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"Collusion in Bidding Markets: The Case of the French Public Transport Industry"

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Collusion in Bidding Markets: The Case of the French Public Transport Industry[1]

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Abstract

We explore empirically the impact of the market sharing collusive practices that were implemented in the French public transportation industry between 1994 and 1999. We build a structural model of bidding markets where innovating firms compete for the market and have the ability to spread the benefits of their innovation through all markets on which they are active. Each local competitive environment shapes the distribution of the prices (the bids) paid by public authorities to transport operators. We recover empirically the distribution of prices and innovation shocks and we show that collusive practices had overall a limited impact on prices. Firms were in reality more interested in avoiding significant financial risks inherent to the activity, as well as the high cost of preparing a tender proposal. As a by-product, we perform a counterfactual analysis that allows us to simulate how an increase in firms' innovation reduces prices significantly.

JEL codes: D22, D44, K21, L9
Keywords: Bidding Markets, Market Sharing, Collusion, Innovation, Public Transport

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1 Introduction

The French public transport sector is a very mature market with well-established actors. This market is organized through bidding procedures which are run at the local level. Through these procedures, political entities (municipalities or group of municipalities) allocate service to firms which stand ready to operate at the lowest price. The first important feature of these bidding markets is that the French public transport sector is not a single unified market but a collection of smaller markets run with independent auctions. Second, key players participate to tender procedures on many markets, with various configurations of participants and thus various potential degrees of competitive pressure on each of those. Typically, nowadays, Veolia, Transdev and Keolis are the three major players, but there are also smaller firms, namely RATP, Carpostal, and Vectalia, which are more marginal and show up under limited circumstances.

As forcefully argued by Klemperer (2007), the abuse of market power remains a serious concern in such setting. In 2005, the French Competition Authority (FCA) imposed financial penalties for an illegal cartel formed between 1994 and 1999, amounting to €3.9 million for Keolis, €5.05 million for Connex, and €3 million for Transdev, and representing 5% of their 2003 revenue (Autorité de la concurrence, 2005). The FCA established that the executives of these transport operators met multiple times to coordinate their bidding strategies and exchange information. They agreed not to compete to ensure that the incumbent operator remains in place, and they would threaten retaliation against any firm that might disrupt their anti-competitive scheme. Thus, the purpose of this cartel was to disrupt the normal competitive process in the awarding of public transport contracts and violate the principles of competition and transparency established by the 1993 loi Sapin. In normal competitive conditions, public tenders provide transport operators with incentives to reduce their need for public subsidies while encouraging them to innovate.[4] Collusive practices have instead led to reduced

[4]Innovation in the field is complex and covers a whole range of activities that go from improving and greening the infrastructure, reducing costs, improving the location of inputs within the network (the main concern is the management of bus drivers), finding cheaper suppliers, bargaining better procurement contracts, subcontracting non-essential activities, monitoring employees, or solving potential labor conflicts. It also entails the development of a computerized information system which allows the operator to observe in real time the position of all vehicles in the network, changes in environmental friendly energy standards and propulsion systems, or trip information to travelers. Finally, the operator might negotiate with the regulator the introduction of bus priority or guided busway on specific network segments in order to improve commercial speed, or the use of smaller vehicles or low floorbus, the design of timetable and frequency, or pricing and marketing strategies.

efficiency and innovation. Moreover, given the limited number of credible competitors in the market, the restriction of competition often eliminated any real choice for public authorities. As a result, the cartel entailed a systematic renewal of incumbent operators, and even reinforced market segmentation in France, discouraging other European companies from competing in the affected tenders. In its 2005 decision, the FCA expected that this explicit anti-competitive coordination could potentially lead to artificially inflated pricing, forcing local authorities to bear higher costs for their transport concessions than they would have under a competitive market.

In this paper, we test empirically whether these market sharing agreements have had any impact on the prices (the bids) proposed by transport operators. The FCA feared that prices could go up, but has until now provided only limited anecdotal evidence on this matter. In our empirical exercise, we compute the but for price that would have prevailed absent the conspiracy and we compare it to the observed cartel price. We focus on the award procedures for public passenger transport contracts that were either newly issued or renewed between 1994 and 1999 in 9 urban public transport networks that were under the particular scrutiny of the FCA. As a first contribution, we show that the price distortions during the cartel period have been in fact very limited.

Our second contribution is methodological: To conduct our analysis, we construct a structural model of bidding markets where several strategic players hold private information on their own costs and express bids to provide the service. The difficulty in studying market power on such markets comes from the fact that, when firms invest in innovation and provide effort to enjoy efficiency gains, they shift their cost distribution, and such changes thus require to analyze asymmetric first-price auctions, which is a notoriously complex analysis. Beyond proofs of existence and uniqueness of equilibrium strategies (Maskin and Riley, 2000; Lebrun, 2006), such asymmetric models are generally non-tractable. In sharp contrast with the symmetric setting, no closed-form solutions exist for the system of differential equations solved by the players' bidding strategies beyond some very specific models.[5] In the real world, the cost structure of

[5]Some researchers focusing on the impact of mergers between firms have focused on highly specified models for which the consequences of a merger can be analytically assessed. Dalkir, Logan, and Masson (1998) and Janssen and Karamychev (2013) have studied the case where bidders have uniform distributions pre-merger. Tschantz et al. (2000) have proposed another tractable model with extreme values distributions. Thomas (2004) has focused on discrete distributions and derived tractable mixed-strategy equilibria in those contexts. Admittedly, real-world data are unlikely to be conveniently calibrated with

players is unlikely to be close to being uniform, discrete or even extreme values. Insights gathered with specific distributions might not be robust when real data dictate other choices. The analysis must definitively move towards being more empirically oriented; a path that we follow in this paper.

We follow the steps of the earlier theoretical literature on asymmetric first-price auctions (Maskin and Riley, 2000; Lebrun, 2006; Dalkir, Logan, and Masson, 1998; Janssen and Karamychev, 2013) in deriving equilibrium conditions of bidding strategies. Yet, we are giving a closer look at real data and we take seriously the best-response behavior of bidders on all bidding markets on which they are active and express this behavior in terms of the distribution of prices they choose under various scenarios. This step allows us to determine expected prices under different competitive interaction scenarios. At a best-response, a bidder forms conjectures on the bid distributions of his rivals. Raising its own bid thus decreases the probability of winning although it also increases its price-cost margin. The optimal bidding strategy balances those two effects. At a best-response, the optimal price-cost margin depends on how elastic is the probability of winning the market; an equilibrium object since it depends on the bidding strategies of competitors.

Thus, instead of working with bidding strategies (or their inverses as, for instance, Maskin and Riley, 2000, and Lebrun, 2006) as previous theoretical literature, we consider that the distributions of realized bids that those strategies induce are the key variables to characterize best responses. An outside observer of the market is unlikely to have direct information on costs but might want to infer that information from the observed winning bids. This approach in terms of distributional strategies was earlier on pioneered by Milgrom and Weber (1985) on the theoretical front. Since then, it has certainly been the cornerstone of the empirical literature on auctions, especially after the seminal work of Laffont, Ossard and Vuong (1995).[6] The system of differential equations that is satisfied by bidding strategies is now replaced by a system of Fredholm equations of the first kind that link the distributions of bids with the underlying distributions of the bidders' innate costs compounded with the distributions of the possible innovations. Realized costs summarizes how innate costs (i.e., the cost of maintain-

uniform or discrete distributions. Marshall et al. (1994) have developed numerical analysis of the system of differential equations that is satisfied by bidding strategies in more general contexts.

