetary Value of Price Detail. We translate the price and price detail parameter estimates into interpretable quantities by calculating price elasticities and the value that consumers attribute to price detail, which we report in Table 6. We first calculate price elasticities by estimating each student’s price responsiveness, given the estimated heterogeneity in price sensitivity by demographic groups from the first stage model and the mean responsiveness from the second stage, before aggregating to the level of the chosen school. For each school’s own price elasticity, which we report below in Table 6, this implies:

$$\eta_j = \sum_{i:j \in J_i} \omega_{ij} (\mathbf{Z}_i' \alpha^z - \alpha) \times p_j \times (1 - \Pr \{ch_{ij} = 1\}), \quad (6)$$

where

$$\omega_{ij} = \frac{\Pr \{ch_{ij} = 1\}}{\sum_{k:j \in J_k} \Pr \{ch_{kj} = 1\}}.$$

Here η_j denotes the own price elasticity for school j and ω_{ij} denotes the weight placed on student i in aggregating school j ’s own-price elasticity across students, corresponding to the student’s demand for the school relative to that of all other students for whom school j is one of their possible choices.

To put the estimated price detail coefficients in perspective, we divide each student’s full price detail response, defined as

$$\text{Female} \times \beta_1^{\text{Detail},1} + \text{Age} \times \beta_2^{\text{Detail},1} + \text{MostlyUrban} \times \beta_3^{\text{Detail},1} + \text{FairlyUrban} \times \beta_4^{\text{Detail},1} + \beta^{\text{Detail},2}$$

by the similarly defined full price contribution to utility. Here, $\beta^{\text{Detail},1}$ denote the first-stage coefficients on the individual characteristics’ contribution to the price detail response, whereas

$\beta^{\text{Detail},2}$ denotes the students’ estimated mean responsiveness to price detail from the second stage. The resulting measure represents the equivalent dollar amount by which the price could be changed to have the same effect on utility as having a school provide price detail, in the first specification, or going from a price detail level of “0” to a price detail level of “1” or “2”, in the second specification. As with price elasticities, we aggregate across students, weighting each student by her contribution to the school’s overall demand. We calculate both the own-price elasticities and the monetized values of price detail using the results from the models estimated using two-stage least squares.

We obtain similar price elasticities for the two model specifications based on each of our definitions of price detail (i.e., Specifications (1) and (2) using two and three levels of price detail, respectively). For Specification (2), the estimated first-stage and second-stage price coefficients translate into an average own-price demand elasticity of -5.5 . The distribution of the schools’ own-price elasticities is shown in Figure 6. The dispersion in price elasticities originates from the fact that students with different demographics have different price sensitivities and that prices and characteristics vary across schools.

Turning to the monetized value of price detail, we find that consumers are willing to pay a significant amount for more information about prices. Holding all else constant, and using the results from Specification (2) (i.e., see the bottom panel of Table 6), a school with a price detail level of “1” generates to consumers the equivalent of a €56 price decrease, on average, or 8.1 percent of the average school’s price, relative to a school that provides no information about prices (i.e., price detail level of “0”). Further, if the school provides fully detailed price information (i.e., price detail level of “2”), this is equivalent to an additional price decrease of €53, or altogether 15.6 percent of the average school’s price. On average, students are willing to pay €76 for any price transparency, which corresponds to 11 percent of the service price (i.e., see the results for Specification (1) in the top panel of Table 6). This is suggestive that price transparency is an economically and statistically meaningful driver of demand.

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Insert Table 6 about here
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Heterogeneity in Price Detail Valuations. The literature on price partitioning (see, for example, the recent review by Greenleaf et al. 2016) highlights that particular characteristics of consumers can moderate the effect of such pricing strategies on consumer purchase behavior. For example, experimental evidence has shown that individual characteristics such as the level of need for cognition (Burman and Biswas 2007 and Cheema 2008) and the information processing style (Kiljae, Choi, and Li 2014) affect consumers’ preferences for partitioned versus all-inclusive prices.²³ Because our data contain significant demographic variation, we are able to analyze whether there

²³The “need for cognition” refers to “the tendency of individuals to engage in and enjoy thinking” (Cacioppo and Petty 1982).

is heterogeneity in price detail valuations, and how such heterogeneity aligns with the students' attributes of age, gender, and location of residence.

To characterize the heterogeneity in transparency valuations, we focus on schools' provision of any degree of price detail, following Specification (1) in Table 4 for the first stage, and Specification (2SLS-1) in Table 5 for the second stage. Figure 7 shows the raw distribution of estimated price detail valuations at the level of the student (truncated at €50, for visualization purposes) for the school that the student chose to attend. In the sample, estimated valuations vary, ranging from €36.5 to €83.4, with a mean of €76.5 and a median of €80.1 (not tabulated), pointing to significantly lower valuations of certain student subgroups that pull down the average. Variation in school size and the demographic composition of the student body reduces this influence at the school level; when aggregated to the level of the school, average and median valuations are both €75.7 (i.e., see the top panel of Table 6).

