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SEMIPARAMETRIC ESTIMATION AND TESTING IN MODELS OF ADVERSE SELECTION, WITH AN APPLICATION TO ENVIRONMENTAL REGULATION.

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Abstract

We propose a flexible framework for estimating and testing structural models with adverse selection. This framework uses semiparametric methods for estimating consistently structural parameters of interest and for assesssing the results by testing procedures. We consider a problem of environmental regulation where firms are regulated through contracts. We show how to check parametric assumptions for the abatement cost function and test for neglected adverse selection. We then apply a semiparametric procedure for estimating models with adverse selection, that does not require to specify the distribution of the private information and avoids costly numerical procedures. The proposed framework can prove useful in a wide variety of problems where adverse selection can be present.

Keywords:
Semiparametric estimation, specification testing, models of adverse selection, environmental regulation.

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Semiparametric Estimation and Testing in Models of Adverse Selection, with an Application to Environmental Regulation

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1 Introduction

The economics of information and incentives has experienced great developments in recent years. In particular, the design of contracting procedures has been the subject of a vast literature, see the monograph of Laffont and Tirole (1994) for references. In the economic theory of contracts, the agent is characterized by a *private information* which determines his ultimate actions. Two possible sources of asymmetric information can be distinguished : (a) an unobservable action undertaken by the agent (effort in a production process, protection against risk,...); (b) an unknown characteristic of the agent (efficiency in terms of cost, willingness to pay for a given good,...). Case (b) is labelled *adverse selection* in the literature, and the agent's characteristic is referred to as his *type*. While the type of the agent is unknown to the principal, the latter nevertheless is assumed to have prior information before the contract is negociated, in terms of the statistical distribution of the type and other relevant characteristics of the agent. The challenge for the principal is to set up a contract scheme enforcing truthful revelation of the private information. thus allowing some optimal solution to be attained for the economic variable of interest (production level, environmental externality, ...).

In practice, contracts are largely used in domains as various as environmental regulation, industrial relationships, agricultural production or employment procedures. This suggests that asymmetric information, and in particular adverse selection, is present in many situations and that this must be investigated when analysing empirical data. Moreover, it is likely that neglecting the issue of imperfect information would lead to unreliable results. However, many problems arise for the econometrician when taking into account adverse selection. First, many features of the model are unobservable : private information is unobserved by both the principal and the econometrician, while prior information of the principal is also unknown to the econometrician. Second, and because of this, the distribution of the type itself is to be estimated jointly with other structural parameters. Third, such theoretical models lead to econometric ones that are highly nonlinear with unobservable (latent) variables, and possibly incorporating a truncation condition in cases where only a fraction of the agents is contracting. Hence, estimation of models with adverse selection generally requires sophisticated and costly numerical procedures, such as direct numerical integration or simulation–based methods (see Laffont, Ossard and Vuong, 1995, for an application to auctions). These empirical difficulties explain that much applied work is based on reduced-form models (e.g. Chiappori and Salanié, 1997; Dalen and Gomez-Lobo, 1997; Gasmi, Laffont and Sharkey, 1997) and that only a few econometric applications of the theory is based on structural models (Ivaldi and Martimort, 1994; Miravette, 1997; Thomas, 1995; Wolak, 1994). Nevertheless, it remains that ignorance of the true distribution function for the agent's type can be an important source of misspecification errors, whose impact is difficult to assess.

The purpose of this paper is to propose a flexible framework for estimating and testing structural models with adverse selection. This framework uses semiparametric methods for estimating consistently parameters of interest and for assessing the results by testing procedures. The advantages are twofold. First, from an estimation viewpoint, a semiparametric model allows to let the distribution of the agents' type unspecified, so that robust estimates can be obtained. Moreover, the estimation does not require costly numerical algorithms to be used. Second, from a testing viewpoint, tests relying on nonparametric methods are consistent against any alternative and then can detect misspecifications that are not uncovered by standard parametric tests, as will be seen in our application. In addition, when the objective function of the agent is separable in the observable and unobservable variables, it is quite easy to entertain a test for neglected asymmetric information without requiring parameterization of the asymmetric information part of the model. Furthermore, it is possible to test maintained parametric assumption that determines the estimation of structural parameters.