[6]See also Guerre, Perrigne and Vuong (2000). Hortacsu and Perrigne (2021) and Perrigne and Vuong (2021) provide up to date surveys of the literature.

ing the network and providing the service), a first dimension of private information for bidders, can be reduced by innovation, a second dimension of private information that pertains to all markets on which the corresponding firm is active. From observed bids, we thus recover empirically not only a distribution of potential innovations but also the magnitude of investment in R&D undertaken by bidders on that front and we relate this value to the realized market shares of those firms.

Hence, in our empirical setting, the distribution of prices for each operator depends closely on the competitive interaction they face in each tender. Thanks to the information provided in our dataset, we are able to identify precisely the participants in each tender and identify the competitive pressure impinging on the operators' strategic decisions. We thus recover the distribution of prices for each operator and each competitive setting. As a by-product, our structural model also allows us to retrieve the distribution of the firms' innate cost, the distribution of their innovation activity, and the technological cost of innovative effort. Once the model is fully identified, we consider counterfactual scenarios where firms increase their innovation activity and we simulate the corresponding price reductions.

The organization of the paper is as follows: Section 2 describes the urban transportation industry in France in more details. Section 3 presents our competitive tendering model which encompasses the main features of the industry and the competitive environment in which operators make their strategic decisions. Section 4 is devoted to the construction of the variables and presents the different competitive structures in the industry. Section 5 presents the empirical model and the simulation exercise that allows us to predict price changes consecutive to an increase in innovation by firms. Section 6 provides some concluding remarks.

2 The French public transport industry

As in most countries around the world, urban transportation in France is a regulated activity. Local transportation networks cover each urban area of significant size, and for each network, a local authority (a municipality, a group of municipalities or a district) is in charge to regulate an operator which has been selected to provide the transportation service. Regulatory rules prevent the presence of several suppliers of transportation services in the same urban network, and each network is therefore operated by a single operator. Each local authority organizes its own transportation system by setting route and fare structures, capacity, quality of service, conditions for subsidizing the service, levels of investment and ownership nature. The local authority may decide to operate the network directly or to acquire the services of a transport service provider. In the latter case, a formal contract defines the regulatory rules that the operator must follow as well as the cost-reimbursement scheme. On average, operating costs are at least twice as high as commercial revenues (Commissariat général au développement durable, 2018). Budgets are therefore rarely balanced and the operator needs to receive a subsidy to balance its budget.[7]

During our period of observation, about eighty percent of local operators are private and are owned by three large companies, two of them being private while the third one is semi-public. These companies are Keolis, Transdev and Veolia Transport (known as Connex before 2005, and denoted as Veolia in what follows). Industrial groups involved in the provision of urban transport services have a long history of mergers in France. Keolis was born out of the merger of several companies created in the beginning of the 20th century. The Société des transports automobiles, created in 1908, its subsidiary (the Société générale des transports départementaux) and the company Lesexel, founded in 1911 to help on the development of tramways, merged to form the VIA-GTI company, mainly focused on urban transport. In the meantime, another company, Cariane, was specialized in the French interurban transport. Ultimately, VIA-GTI and Cariane merged in 2001 to give birth to Keolis. The industrial group Connex was born out of the merger of the Compagnie Générale Française des Transports et Entreprises (CGFTE) and the Compagnie Générale d'Entreprises Automobiles (CGEA) in the late 1980's. The company was ultimately renamed Veolia Transport in 2005. Finally, the Transdev group was created in 1955.

The automatic renewal of the contract between the local authority and the operator in place was effectively ended, by law, in 1993. Since then, local authorities are required to use tenders to allocate the construction and management of infrastructures of urban

[7]One reason is that operators face universal service obligations and must operate in low demand areas. Low prices are maintained to ensure affordable access to all consumers of public transportation. Moreover, special fares are given to targeted groups like seniors and students. Subsidies come from the State's budget, the local authority's budget, and a special tax paid by local firms (employing more than nine full-time workers). In addition to the price distortions causing deficits, informational asymmetries that affect the cost side and lead to inefficiencies make it more difficult to resume these deficits.

transportation. In practice, however, until 2000, very few networks have experienced change of operators from one regulatory period to another. As a matter of fact, the three main groups succeeded in committing to distinct geographical areas and reducing the degree of competition in the awarding of transport operations in urban areas where the regulatory contract came to an end. The lack of competition before the 2000s was also reinforced by the fact that these groups typically operate other municipal services such as water distribution or garbage collection, which makes it even harder for public authorities to credibly punish operators following bad performance. Obviously, this effect got reinforced between 1994 and 1999, when the largest operators implemented collusive strategies to kill competition.

Our database provides information on both the performance and the organization of the French urban transport industry. Such a database was created in the early 1980s from an annual survey conducted by the Centre d'Etude et de Recherche du Transport Urbain (CERTU, Lyon) with the support of the Groupement des Autorités Responsables du Transport (GART, Paris), a nationwide trade organization that gathers most of the local authorities in charge of an urban transport network. In France, this rich source is a unique tool for comparing observed regulatory schemes both across year and over time. In our econometric analysis, we consider the regulatory scheme adopted in each urban area during a year as a realization of the same regulatory contract. Overall, the panel data set covers 205 different urban transport networks over the period 1995–2014.

3 The Model

We present in this section a stylized theoretical model of the French market for urban transport. It allows us to build a structural framework that we take to the data in order to identify the main building blocks of interest in our empirical investigation: The distributions of prices that are conditional on the competitive structure of each local market, the distribution of the innovation shocks, and the cost of the innovation effort.

3.1 Preferences, Technology, and Markets

There are m municipalities indexed by $j \in \mathcal{M} = \{1, ..., m\}$ and on each of those markets, there are n potential firms that could bid for providing the services. We index those firms by $i \in \mathcal{N} = \{1, ...n\}$. In our empirical analysis, the largest bidders are Veolia, Transdev, and Keolis, but there are also smaller firms, namely RATP, Carpostal, and Vectalia, who participate in the tenders.

We are ranging those markets into subsets for which the same set of firms $\mathcal{K} \subseteq \mathcal{N}$ are active. There are thus *a priori* $C^n_{|\mathcal{K}|}$ such subsets of size $|\mathcal{K}|$. Indeed, for some exogenous reasons (costs of submitting bids, overall deployment strategy, etc.) a given firm may not be active on all markets at once. We have no a priori information on the determinants of such participation. We will thus proceeds in two steps. First, we will take these participations as given and derive some first results for a fixed market configurations. To illustrate, our empirical analysis will focus on several possible configurations, depending on which firms participate in the competitive bidding. In the short-run, the number and identities of participants on a given market are well known so that entry considerations can be put aside. Second, we shall also provide techniques to endogenize participation decisions and study how market configurations evolve in the long run.