The valuation distribution in Figure 7 exhibits several local modes – corresponding to discrete jumps in valuations due to the student's gender and degree of urbanization of their location – and a heavy concentration of students at high valuation levels. As the demand model implies valuations decline in age, these valuation levels represent younger students at the end of high school who account for a significant share of the sample. In Figure 8, we show the relationship between the value of price detail and student age graphically. The figure presents a binned scatterplot of the monetary value of price detail at the chosen school on the student's age. We condition on the student's gender and degree of urbanization of her location as the remaining demographic attributes along whose lines we allow transparency valuations to differ.

Figure 8 suggests that gender and urbanization affect the value placed by students on price detail, but to differing degrees: the average female student attributes only the equivalent of an additional €1.43 over the average male student's €75.76 to attending a school that provides any level of price detail. At the same time, students in the most urban parishes value price detail between €5.70 and €17.05 more, on average, than their counterparts in less predominantly urban locations. Student age is similarly an important moderator of price detail valuation. The youngest students under the age of 20 (corresponding to 62.0 percent of the sample) place on average a value of €77.30 on attending a school that is transparent in its pricing, compared to €66.31 among the oldest students above the age of 40 (3.7 percent of the sample). A simple regression of valuations on age and urbanization and gender indicators suggests that a one standard deviation increase in age, or 6.8 years, decreases valuations by €2.80. While not as economically significant as the urbanization effects among the bulk of the younger students, the wide age distribution entails similar disparities in detail valuations for the sample as a whole.

On net, we find that valuations for price detail are positive across all students groups, albeit with significant heterogeneity. We, thus, find no evidence to support arguments put forth in the policy debate that consumers may prefer all-inclusive prices for their simplicity and ease of comprehensibility in environments where firms' charges are made up of a significant number of individual price components. Instead, our results are consistent with consumers valuing an understanding of

individual charges. Since schools always present the full price of the course, we cannot affirm a conclusion frequently put forth by the partitioned pricing literature that such a valuation of price detail derives from an underestimation of the all-inclusive price by relying on the primary component's price as a stand-in. Further, the fact that younger and urban students place higher value on price detail suggests that the specific information provided might be more valuable to them in lowering their school search costs, or, alternatively, that there are differences in students' ability to understand and act on the information provided.

5 Conclusion

In this article we estimate a structural model of demand for driving schools and uncover consumers' valuations for price transparency. We take advantage of unusually detailed data that allows us to study how a wide range of customers respond to how price information is relayed to them. We find that consumers are willing to pay a significant amount for price transparency, and that there is significant heterogeneity in preferences for transparency.

Our work is distinct from most of the research on price obfuscation (e.g., Ellison and Ellison 2009) insofar as we study the pure value of providing more information on the different components of price. Some of the previous empirical research on price obfuscation has associated more price components to unexpected (by the consumer) surcharges that may be seen as deceiving pricing practices.

Our results suggest that more price information, per se, may be beneficial to consumers. Such positive effects of additional price detail may arise from a reduction in search costs and increased ease of comparing prices (cf. Carlin 2009, Wilson 2010, and Ellison and Wolitzky 2012). Cleanly detailing additional fees, in particular if they appear cost-based, can also serve as an informative signal about product quality (Völckner, Rühle, and Spann, 2012), or to enhance consumer perceptions of the seller's trustworthiness and, thus, purchase intentions (Xia and Monroe, 2004). Experimental evidence (Bertini and Wathieu, 2008) further suggests that providing a detailed price breakdown results in consumers making a more thorough assessment of the product and devoting more attention to the components' product attributes and their benefits, thereby similarly raising demand. Disentangling, possibly by combining observational data such as ours with survey information, which of these mechanisms bears primary responsibility for the transparency effects we estimate is an interesting avenue for future research.

Our results also raise a number of public policy questions. Regulatory interventions are typically motivated by a concern that additional price information results in consumer confusion and take the form of standardizing price disclosures around pertinent price information. Here we focus on the provision of information per se, regardless of format; firms use a wide variety of ways of communicating the price information. By lowering price comparison costs, both the provision of information and standardization might improve consumer choice and the competitiveness of markets. We leave the assessment of the interplay between these two forces for future work.