At the local level, say on market j, (a single municipality, a group of such municipalities, or sometimes a sub-municipality when several networks cover such area), public bodies (sometimes referred to as principals in the sequel) run first-price auctions for the provision of the service. In each of those auctions, potential service providers bid by proposing a price for the service. For simplicity, we assume that the overall consumers gross surplus from the service S^j is supposed to be large enough so that running the service is always optimal.[8] S^j can be viewed as the per capita value of one unit of service. Note that those surplus may vary across municipalities. Let Φ denote the corresponding cumulative distribution on $\mathbb{R}_+$ and let ϕ be the corresponding positive density function. In the case of the French public transport, it appears relevant to consider that demand is inelastic.

[8]In other words, there are no reserve prices on those markets. The reason is that public transport and waste services are essential activities that need to be provided anyway.

On each market j belonging to a subset $\mathcal{K}$ for which it is active, bidder i stands ready to serve local consumers at a price p_i^j. Of course, the distribution of prices may differ across markets and will depend on the subset $\mathcal{K}$ of active firms since different competitive pressures pertain to those subsets. The cases $|\mathcal{K}| \geq 2$ cover market configurations for which there is competition. For simplicity, we leave explicit the dependence of the bidding strategies on $\mathcal{K}$ in that case. This variability also reflects the fact that costs on each markets are related to the innate quality of the network and to some management practices which are to a large extent idiosyncratic. Formally, we assume that innate costs θ_i^j are independently and identically drawn for each bidder i and across markets j from a distribution F whose support is $\Theta = \left[\underline{\theta}, \overline{\theta}\right]$. For simplicity, we assume that F has no atom and we denote by $f = F'$ the corresponding positive density.[9]

To reduce these innate costs, some bidders engage in innovation. Nowadays, $R\&D$ has become a key aspect of environmental services. For each innovating firm, innovation is effective throughout all markets where such firm is active. An innovation, when successful, reduces costs on all such markets. Let denote by e_i this investment. As a first normalization, we assume that this investment is in fact equal to the probability that an innovation is realized by bidder i. A second normalization is that the cost of investment is proportional to the overall number of markets, capturing thereby the magnitude of such activities for the sector as a whole. The corresponding investment cost writes thus as $m\psi_i(e_i)$ and, for simplicity, we suppose a quadratic expression, namely $\psi(e_i) = \frac{\lambda_i e_i^2}{2}$ where $\lambda_i \geq 0$ is a scale parameter. For simplicity and to facilitate the empirical analysis, we assume that players face the similar costs and thus $\lambda_i = \lambda$ for all those innovating firms.

The size $\sqrt{\delta_i}$ of firm i's innovation is a random variable. The shock δ_i is drawn from a distribution, again assumed to be common to all bidders, H whose support is $\Delta = \left[0, \overline{\delta}\right]$. The distribution H has no atom and we denote by $h = H'$ the corresponding positive density. To ensure that costs remain positive under all circumstances below, we shall also assume that $\underline{\theta} \geq \overline{\delta}$.

[9] Our theoretical model could entertain the possibility of firm-specific distributions of innate costs. Our empirical procedure, that infers such distribution from data on yields in the field, requires that we posit the same distribution for identification purposes.

Those different elements allow us to express the cost of a bidder i on market j as

$$\theta_i^j - \sqrt{\delta_i} e_i \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{M}$$

and a non-innovating bidder chooses $e_i = 0$.

3.2 Equilibrium Distribution of Prices

Given the randomness of its own cost, the bidding behavior of each firm i active on market j generates a distribution of possible bidding prices for this bidder.

When $|\mathcal{K}| \geq 2$, there is competition and this distribution depends on the corresponding subset $\mathcal{K}$ since the competitive pressure is different on different markets and there are *a priori* as many such distributions as such subsets. Let denote by $G_i^{\mathcal{K}}$ such distribution. Let also denote by $\mathcal{M}_{\mathcal{K}}$ the subset of municipalities where firms in the subset $\mathcal{K}$ are all active. Observe that the collection $(\mathcal{M}_{\mathcal{K}})_{\mathcal{K} \subseteq \mathcal{M}}$ forms a partition of $\mathcal{M}$. In a first-price auction run on market $j \in \mathcal{M}_{\mathcal{K}}$, bidder i wins if its price $\tilde{p}_i^j$ is below those of its competitors on this market; an event that thus arises with probability

$$\Pi_{k \neq i; k \in \mathcal{K}, i \in \mathcal{K}}(1 - G_k^{\mathcal{K}}(\tilde{p}_i^j)).$$ [10]

Equipped with this piece of notation, we may rewrite bidder i's optimization problem as that of finding a vector of bids $\mathbf{p}_i = (p_i^j)_{j \in \mathcal{M}}$ together with an investment e_i that maximizes its expected profits across all bidding markets on which it is active, namely

$$(\mathbf{p}_i, e_i) \in \arg \max_{(\tilde{\mathbf{p}}_i, \tilde{e}_i), \tilde{p}_i^j \leq S^j} \sum_{\mathcal{K} \subseteq \mathcal{N}, i \in \mathcal{K}} \sum_{j \in \mathcal{M}_{\mathcal{K}}} (\tilde{p}_i^j - (\theta_i^j - \sqrt{\delta_i} \tilde{e}_i)) \Pi_{k \neq i; k \in \mathcal{K}, i \in \mathcal{K}}(1 - G_k^{\mathcal{K}}(\tilde{p}_i^j)) - m\psi_i(\tilde{e}_i).$$

When $|\mathcal{K}| \geq 2$, bidder i can no longer raise its bid towards the monopoly level without decreasing the probability of winning the market and losing its margin. As a result of such pass-through, prices reflect the underlying distribution of innate costs cum innovation. Assuming that the above objective is quasi-concave,[11] we may first

[10] As econometricians, we observe only winning bids on the markets. Conditioning on winning does not change the distributions of bids and thus we can as well use winning bids to recover an actual distribution.

[11] A sufficient condition is that $1 - G_k^{\mathcal{K}}(\tilde{p}_i^j)$ is log-concave.

write the first-order conditions for optimality of the research investment as

$$e_i = \frac{\sqrt{\delta_i}}{\lambda_i}\frac{1}{m}\sum_{\mathcal{K}\subseteq\mathcal{N}, i\in\mathcal{K}}\sum_{j\in\mathcal{M}_\mathcal{K}}\Pi_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}}(1-G_k^\mathcal{K}(p_i^j)) \tag{1}$$

(with the convention $\Pi_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}}(1-G_k^\mathcal{K}(p_i))=1$)) and, for the bids on market j where firm i is active and faces some competition

$$p_i^j - (\theta_i^j - \sqrt{\delta_i}e_i) = \frac{1}{\sum_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}}\frac{g_k^\mathcal{K}(p_i^j)}{1-G_k^\mathcal{K}(p_i^j)}} \quad \forall j\in\mathcal{M}_\mathcal{K}, \forall\mathcal{K}\subseteq\mathcal{N}, |\mathcal{K}|\geq 2, i\in\mathcal{K}. \tag{2}$$

The first optimality condition (1) shows that the optimal investment of a given firm is proportional to the overall probability of winning across all markets and to the magnitude of its innovation.

The second optimality condition (2) characterizes firm i's bid in response to a bidding strategies of other firms which are active on $\mathcal{K}$-markets. This condition illustrates an important trade-off. On the one hand, raising its own bid increases firm i's margin. On the other hand, it also decreases the probability of winning.

APPROXIMATION FOR A LARGE NUMBER OF MARKETS. To facilitate the analysis of this model and to be consistent with evidence, we assume that $|\mathcal{M}_\mathcal{K}|$ (and thus $m = |\mathcal{M}| = \sum_{\mathcal{K}\subseteq\mathcal{N}}|\mathcal{M}_\mathcal{K}|$) is large enough, i.e., each configuration contains a sufficiently large number of markets.

From (2), the optimal price p_i^j are independently drawn from the same distribution $G_i^\mathcal{K}$ conditionally on a given subset of competitors $\mathcal{K}$, and a level of investment since innate costs θ_i^j are themselves independently drawn and $\sqrt{\delta_i}$ is a common shock throughout all markets. We can then use the *Weak Law of Large Numbers* to get the following approximation:

$$e_i = \frac{\sqrt{\delta_i}}{\lambda_i}\left(\sum_{\mathcal{K}\subseteq\mathcal{N}, i\in\mathcal{K}} x^\mathcal{K}\mathbb{E}_{G_i^\mathcal{K}}\left(\Pi_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}}(1-G_k^\mathcal{K}(p_i))\right)\right) \tag{3}$$

where $\mathbb{E}_{G_i^\mathcal{K}}(\cdot)$ is the expectation operator with respect to the distribution $G_i^\mathcal{K}$ and $x^\mathcal{K}$ is the probability of having bidders from the subset $\mathcal{K}$ being active. In our empirical analysis, we will identify this probability with the empirical frequency of observing subset $\mathcal{K}$ of active bidders.

Notice that bidder i's expected market share across markets writes as

$$s_i = \sum_{\mathcal{K}\subseteq\mathcal{N}, i\in\mathcal{K}} x^{\mathcal{K}} \mathbb{E}_{G_i^{\mathcal{K}}} \left(\Pi_{k\neq i; k\in\mathcal{K}, i\in\mathcal{K}} (1 - G_k^{\mathcal{K}}(p_i)) \right).$$

Accordingly, we rewrite (3) in a more compact way as

$$e_i = \frac{\sqrt{\delta_i}}{\lambda_i} s_i. \tag{4}$$

In other words, the investment is proportional to equilibrium market shares.

Inserting into the optimality condition for prices (2) yields a more compact expression of the price-cost margin on competitive markets as

$$p_i^j - \left(\theta_i^j - \frac{\delta_i}{\lambda_i} s_i \right) = \frac{1}{\sum_{k\neq i; k\in\mathcal{K}, i\in\mathcal{K}} \frac{g_k^{\mathcal{K}}(p_i^j)}{1 - G_k^{\mathcal{K}}(p_i^j)}}. \tag{5}$$

This expression of the price-cost margin in turn can be rewritten as

$$\frac{p_i^j - \left(\theta_i^j - \frac{\delta_i}{\lambda_i} s_i \right)}{p_i^j} = \frac{1}{\varepsilon_i^{\mathcal{K}}(p_i^j)} \tag{6}$$

where

$$\varepsilon_i^{\mathcal{K}}(p_i^j) = \sum_{k\neq i; k\in\mathcal{K}} \frac{p_i^j g_k^{\mathcal{K}}(p_i^j)}{1 - G_k^{\mathcal{K}}(p_i^j)} \tag{7}$$

stands for the elasticity of the probability of winning; which of course depends on the equilibrium bidding strategy of competing firms.

Let denote by $G_i^{\mathcal{K}}(\cdot|\delta_i)$ the conditional distribution of prices for a given realization of the innovation shock δ_i that is so induced by the bidding strategies. By definition, this distribution must reflect the distribution of innate costs and so, using (5), we must have

$$G_i^{\mathcal{K}}(p_i|\delta_i) = F\left(p_i + \frac{s_i}{\lambda_i}\delta_i - \frac{1}{\sum_{k\neq i; k\in\mathcal{K}, i\in\mathcal{K}} \frac{g_k^{\mathcal{K}}(p_i)}{1 - G_k^{\mathcal{K}}(p_i)}} \right) \quad \forall p_i \in \text{supp } G_i^{\mathcal{K}}.$$

Integrating over all possible values of the innovation shock yields the following functional equation:

$$G_i^{\mathcal{K}}(p_i) = \int_0^{\overline{\delta}} F\left(p_i + \frac{s_i}{\lambda_i}\delta_i - \frac{1}{\sum_{k\neq i; k\in\mathcal{K}, i\in\mathcal{K}} \frac{g_k^{\mathcal{K}}(p_i)}{1 - G_k^{\mathcal{K}}(p_i)}} \right) h(\delta_i) d\delta_i \quad \forall p_i \in \text{supp } G_i^{\mathcal{K}}. \tag{8}$$

The distribution $G_i^{\mathcal{K}}$ is the distribution of bids made by bidder i when competitors belong to $\mathcal{K}$. Thanks to the fact that firms have independent strategies, this distribution actually is also the distribution of the winning bids for that firm, a distribution which is actually observed. The market share s_i for bidder i is also observed. This distribution depends on the array of hazard rates $\frac{g_k^{\mathcal{K}}(p_i)}{1-G_k^{\mathcal{K}}(p_i)}$ for all other bidders indexed by $k \neq i$ and $k \in \mathcal{K}$ but again these distributions are observed.

4 Data and competitive interactions

We present in this section a discussion of the main features of our dataset. We describe the main variables of interest in our empirical model, and we provide descriptive statistics on the strategic interactions of transport operators.

4.1 Construction of the variables

Different types of variables are required in order to identify our model. The cost side of the empirical analysis calls for covariates that capture elements of the economic environment, which entails both group-specific and network-specific characteristics. As in Gagnepain and Ivaldi (2002) and Gagnepain, Ivaldi and Martimort (2013), estimating the Cobb-Douglas cost function requires information on the level of operating costs, the quantity of output, capital, and the input prices. Total costs C, expressed in real terms, are defined as the sum of labor and material costs. Output Q is measured as the number of seat-kilometers, i.e., the number of seats available in all components of rolling stock times the total number of kilometers traveled on all routes. This measure accounts for the length of the network, the frequency of the service and the size of the fleet. It is also meant to be a measure of the quality of service. Capital K, which plays the role of a fixed input in our short-run cost function, is the size of the rolling stock, which is measured as the total number of seats available. The network size I, which also plays the role of a fixed input, is measured as the total length of the transport network in kilometers.

Since the authority owns the capital, the operators do not incur capital costs. The average wage rate w_l is obtained by dividing total labor costs by the annual number of employees. The price of materials w_m has been constructed as the average fuel price for France (published by the OECD). We also add network characteristics such as the average speed and age of the public transport vehicles, the type of contract used (fixed-price or cost-plus), and firms characteristics such as whether they are private or public, and their identity: Transdev, Veolia, Keolis, or Small operator (RATP, Carpostal, Vectalia, or an independent firm). Finally, we account for the number of bidders that compete for a concession in one particular network, and the price (the bid) paid by the local regulator to the operator, which is computed as the total subsidy paid to balance the deficit between the commercial revenue of the operator and the operating costs, divided by the total number of seat-kilometers produced. Summary statistics are provided in Table 1.