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Figures and Tables

Figure 1: Driving Schools by Municipality, Mainland Portugal

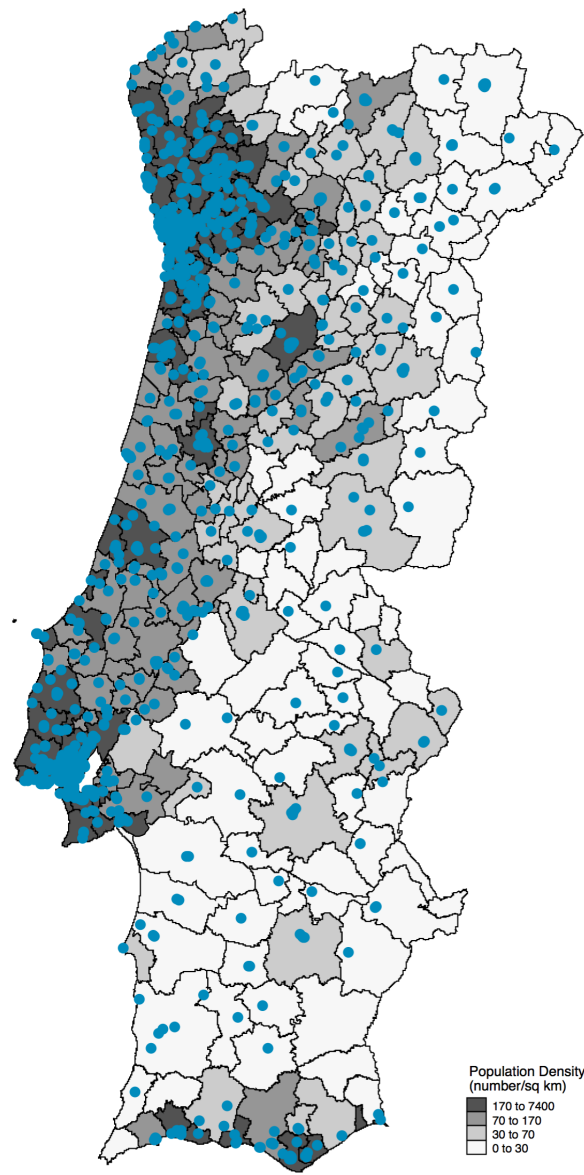
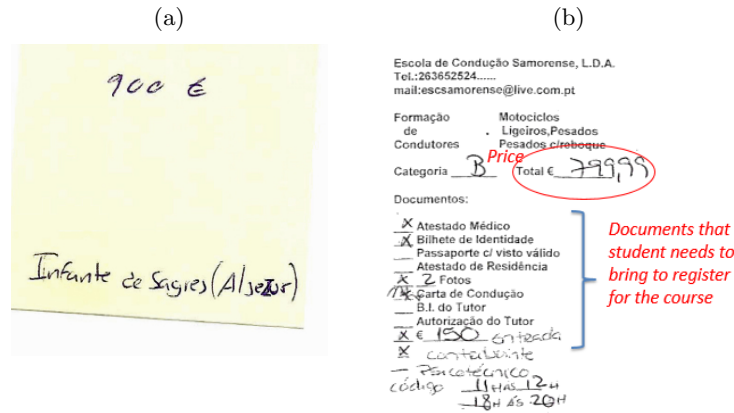
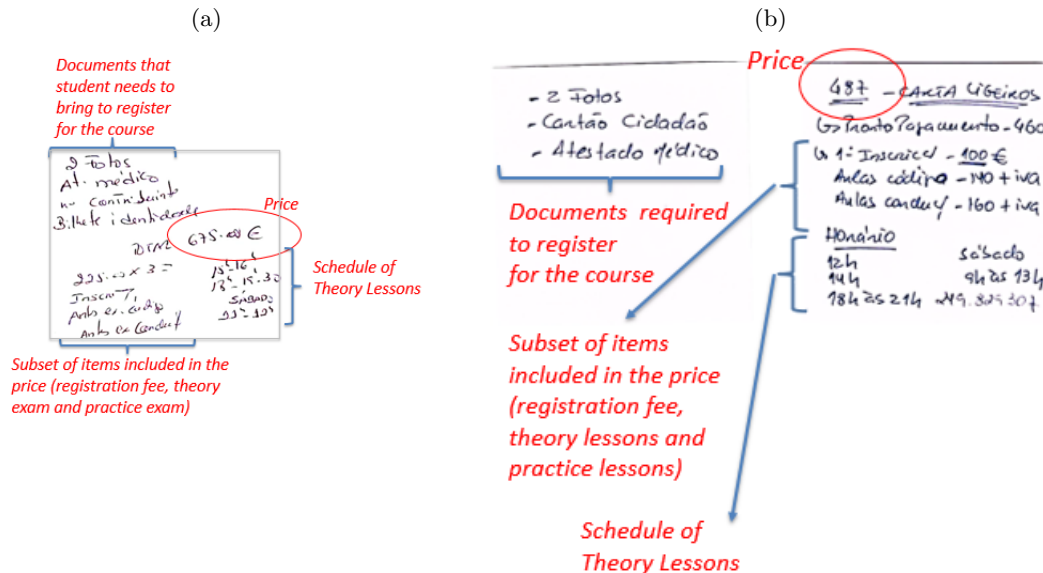


Figure 2: Examples of Price Detail Level Zero (not transparent)



Note: This figure provides two examples of schools classified to be providing a price detail level of zero, where they quote a single total base price only (either via post-it in panel [a], or pre-printed in panel [b], together with a list of the documents required for registration).

Figure 3: Examples of Price Detail Level One



Note: This figure provides two examples of schools classified to be providing a price detail level of one, where they quote a single total base price, together with a list of some, but not all, price components.

Figure 4: Examples of Price Detail Level Two (transparent)

(a)

ESC. DE CONDUÇÃO DAMIÃO DE GOES CAT.B – LIGEIOS			
Fracções	1	207,30 €	(acto inscrição)
	2	88,58 €	(inicio aulas prat.)
	3	66,46 €	(marcar exame cond.)
	4	359,69 €	(rest. Aulas de cond.)
	5	155,31 €	(marcar exame prat.)
	Total	877,34 €	Price
3 FOTOCOPIAS DO B.I			
3 FOTOGRAFIAS			
3 FOTOCOPIAS CONTRIBUINTE			
ATESTADO MEDICO			
NÃO INCLUI TAXA DE EMISSÃO			

Payment upon registration
Payment when start practice lessons
Theory Exam
Practice Lessons (second half)
Practice Exam

Documents that student needs to bring to register for the course

Driver License's issuance fee not included

(b)