In terms of data organization, we note that one contract in one network should in principle correspond to a unique observation in our empirical model, i.e., all the contract items should remain constant over the—say—five years of a contract length. In practice, the dataset shows that, over a single contract period, many items can be affected by small changes. This may, for instance, be the case of the operators supply measured by the number of seat-kilometers available which, in turn, forces the costs and subsidy levels to change as well. These changes are assumed to be generated by independent and identically distributed exogenous shocks that could affect the activity of the operator over the contract length. Changes in traffic conditions, temporary changes in network configuration, road construction which cut a service route over a certain period, or strikes are all such examples. The economic responses to these unpredictable shocks are anticipated in the contract, which is why they are assumed to pertain to the same contract. Instead of calculating a simple average value of each item over the contractual period when changes are present, we choose to treat each contract-year as a separate observation, so that the number of degrees of freedom of our study is increased. The identification of our asymmetric information model requires being able to identify through a cost system the technology of the industry and the firm's inefficiency, which is firm specific and constant over time. We improve significantly our estimation if the transport operators are observed several times, i.e., if we exploit the panel structure of our data.

4.2 Competitive interactions

A particularly important source of information in our dataset is the one that lists all the participants of all tenders in the French public transport industry. With this information, we are able to construct all the competitive interactions $\mathcal{K}$ of our theoretical model.

Table 2 and 3 provide descriptive statistics on respectively the number of networks operated by each firm and the number of tenders in which they participate. We note first that Veolia, Transdev and Keolis are the largest firms since they operate 22.7%, 12.3%, and 32.9% of the networks respectively. As suggested previously, RATP, Carpostal, and Vectalia are smaller actors, and there are also independent firms; in what follows, these firms are all gathered in one single category, "Small".

The firms' market shares are reflected in their bidding participation rate. Table 3 lists in more details the competitive interactions across tenders. We first notice that firms do not participate to all auctions. Moreover, there is quite an important number of cases of tenders where there is only one bidder: Keolis, Veolia, or Transdev. The most frequent competitive settings entail the participation of Veolia and a "small" firm (23 tenders), Veolia and Keolis (22 tenders), Keolis and a "small firm" (22 tenders), Veolia, Transdev, and Keolis (20 tenders), etc. In what follows, we will focus on the competitive interactions that entail the highest number of tenders to try to keep the number of observations at a reasonably high enough level at the moment of estimating price distributions.

5 Empirical applications of the theory

The main equation of reference in our theoretical model is Equation 8. It models, in a bidding environment $\mathcal{K}$, the direct relationship between $G_i^{\mathcal{K}}(.)$, the price distribution of firm i, and $G_k^{\mathcal{K}}(.)$ the price distribution of firms $k \neq i$, evaluated at p_i. Based on this main equation, we conduct two empirical exercises: First, we recover the $G_i^{\mathcal{K}}(.)$ for all firms i and bidding environments $\mathcal{K}$ and we compare these distributions to the prices set by the cartel participants between 1994 and 1999. Second, we explore more in details the role of innovation on price formation. To do so, we identify first the main primitives of our theoretical model which are the distribution of the innate costs $F(\theta_i^j)$

and the distribution of the innovation shocks $h(\delta_i)$.

5.1 Cartel prices versus competitive prices in 1994-1999

Our first objective is to compare the observed cartel prices with the hypothetical competitive prices that could have been obtained absent the cartels between 1994 and 1999. To do so, we focus on the two main cartels that were clearly identified by the FCA. They involved on the one hand Keolis and Connex (the former Veolia) in the cities of Bordeaux, Rouen, Chateauroux, and Toulon, and, on the other hand, Keolis and Transdev in the cities of Chalon, Bar le Duc, Epernay, Saint-Claude, and Sens.

Keolis and Connex systematically refrained from submitting bids against the incumbent contract holder or attempted to create a false appearance of competition through the submission of cover bids. These practices resulted in jointly developing bidding strategies and freezing the allocation of these contracts between the two groups. Additionally, given the limited number of companies capable of submitting technically and financially competitive bids, these actions deprived the contracting authorities of the ability to foster genuine competition when renewing these contracts. In a similar fashion, Keolis and Transdev refrained from submitting bids against the cartel member already holding the contract or by submitting incomplete or non-competitive proposals that had no real chance of being selected. These practices resulted in pre-determining the contract winners in advance and preventing transport authorities from ensuring fair competition based on truly independent bids stemming from the autonomous choices of each company.

To compute our price comparison, we proceed as follows:

- We derive the but-for-price p_i^N as the competitive price that would be obtained absent the cartel. To identify it, we consider our complete dataset and we recover for each firm the individual $\widehat{g}_i^{\mathcal{K}}(p_i)$ conditional on $\mathcal{K} = \{Keolis, Connex\}$ and $\mathcal{K} = \{Keolis, Transdev\}$. We approximate the $\widehat{g}_i^{\mathcal{K}}(p_i)$ with normal densities which depend on a mean m_i and a standard deviation sd_i to be estimated. We therefore predict p_i^n to be $\widehat{m}_i$.
- In a second step, we compare the estimated $\widehat{m}_i$ to the observed collusive prices p_i^c implemented during the cartel period under the same bidding environments

$\mathcal{K} = \{Keolis, Connex\}$ and $\mathcal{K} = \{Keolis, Transdev\}$. When the cartel is active, we expect the hypothetical competitive prices p_i^n to be distorted upward, i.e., we are interested in the potential difference $p_i^c - p_i^N$.

As preliminary evidence, we investigate how the observed prices p_i in our dataset depend on a series of covariates, including the number of bidders $\#Bid^j$, and firm i.d. $FIRM^j$ (Keolis, Transdev, Veolia, or Small). We thus estimate for all networks j and periods *t* the expression

$$\ln p_{it} = \beta_0 + \beta_Q \ln Q_{it} + \beta_{Bid} \ln \#Bid_t^j + \beta_X \ln X_{it}^j + \beta_t t + \beta_F FIRM_t^j + \theta^j + \xi_t^j, \quad (9)$$

where X_{it}^j is a vector of characteristics that pertain to the local network j and the operator i, t is a trend, θ^j is a vector of networks fixed effects, and ξ_t^j is an error term. The estimation results are provided in Table 5. Several effects are worth noticing: First, a higher number of participants in the local auctions enhances the competitive pressure on bidders and has thus a negative impact on bids. The winning bid (the price) thus decreases accordingly. Transdev and smaller operators usually bid more aggressively compared to Keolis and Veolia. Finally, prices decrease with the quantity of seats-kilometers produced, which suggests that they are lower in larger networks where the scale of the activity is more important.