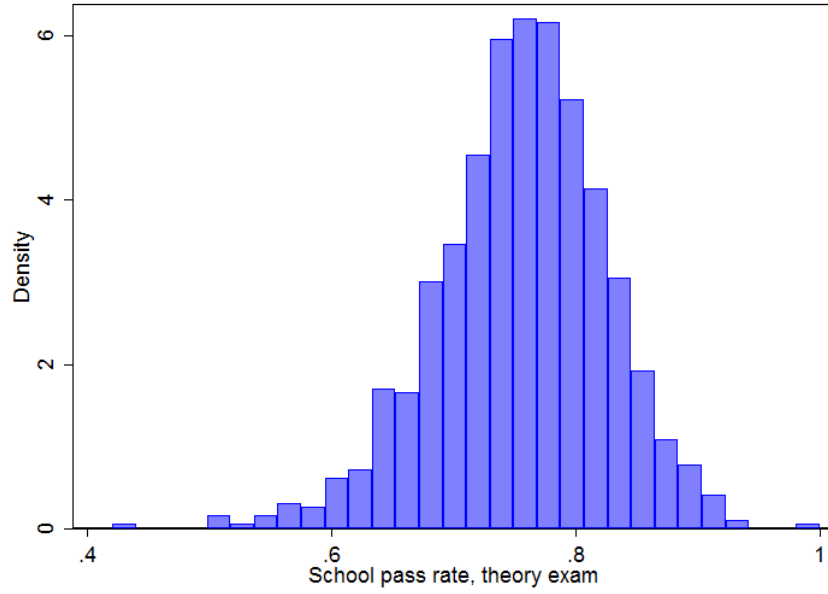
TABELA CATEGORIA B		
Designação	P/unidade	Preço
Inscrição		30,00 ✕
Licença aprend.		20,00 ✕
Lições teóricas		64,65 ✕
Lições práticas	16,00	512,00
Exame teórico		110,95
Exame prático		121,00
Utilização veículo		42,00
Deslocação veículo		12,00
Emissão carta		30,00
Total		892,60

Registration Fee
Learner's Permit Fee
Theory Lessons
Practice Lessons
Theory Exam
Practice Exam
Transportation
Practice Exam
Driver License's issuance fee

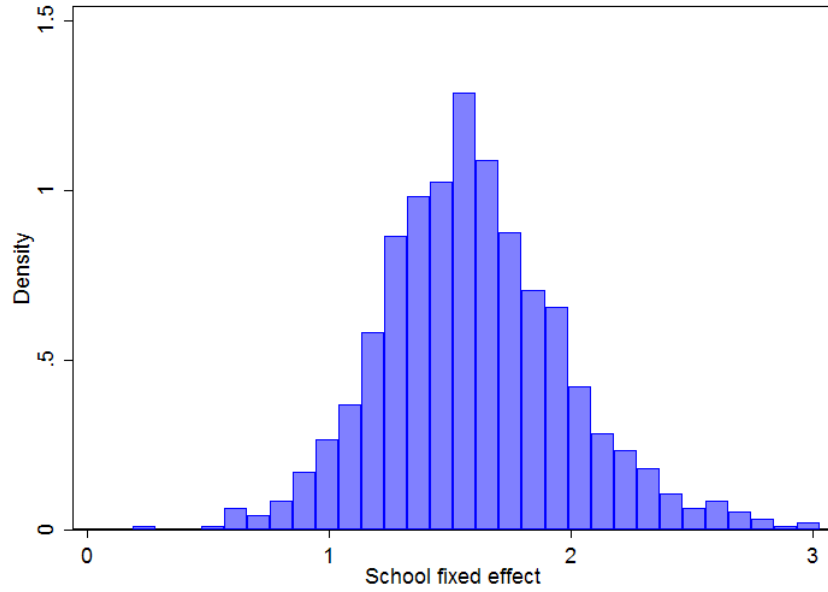
Note: This figure provides two examples of schools classified to be providing a price detail level of two, where they quote a single total base price, together with a list of all price components, itemized for at least some.