Table 6 presents then for each firm i the features of the estimated $\widehat{g}_i^{\mathcal{K}}(p_i)$ conditional on $\mathcal{K}$. One potential concern is that the number of observations is limited because we observe only the price for the operating firm in each network (the winning bid). We note however that all the $\widehat{m}_i$ and $\widehat{sd}_i$ are significant at the 1% level. The two competitive regimes that are of particular interest for us are $\mathcal{K} = \{Keolis, Veolia\}$ and $\mathcal{K} = \{Keolis, Transdev\}$. A direct comparison in the collusive period of the estimated $p_i^N = \widehat{m}_i$ with the observed prices p^c in each scenario allows us to test whether the market sharing agreements implemented over the period had any positive impact on prices.

Table 7 compares p_i^N and p^c in all cities where the operating cartels were clearly identified by the FCA. These networks typically have a new concession contract that starts between 1995 and 1997, which coincides with the period during which Veolia, Transdev, and Keolis decided not to compete against each other.[12] In each case, the incumbent operator is reconducted as it is the sole participant to the tender. Surprisingly,

[12] The case of Rouen is slightly different in the sense that the main concession contract is a long term

the observed price over the collusive period is systematically lower than our predicted price, i.e., $p_i^N > p^c$. This suggests that the market sharing agreements implemented over the period were not primarily aimed at increasing prices. Instead the members of the cartels were mostly interested in implementing bilateral exchanges of favors and non-aggression pacts. Firms typically attempted to avoid significant financial risks inherent to the activity, as well as the high cost of preparing a tender proposal, which could vary, depending on the size of the sites to be managed, from 46,000 to 760,000 euros. The usual tactic of firms would then consist in, when faced with the risk of losing a market, not responding by proposing more aggressive bids, but instead deciding to open negotiations on another market where it is also a potential competitor in order to have a bargaining chip. We also note that the difference between p_i^N and p^c shrinks in larger urban networks such as Bordeaux, Rouen, or Chalon. This difference is larger in smaller networks, which is probably symptomatic of the fact that the specific characteristics of the smallest networks that pull prices down on the left tail of our price distribution are ignored in our theoretical model. In other words, our theoretical model states that the pricing strategy of firms mostly depends on their innate costs and innovation effort, but additional heterogeneity that could be driven by differences in network features is left unexplored in our analysis.

5.2 The effect of positive innovation shocks on prices

As a second empirical exercise, we propose now to focus again on Equation (8) and test for the impact on prices of an increase of firms' innovation effort. Following our previous observation that p^c lies further below p_i^N in smaller networks, we are interested in exploring other alleys that could explain this particular price difference. We note that Keolis, Veolia and Transdev are large industrial corporations which are present in several urban networks simultaneously. As shown in Aguiar and Gagnepain (2022), the innovation effort exerted in a specific network generates a positive externality on the operating costs of the remaining operators of the group. Thus, an operator belonging to a group will benefit from spillovers coming from the effort exerted by all the remaining operators of the group. Whether the knowledge generated in a given

contract that runs over a longer period (1991-2025). In this particular case, the collusive agreement referred to a subset of routes of the public transport network that were opened to competition but were eventually operated by a subcontractor of Veolia.

location is transferable or applicable to another network of the group might depend on the absorptive capacity of the operators and/or network characteristics. Our theoretical model presented here does not account for these features, and we potentially underestimate the innovation intensity produced in some specific networks (we overestimate prices). At this stage, our aim is not to complexify again our framework, but to illustrate instead how much a change in $h\left(\delta_i\right)$ would affect prices in the following equation:

$$G_i^{\mathcal{K}}(p_i) = \int_0^{\overline{\delta}} F\left(p_i + \frac{s_i}{\lambda}\delta_i - \frac{1}{\sum_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}} \frac{g_k^{\mathcal{K}}(p_i)}{1-G_k^{\mathcal{K}}(p_i)}}\right) h(\delta_i)d\delta_i \quad \forall p_i. \tag{10}$$

To do so, we solve for the hypothetical p_i in (10) after a rightward shift of $h\left(\delta_i\right)$. As $F\left(\theta\right)$ and $h\left(\delta\right)$ are unknown to us, they need to be identified beforehand.

THE DISTRIBUTION OF THE INNATE COSTS. We recover in a first step the empirical distribution $F\left(\theta\right)$ through the estimation of an operating cost function. To provide the required level of services Q, the transit operator needs to combine variable and fixed inputs. Let w_l and w_m be the price of variable inputs, namely labor and materials. Let k and I be, respectively, the stock of capital and the size of the network used by the operator, which are both fixed in the short run. We denote by C the observed operating cost. As the stock of capital k and the size of the infrastructure I are determined by the local regulator, our cost function is determined in the short run, and is conditional on the stock of capital and on the size of the infrastructure.[13] Each operator i in network j chooses the cost-minimizing input allocation subject to technological constraints, which leads to a deterministic cost expression of the form $\ln C_{it}^j(w_{l,it}^j, w_{m,it}^j, Q_i^j, I^j, k^j|\beta)$, where β is a vector of parameters describing the technology.

In practice, the observed operating cost differs from the deterministic structure as inefficiencies θ may prevent operators from reaching the required level of service q at the minimum cost, which will result in upward distorted costs. Hence, each operator i

[13]In practice, the operator plays a role in the choice of investment, which, potentially, introduces another dimension that can be affected by information asymmetries. Our understanding of the industry is that this question is of second-order since, for instance, the production of new buses, which could have a drastic impact on the efficiency of the transport network, takes time and refers to periods longer than regulatory periods.

faces the empirical cost

$$\ln C_{it}^j(w_{l,it}^j, w_{m,it}^j, Q_i^j, I^j, k^j|\beta) + \theta_i. \tag{11}$$

The estimation of the individual θs provides us a relevant proxy of the innate costs θ_i^j of our theoretical model. As we assume that the innate costs θ_i^j are independently and identically drawn for each bidder i and across markets j, and since we observe only the cost information of the winning bidder, we approximate $F\left(\theta_i^j\right)$ with the empirical distribution $\widehat{F}\left(\theta^j\right)$. Hence, assuming a Cobb-Douglas technology, we estimate for a market j and a period t the cost function

$$\ln C_{it}^j = \beta_0 + \beta_l \ln w_{l,it}^j + \beta_m \ln w_{m,it}^j + \beta_Q \ln Q_{it}^j + \beta_I \ln I_t^j + \beta_k \ln k_t^j + \beta_X \ln X_t^j + \theta^j + \varepsilon_t^j \tag{12}$$

We impose homogeneity of degree one in input prices, i.e. $\beta_l + \beta_m = 1$. We introduce in the equation additional explanatory variables X_t^j that capture network characteristics. We also introduce an error term, ε_t^j, to account for the fact that our Cobb-Douglas technology is potentially a rough approximation of the data reality; moreover, small measurement errors in the database cannot be discarded for some markets. The error term is distributed as a normal density function with mean 0 and variance σ_ε^2. The likelihood of a data point defined by a cost level is then

$$L\left(C_t^j\right) = L(C_t^j \mid w_{l,it}^j, w_{m,it}^j, Q_i^j, I^j, k^j, \theta^j, \beta). \tag{13}$$

The unobservable θ^js are treated as fixed effects specific to each market. Assuming that observations are independent, then the log-likelihood function for our sample is just the sum of all individual log-likelihood functions obtained from Equation (13).