Figure 5: School Pass Rates and Contributions to Passing

(a) School pass rate on theory exam

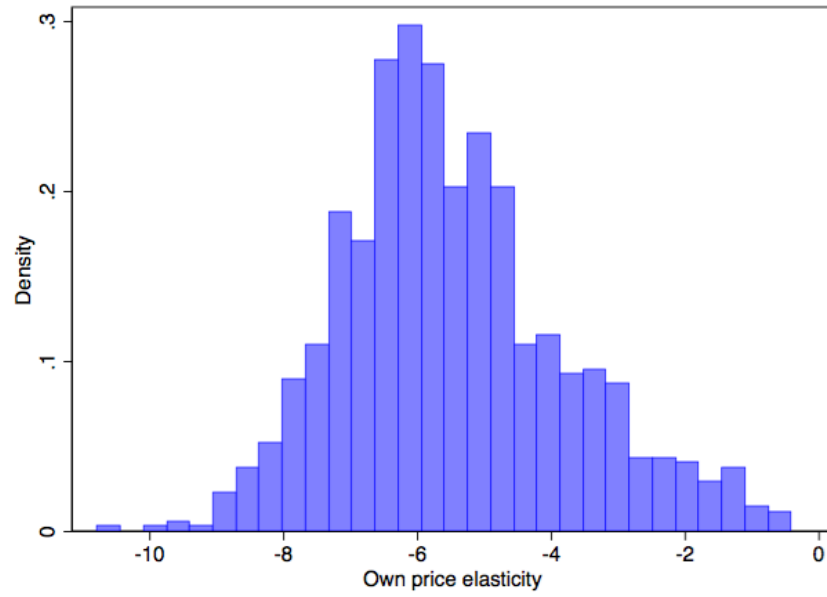


(b) Estimated school fixed effects: school mean quality



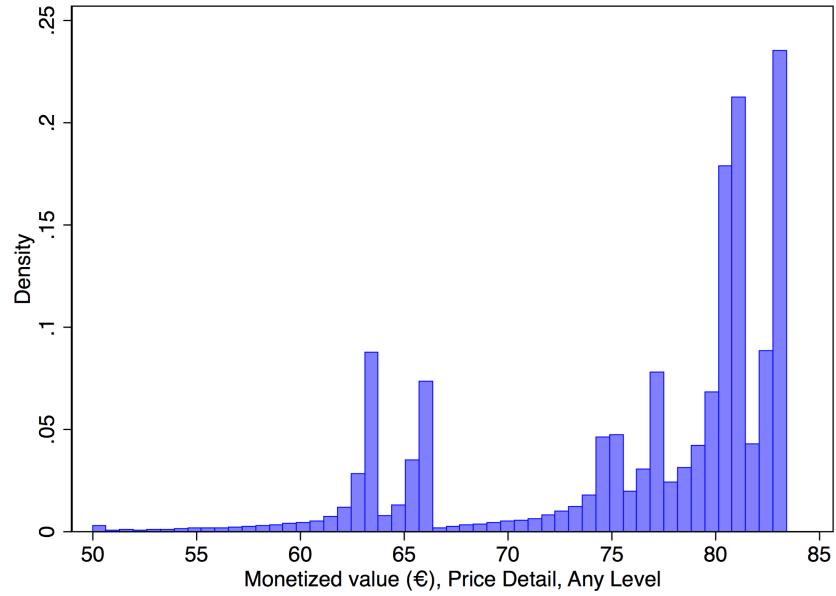
Note: These figures show the distributions of pass rates on the theory exam, defined as the share of first-time theory exam takers who pass, and of the school fixed effect estimated in the logit model of the probability of passing in Table 3.

Figure 6: Own Price Elasticities of Demand



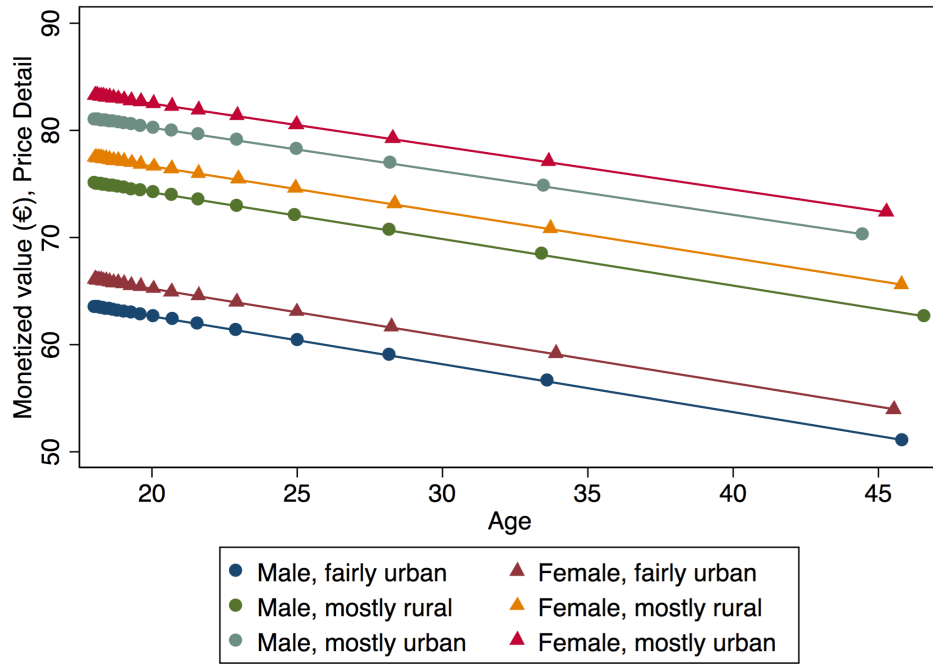
Note: This figure shows the distribution of mean own-price elasticities for the sample of driving schools (obtained as a probability weighted average across students) using the results from the demand model given by Specification (2) in Table 4 (first stage) and (2SLS-2) in Table 5 (second stage).

Figure 7: Distribution of Monetized Value of Price Detail



Note: This figure shows the distribution of the monetized value of schools providing any level of price detail for the student sample at their chosen school using the results from the demand model given by Specification (1) in Table 4 (first stage) and (2SLS-1) in Table 5 (second stage). Monetized values are truncated at €50, for visualization purposes.

Figure 8: Monetized Value of Price Detail, by Age, Gender, and Degree of Urbanization



Note: This figure shows a binned scatterplot of the monetized value of schools providing any level of price detail on student age for the student sample at their chosen school using the results from the demand model given by Specification (1) in Table 4 (first stage) and (2SLS-1) in Table 5 (second stage).