The estimation results of the cost function are presented in Table 8. We note that private operators face lower costs, everything else being equal. A higher commercial speed within the network is beneficial to the operator as costs are also lower in this case. Costs are also lower in networks where the age of the rolling stock is higher, which is rather counterintuitive. We present in Figure 1 a non-parametric estimation $\widehat{F}\left(\theta^j\right)$. To ease our empirical exercise, we approximate $\widehat{F}\left(\theta^j\right)$with a parametric normal density. We denote the empirical mean and standard deviation of the normal density as m_f = 1.471 and sd_f = 0.507 respectively.

INNOVATION. In a second step, we need to recover the empirical density $h(\delta_i)$. To do so, we assume that $h(\cdot)$ is normal, with mean and variance parameters μ and ν

respectively. In order to obtain maximum likelihood estimates $\widehat{\lambda}$, $\widehat{\mu}$, and $\widehat{\nu}$, we fix $\mathcal{K} = \{Keolis, Connex\}$ and add an error term φ_{it} in (10). We thus estimate the equation

$$\widehat{G}_i^{\mathcal{K}}(p_{it}) = \int_0^{\overline{\delta}} \widehat{F}\left(p_{it} + \frac{\widehat{s}_{it}}{\lambda}\delta_{it} - \frac{1}{\sum_{k\neq i;k\in\mathcal{K},i\in\mathcal{K}} \frac{\widehat{g}_k^{\mathcal{K}}(p_{it})}{1-\widehat{G}_k^{\mathcal{K}}(p_{it})}}\right) h(\delta_{it},\mu,\nu)\, d\delta_i + \varphi_{it},\ \mathcal{K} = 3, \quad (14)$$

where p_{it} is a vector of observed prices, and $\widehat{G}\,(.)$ and $\widehat{g}\,(.)$ are derived from Section 5.1. The estimation results are provided in Table 9. The average δ_{it} is estimated to be equal to 0.11, and the standard deviation is 0.23.

EFFECT ON PRICES. Finally, with all our estimates $\widehat{F}\,(.)$, $\widehat{G}\,(.)$, $\widehat{g}\,(.)$, and $\widehat{\lambda}$ in hand, we go back to Equation (10) and we simulate the impact of an increase in the innovation intensity δ_i on p_i: By increasing slightly μ in $h(\delta,\mu,\widehat{\nu})$ and keeping $\widehat{\nu}$ fixed, we search for the value of p_i that solves Equation (10). The results are provided in Table 10. An interesting result here is that increasing the average innovation intensity from 0.11 to 0.3 leads to a price decrease of 10.3%. This is already a large increase in the innovation activity, given the standard deviation of $h(.)$, which suggests that a 10.3% price decrease is probably close to the maximum amount feasible. Going back to our price comparison in Table 7, a 10.3% price decrease is not sufficient to explain the price difference in the cities of Chateauroux (2.72 versus 3.36) and Toulon (2.23 versus 3.16). As suggested above, the remaining unexplained difference is probably driven by differences in network characteristics, a feature that our theoretical model does not capture for the moment.

6 Conclusion

This paper proposes a structural model of strategic bidding in the French public transport industry. Our analysis takes very seriously the best-response functions of bidders in each local market and expresses this behavior in terms of the bidders' price distributions under various competitive scenarios. Thanks to the information provided in our dataset, we are able to identify precisely the participants in each tender and identify the competitive pressure impinging on the operators' strategic decisions. We thus recover the distribution of prices for each operator and each competitive setting. Our structural model then allows us to identify firms' innate costs and innovation intensity, and to assess empirically how an increase in the innovation activity fosters price reductions.

Here, we have focused more in particular on the market sharing collusive agreements that were implemented in the industry at the end of the 1990s. A reduction in the competitive pressure shifts the price distributions of at least a subset of bidders, which obliges the researcher to conduct her/his analysis in a context of asymmetric first-price auctions, which complicates a lot the analysis. Working with price distributions in firms' best-response functions is a potential strategy to ease the analysis, at least from an empirical perspective.

The methodology proposed here applies to bidding environments, and can serve as a tool to evaluate the impact of other natural experiments. For instance, our model could also prove fruitful in the particular case of mergers between participants in bidding markets. The merger of two firms, it if has any efficiency gains at all, also shifts the cost distribution of the merged entity. Even if cost distributions of bidders could be rather similar pre-merger, they won't be post-merger, which requires once again to analyze asymmetric first-price auctions. The French public transport industry has gone through a series a mergers, and is again a nice candidate for an empirical exercise in this context. This is certainly an interesting alley of research that we plan to explore in a near future.

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Table 1: Summary statistics (1995-2014)

Name	Variable	Mean	Std dev.	Quantity
Cost (Euros$\times 1000$)	C	15,020	32,120	
Price (per seat-kilometer, Euro)	$R(q)$	0.041	0.027	
Production (Seat-kilometers$\times 1000$)	Q	451,000	979,300	
Wage (Euros$\times 1000$)	w_l	38.3	8.647	
Price of materials (Index)	w_m	0.167	0.105	
Size of the network (Kilometers)	I	232.4	259.3	
Capacity (# of vehicles)	k	113.8	173.9	
Speed (Km/h)		18.9	3.1	
Private		0.85	0.35	
Age (Years)		7.9	2.7	
Fixed-Price		0.86	0.34	
# of bids		1.78	0.9	
Keolis		0.39		
Transdev		0.14		
Veolia		0.23		
Small		0.20		
# of networks				205
# of tenders				245
# of observations (before cleaning)				3,944

Table 2: # of networks operated

	Keolis	Veolia	Transdev	RATP	Carpostal	Vectalia	Independent	Total
# of net.	110	76	41	10	12	6	50	305
in %	36	24.9	13.4	3.3	3.9	1.9	16.4	100

Table 3: # of bids

	Keolis	Veolia	Transdev	RATP	Carpostal	Vectalia	Independent	Total
# of bids	177	132	86	29	19	21	94	558
in %	31.7	23.6	15.4	5.2	3.4	3.8	16.8	100

Table 4: Bidding interactions

Bidding operators	# of Tenders
Keolis	46
Veolia	34
Veolia-Small	23
Veolia-Keolis	22
Keolis-Small	22
Veolia-Transdev-Keolis	20
Transdev	18
Transdev-Keolis	17
Veolia-Keolis-Small	12
Veolia-Transdev	10
Transdev-Keolis-Small	7
Veolia-Transdev-Keolis-Small	6
Transdev-Small	5
Veolia-Transdev-Small	3
TOTAL	245

Note: The "Small" category includes RATP, Carpostal, Vectalia, and independent firms.

Figure 1: Density of the innate costs, $F\left(\theta_i^j\right)$

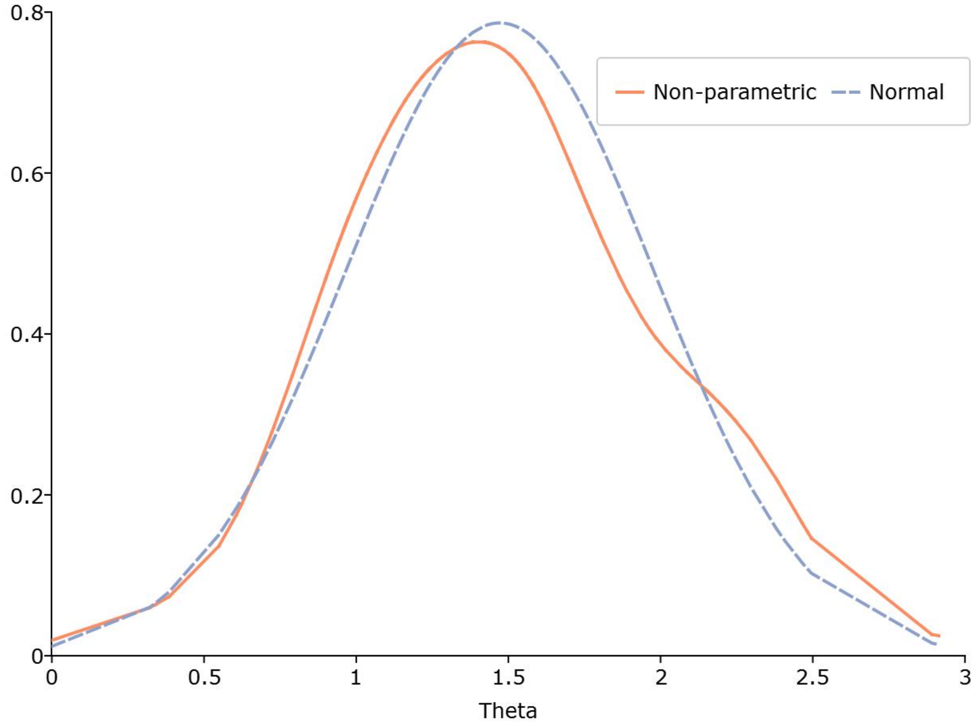

Table 5: Estimation results, prices (bids)

Variable	(1)	(2)
Constant	-4.411***	-1.625***
	(0.39)	(0.46)
Seats-kilometers	-0.139***	-0.207***
	(0.01)	(0.03)
# of bids	-0.068***	-0.043***
	(0.02)	(0.02)
Speed	0.416***	-0.180*
	(0.09)	(0.10)
Private	-0.023	-0.559***
	(0.05)	(0.12)
Fixed-price	0.239***	0.404***
	(0.04)	(0.05)
Trend	0.527***	0.556***
	(0.09)	(0.05)
Small		-0.300***
		(0.07)
Keolis		-0.071
		(0.08)
Transdev		-0.219***
		(0.08)
s.e. ϵ	0.514***	0.252***
	(0.01)	(0.00)
Network FE	No	Yes
Log-likelihood	0.164	0.878
# of obs.	982	957

Note: Standard errors in parenthesis.

***Significant at the 1% level

*Significant at the 10% level

Table 6: Estimated price densities, $\widehat{g}_k^{\mathcal{K}}(p_i)$

		Veolia	Transdev	Keolis	Small
$\mathcal{K}=1$	m_g	3.679***	2.570***	2.993***	
		(0.18)	(0.07)	(0.16)	
	sd_g	1.008***	0.225***	1.013***	
		(0.12)	(0.05)	(0.12)	
	# *obs*	31	10	38	
$\mathcal{K}=2$	m_g		3.678***	3.736***	
			(0.14)	(0.18)	
	sd_g		1.027***	0.879***	
			(0.11)	(0.13)	
	# *obs*		51	23	
$\mathcal{K}=3$	m_g	3.161***		3.364***	
		(0.10)		(0.06)	
	sd_g	0.490***		0.461***	
		(0.07)		(0.04)	
	# *obs*	18		64	
$\mathcal{K}=4$	m_g	4.093***			3.662***
		(0.22)			(0.19)
	sd_g	1.266***			1.278***
		(0.16)			(0.13)
	# *obs*	32			46
$\mathcal{K}=5$	m_g			3.794***	3.364***
				(0.12)	(0.005)
	sd_g			0.474***	0.551***
				(0.08)	(0.004)
	# *obs*			16	14
$\mathcal{K}=6$	m_g	3.523***		2.635***	3.012***
		(0.37)		(0.09)	(0.15)
	sd_g	1.431***		0.327***	0.511***
		(0.26		(0.06)	(0.11)
	# *obs*	15		13	14

Note:
$\mathcal{K}=1$: Veolia, Trandev, and Keolis
$\mathcal{K}=2$: Trandev and Keolis
$\mathcal{K}=3$: Veolia and Keolis
$\mathcal{K}=4$: Veolia and Small
$\mathcal{K}=5$: Keolis and Small
$\mathcal{K}=6$: Veolia, Keolis, and Small
***Significant at the 1% level

Table 7: Collusive agreements (1994-1999)

Network	Contract lenght	Operator	Obs. Price	Pred. price
Keolis-Connex (Veolia)				
Bordeaux	1995-2000	Connex (Veolia)	3.15	3.16
Rouen	1991-2025	Connex (Veolia)	3.05	3.16
Chateauroux	1995-2000	Keolis	2.72	3.36
Toulon	1996-2002	Connex (Veolia)	2.23	3.16
Keolis-Transdev				
Chalon	1997-2004	Transdev	3.63	3.67
Bar le Duc	1995-2000	Keolis	2.71	3.74
Epernay	1995-2000	Transdev	2.04	3.67
Saint-Claude	1996-2001	Keolis	3.10	3.74
Sens	1997-2004	Transdev	2.5	3.67

Note: Observed (Obs.) and predicted (Pred.) prices are expressed in euro cents.

Table 8: Estimation results, operating costs

		(1)	(2)
Constant	β_0	-2.428***	-0.228
		(0.176)	(0.196)
Price labor	β_l	0.808***	0.780***
		(0.015)	(0.010)
Seats-kilometers	β_q	0.626***	0.462***
		(0.014)	(0.015)
Network size	β_n	0.054***	0.038***
		(0.011)	(0.008)
Capital stock	β_k	0.347***	0.185***
		(0.018)	(0.017)
Private		-0.048***	-0.123***
		(0.014)	(0.028)
Speed		-0.206***	-0.132***
		(0.037)	(0.035)
Age		-0.063***	-0.040***
		(0.016)	(0.011)
Standard error	ϵ	0.209***	0.082***
		(0.004)	(0.002)
Network FE		No	Yes
Log-likelihood		1.064	1.995
# of obs.		1,218	1,218

Note: Standard errors in parenthesis.
***Significant at the 1% level

Table 9: Estimated innovation density, $h(\delta_i, \widehat{\mu}, \widehat{\nu})$

Parameter	Coefficient
λ	0.045***
	(0.013)
μ	0.110***
	(0.02)
ν	0.231***
	(0.02)
s.e. ξ	0.126***
	(0.01)
# of obs.	86

Note: Standard errors in parenthesis.
***Significant at the 1% level

Table 10: Innovation shocks δ_i

Average innovation μ	Change in price p_i
0.110	-
0.200	-0.6%
0.250	-4.5%
0.300	-10.3%

Note: Predicted price change in networks where Veolia and Keolis interact ($\mathcal{K} = 3$).
The standard deviation $\widehat{\nu}$ is kept fixed.