Table 1: Summary Statistics, School Characteristics ($N = 1,001$)

	Mean	Std Dev	Q25	Med	Q75
Price, base course of instruction (€)	695.335	108.261	620.000	695.000	765.000
Price detail, full categorization					
Level 0 (0=N, 1=Y)	0.118	0.323	0.000	0.000	0.000
Level 1 (0=N, 1=Y)	0.484	0.500	0.000	0.000	1.000
Level 2 (0=N, 1=Y)	0.399	0.490	0.000	0.000	1.000
Price detail provided (0=N, 1=Y)	0.882	0.323	1.000	1.000	1.000
Web Presence (0=N, 1=Y)	0.404	0.491	0.000	0.000	1.000
Secondary School (0=N, 1=Y)	0.275	0.447	0.000	0.000	1.000
Instructor Experience (years)	7.678	5.441	3.875	6.111	9.944
Number of Passenger Vehicles	3.614	2.396	2.000	3.000	4.000
Age of Passenger Vehicles (years)	5.677	3.433	2.836	4.917	8.337
School Age (years)	20.133	16.072	8.189	10.407	28.945
Number of License Types	5.477	2.088	4.000	4.000	7.000
Total Classroom Capacity (students)	30.880	12.395	22.000	27.000	37.000
Distance to exam center (km)	19.913	17.774	6.286	15.197	27.828
Gas price in school's municipality (€)	1.419	0.035	1.398	1.409	1.439

Note: This table reports descriptive statistics for prices and price reporting indicators (top panel) and non-price characteristics (bottom panel) for the sample of 1,001 driving schools in mainland Portugal. “Price detail, full categorization” refers to a categorization of schools into three levels of price detail, as described in Section 2.2. “Price detail provided” is a binary variable that classifies schools as transparent (price detail levels “1” or “2”) or not transparent (price detail level “0”). “Web presence” indicates whether the school maintains a website. “Secondary school” is a binary variable that indicates whether there is a secondary school located within 500 meters of the school. “Age of passenger vehicles” is the median age of the school’s instruction vehicles. “Number of license types” refers to the number of different license types (e.g., passenger vehicles, trucks) offered by the school. “Distance to exam center” is the distance from the school to the school’s most frequently used exam center. “Gas price in school’s municipality” is the lowest gas price for one liter of diesel fuel in the school’s municipality.

Table 2: Summary Statistics, Student Characteristics ($N = 142,913$)

	Mean	Std Dev	Q25	Med	Q75
Age at theory exam (years)	22.335	7.202	18.396	19.217	22.524
Gender (0=M, 1=F)	0.520	0.500	0.000	1.000	1.000
Parish population density (number/sq km)	243.499	316.968	36.700	118.600	314.200
Parish urban-rural classification					
Mostly rural (0=N, 1=Y)	0.128	0.334	0.000	0.000	0.000
Fairly urban (0=N, 1=Y)	0.195	0.396	0.000	0.000	0.000
Mostly urban (0=N, 1=Y)	0.678	0.467	0.000	1.000	1.000
Parish Mean Income (€)	852.486	229.573	694.970	825.010	958.650
Parish Compulsory Education (% inhabitants)	30.714	12.671	20.680	29.660	39.080
Distance to chosen school (km)	3.324	3.462	0.821	2.111	4.659
Is choice closest school? (0=N, 1=Y)	0.402	0.490	0.000	0.000	1.000
Rank of choice by distance	3.403	3.901	1.000	2.000	4.000
Number of theory exams taken	1.536	1.040	1.000	1.000	2.000
Number of on-road exams taken	1.450	0.785	1.000	1.000	2.000
Passed first theory exam taken (0=N, 1=Y)	0.762	0.426	1.000	1.000	1.000
Passed first on-road exam taken (0=N, 1=Y)	0.753	0.431	1.000	1.000	1.000
Time to completion (days)	255.423	155.092	144.000	213.000	324.000

Note: This table reports descriptive statistics for demographic characteristics (top panel), school choices (middle panel), and exam performance (bottom panel) for the sample of 142,913 students who obtained their driver's license in 2009 or 2010. "Parish urban-rural classification" refers to *Portugal Statistics'* categorization of parishes into three levels based on population density, total population, and land use: mostly rural, fairly urban, and mostly urban. "Parish compulsory education" is the percentage of population in the student's parish who have completed compulsory education. "Rank of chosen school" refers to the rank of the student's chosen school in terms of proximity to the student's residence. "Number of theory exams taken" and "Number of on-road exams taken" are the number of theory and on-road exams taken by the student, respectively, before obtaining the driver's license. "Time to completion" is the number of days that lapsed between a student obtaining the learner's permit and the driver's license.

Table 3: Logit Model of Probability of Passing the Theory Exam

Female	0.458*** (0.050)
Age	−0.037*** (0.005)
AgeSquared/10	0.003*** (0.001)
Female×Age	−0.016*** (0.002)
Female×FairlyUrbanParish	0.054 (0.035)
Female×MostlyUrbanParish	0.013 (0.032)
Log(IncomeParish/1000)	−0.007 (0.048)
ParishPopulationDensity	0.005 (0.004)
ParishCompulsoryEducation	0.006*** (0.001)
Observations	142,913

Note: This table reports estimates for a logit model of the student’s outcome of their first theory exam taken. Student characteristics are described in Table 2. The omitted reference category is Female×MostlyRuralParish. School fixed effects are suppressed. Standard errors are reported in parentheses under the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Model of School Choice (First Stage Results)

	(1)		(2)	
Distance	-7.246***	(0.078)	-7.245***	(0.078)
DistanceSquared	1.652***	(0.032)	1.652***	(0.032)
Distance×Female	0.068**	(0.028)	0.068**	(0.028)
Distance×ParishPopDensity	-0.856***	(0.013)	-0.856***	(0.013)
Distance×FairlyUrbanParish	0.207***	(0.043)	0.206***	(0.043)
Distance×MostlyUrbanParish	0.203***	(0.051)	0.202***	(0.051)
ClosestSchool	0.333***	(0.008)	0.333***	(0.008)
Female×SchoolAge	0.002***	(0.000)	0.002***	(0.000)
Female×SchoolWebPresence	-0.007	(0.014)	-0.009	(0.014)
Age×SchoolAge	-0.002***	(0.000)	-0.002***	(0.000)
Age×SchoolWebPresence	-0.041***	(0.010)	-0.038***	(0.010)
Price×Female	-0.122	(0.104)	-0.127	(0.104)
Price×Age	0.091	(0.076)	0.098	(0.076)
Price×FairlyUrbanParish	0.091	(0.225)	0.092	(0.225)
Price×MostlyUrbanParish	-0.619***	(0.230)	-0.620***	(0.230)
DetailProvided×Female	0.037	(0.025)		
DetailProvided×Age	-0.056***	(0.018)		
DetailProvided×FairlyUrbanParish	-0.139***	(0.046)		
DetailProvided×MostlyUrbanParish	0.119***	(0.044)		
DetailLevel1×Female			0.028	(0.026)
DetailLevel1×Age			-0.043**	(0.018)
DetailLevel1×FairlyUrbanParish			-0.142***	(0.049)
DetailLevel1×MostlyUrbanParish			0.110**	(0.047)
DetailLevel2×Female			0.050*	(0.026)
DetailLevel2×Age			-0.074***	(0.019)
DetailLevel2×FairlyUrbanParish			-0.135***	(0.051)
DetailLevel2×MostlyUrbanParish			0.131***	(0.048)

Note: This table reports the first-stage estimation results from two different specifications of a multinomial logit model of school choice. School and student characteristics are described in Tables 1 and 2. Interactions between student and school variables are denoted with a “×”. “Distance” refers to the distance (in km) between the student and a school in the choice set. Omitted reference categories are interactions of the variables “DetailProvided” and “DetailLevel” with the variable “MostlyRuralParish” in Specifications (1) and (2), respectively. School fixed effects are suppressed. Standard errors are reported in parentheses next to the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Model of School Choice (Second Stage Results)

	(OLS-1)	(2SLS-1)	(OLS-2)	(2SLS-2)
Price	−6.597*** (0.800)	−11.720** (5.430)	−6.557*** (0.796)	−11.379** (5.426)
PriceDetailProvided	0.977*** (0.264)	0.968*** (0.360)		
PriceDetailLevel1			0.692** (0.275)	0.696* (0.367)
PriceDetailLevel2			1.343*** (0.282)	1.319*** (0.375)
SchoolWebPresence	0.345* (0.181)	0.328* (0.171)	0.299* (0.180)	0.285* (0.171)
SecondarySchool	0.406** (0.194)	0.399** (0.191)	0.381** (0.193)	0.375** (0.188)
InstructorExperience (years)	0.037* (0.019)	0.032 (0.023)	0.039** (0.019)	0.034 (0.022)
NumberPassengerVehicles	0.101** (0.040)	0.067 (0.042)	0.089** (0.040)	0.058 (0.042)
SchoolAge	0.004 (0.007)	0.009 (0.009)	0.003 (0.007)	0.008 (0.009)
MeanQuality	0.435* (0.222)	0.499** (0.253)	0.483** (0.221)	0.541** (0.251)
AgePassengerVehicles (years)	−0.037 (0.026)	−0.045* (0.027)	−0.032 (0.026)	−0.040 (0.027)
NumberLicenseTypes	0.122*** (0.045)	0.151** (0.064)	0.128*** (0.045)	0.156** (0.064)
Constant	1.413* (0.729)	4.828 (3.615)	1.290* (0.726)	4.507 (3.616)
Log-likelihood	−2399.372	−2419.690	−2393.804	−2412.035

Note: This table reports the second-stage estimation results from the demand model where the dependent variable is the estimated first-stage school fixed effect. Models (OLS-1) and (2SLS-1) use the school fixed-effects resulting from Specification (1) in Table 4, and (OLS-2) and (2SLS-2) use those resulting from Specification (2). Independent school characteristics are described in Table 1; “MeanQuality” denotes the case-mix adjusted pass rate from Table 3. The 2SLS specifications use the municipality’s lowest price per liter of diesel fuel and the distance from the school to the school’s most frequently used exam center as instruments for price. The first stage F -statistics are 11.05 for column (2SLS-1) and 10.83 for column (2SLS-2). Standard errors are reported in parentheses under the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Price Elasticities and Value of Price Detail

	Mean	Std Dev	Q25	Med	Q75
Own price elasticity	−5.639	1.734	−6.784	−5.909	−4.719
Monetized value (€)					
Price detail, any	75.781	3.420	73.407	75.743	79.026
Own price elasticity	−5.472	1.684	−6.586	−5.733	−4.575
Monetized value (€)					
Price detail, Level 1	55.785	3.714	53.232	55.696	59.301
Price detail, Level 2	108.318	3.170	106.111	108.381	111.322

Note: This table reports summary statistics for schools' (obtained by summarizing across students within each school) own-price elasticities and the monetary value of price detail calculated using the demand model estimates. The top panel shows results using the estimates for Specification (1) in Table 4 and (2SLS-1) in Table 5 and the bottom panel shows results using Specification (2) in Table 4 and (2SLS-2) in Table 5. Monetized values of price detail are relative to the omitted category "Price detail, Level 0".

Appendix

A Mystery Shoppers Query Script

Figure A.1: Mystery Shoppers' Price Query Script

Portuguese Version:

Guião

- Tenho um sobrinho que brevemente vai completar 18 anos. Como presente de aniversário e em conjunto com outros familiares, estou a pensar em pagar-lhe a carta de condução de automóveis ligeiros.
- Dado que as despesas vão ser **divididas, quanto é que nos vai custar a carta e o que está incluído?** (nota: Como vão ser divididas o cliente tem interesse em saber os diferentes itens para diferentes pessoas da família pagarem itens diferentes, por exemplo, um paga as aulas teóricas, o outro as práticas, etc.)
- Por favor, ponha isso **por escrito**, para apresentar aos outros.
- E, já agora, caso o meu sobrinho chumbe na prova de **código** ou da **condução**, quanto teremos de pagar a mais? (Isso inclui as aulas adicionais?)
- Já agora, posso levar uma **cópia dos horários das aulas disponíveis?**

Situações possíveis

- Se só escreverem o total NÃO insistir para dar mais detalhe
- Se não quiserem escrever e apenas queiram dar o preço oralmente, apontar o preço e outras informações que queiram dar e anotar que só deram o preço oralmente
- Estar preparado para responder a perguntas do género: “de onde é você?” ou “onde vive o seu sobrinho?” (convém estar preparado com uma historia credível antes de visitar as escolas de uma determinada zona)

English Version:

Mystery Shopper Script

- My nephew is turning 18 soon. As a birthday gift, some of my relatives and I would like to pay for his driver's license training.
- Because there are several relatives **sharing the expenses**, can you let me know **what the price is and what is included in the price?** (note: this will allow different family members to pay different items such as the theory training or the on-road training, for example)
- Please put that **in writing** so that I can share it with the other family members.
- By the way, if my nephew fails the **theory** or the **on-road exam**, how much more will we have to pay for him to retake the exams?
- And can you provide me with a copy of the schedule of the **theory lessons?**

Additional notes

- If, even after you asked for it, the school chooses to provide only the total price and no further details, then do NOT insist further.
- If the school employee does not want to write down things him- or herself, you can write it down yourself but note in the report that the information was written by you
- Be prepared to respond to questions such as “Where are you from?” or “Where does your nephew live?”, etc. (some schools are located in less urban areas and know the region and its people well)

B Hedonic Price Regressions

	(1)		(2)	
PriceDetailProvided	0.031*	(0.017)		
PriceDetailLevel1			0.030*	(0.017)
PriceDetailLevel2			0.032*	(0.020)
SchoolWebPresence	0.015*	(0.008)	0.015*	(0.008)
SecondarySchool	−0.008	(0.007)	−0.008	(0.008)
InstructorExperience	−0.000	(0.001)	−0.000	(0.001)
NumberPassengerVehicles	−0.003	(0.002)	−0.003	(0.002)
SchoolAge	0.001*	(0.000)	0.001*	(0.000)
MeanQuality	0.023*	(0.013)	0.023*	(0.013)
AgePassengerVehicles	−0.004***	(0.001)	−0.004***	(0.001)
TotalRoomCapacity	0.001**	(0.001)	0.001**	(0.001)
Log(Population)	−0.025**	(0.012)	−0.025**	(0.012)
PopulationDensity/1000	−0.010	(0.008)	−0.011	(0.008)
PropPopUsingCarDaily	0.001*	(0.001)	0.001*	(0.001)
Income/1000	0.059	(0.077)	0.061	(0.078)
FairlyUrbanMunicipality	−0.031	(0.022)	−0.031	(0.022)
MostlyUrbanMunicipality	−0.053**	(0.023)	−0.053**	(0.023)
R-Squared	0.391		0.391	

Note: This table reports the results from two specifications of a hedonic regression of the log of school prices on school and municipality characteristics. Independent school characteristics are described in Table 1; “MeanQuality” denotes the case-mix adjusted pass rate from Table 3. “PropPopUsingCarDaily” refers to the proportion of the population in the school’s municipality with daily car use. “Income” refers to the average monthly income (in €) of the population in the school’s municipality. The omitted reference categories are “MostlyRuralParish” in both specifications, and “PriceDetailLevel0” in Specification (2). District fixed effects are not reported. Standard errors clustered at the municipality level are reported in parentheses next to the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.