More specifically, we consider a problem of environmental regulation. Section 2 describes a simple model with adverse selection, where the principal is a local environment protection agency, and the agent is a polluting firm whose effluent emissions are to be reduced. In this case, the source of asymmetry lies in a private–information parameter reflecting the efficiency of the firm in abatement activity. In Section 3, we present the econometric models jointly with the estimation and testing procedures. In Section 4, we apply our econometric framework to a sample of French industrials for the period 1985-1992. We believe that the structure of the economic model and the econometric procedures for estimating the structural parameters and testing the competing models are mode widely applicable to many regulation situations with adverse selection. As will be seen, the basic requirement is that the effects of the agent's type and of the other variables on his profit could be separated.

2 Environmental Regulation with Asymmetric Information

2.1 The Basic Abatement Model

Let us consider a firm whose production generates some effluent emission level, denoted B. The firm is able to reduce its emission level by investing in an abatement capital stock, K. In that case, the operating cost of the abatement plant depends on the incoming emission flow B, on the pollution abatement rate (percentage of reduced emissions) δ, and on an efficiency parameter θ. Let $C(\theta, B, \delta)$ denote the operating abatement cost. The outcoming (net) emission level is equal to $(1-\delta)B$. The regulator is a local environment protection agency, designing an emission charge scheme and granting subsidies to support the firm's abatement activity. Note that the emission tax is based on *actual* effluent emissions $(1-\delta)B$, i.e. after possible abatement, and that subsidies may not be systematically granted, depending on the regulatory policy adopted. Let t and $T(\theta)$ respectively denote the unit emission charge and the transfer from the regulator to the firm that may depend on its efficiency parameter. The profit of the firm is

$$pQ - d(Q) - t(1-\delta)B - C(\theta, B, \delta) - K + T(\theta)$$

where Q is the output level, p is output price and $d(Q)$ is the production cost. The price of capital is normalized to 1. We assume that production and abatement activities are separable, so that production output level Q and effluent emission B are fixed when considering abatement decisions.[1] Therefore, profit in the abatement activity can be written

$$\Pi(\theta, \delta, T(\theta)) = t\delta B - C(\theta, B, \delta) - K + T(\theta), \tag{1}$$

because all predetermined terms depending only on Q and B can be dropped. Hence, the firm receives a positive amount $t\delta B$ from the regulator, when abating the emission level B by $100 \times \delta$ percent, plus a transfer $T(\theta)$ depending only on its efficiency parameter. The abatement cost function $C(\theta, B, \delta)$ is assumed to be increasing and convex in δ, increasing in B but decreasing

[1]This assumption is justified by the fact that t is low compared to marginal profit from production. Furthermore, we deal here with *external* (end-of-pipe) abatement, and not clean technologies, for which production and abatement activities are technically entangled.

in parameter θ. Hence, for a given level of emission and a given abatement rate, a firm with a higher parameter θ will be more efficient.

In our application, the abatement cost function is chosen as a Cobb–Douglas function, i.e.

$$C(\theta, B, \delta) = c\theta^{\beta} B^{\alpha_0} \delta^{\alpha_1}, \tag{2}$$

where $c > 0$ is a scale parameter, $\beta < 0$, $\alpha_0 > 0$, and $\alpha_1 > 1$ to ensure convexity of the cost function.

2.2 No Regulation

When it is not regulated (i.e. $T(\cdot) \equiv 0$), the firm will select the abatement rate by maximizing profit in Equation (1) with respect to δ. This yields the *status quo* solution:

$$\log \delta^0 = \frac{1}{\alpha_1 - 1} \{-\log(c\alpha_1) + \log t - (\alpha_0 - 1)\log B - \beta \log \theta\}. \tag{3}$$

With the above conditions on parameters, it is easily seen that abatement rate is increasing in the emission charge t and the efficiency parameter θ. Note also that it is increasing in emission level B, when there are increasing returns to scale in abatement (i.e. α_0 is less than 1).

In the theory of environmental regulation, the so–called Pigouvian tax, which is equal to marginal utility of consumers for abatement, achieves the *socially–optimal* rate of abatement. Where firms are faced with the Pigouvian tax, they fully internalize the social cost of environmental damages caused by their pollution. This is known as the *Polluter–Payer* principle. But in practice the emission charge can be restricted for practical and institutional reasons. For example, during the 1980's in France, anti–inflationary measures imposed a virtually null growth rate for the unit emission tax in constant terms. Furthermore, local environment protection agencies ("Water Agencies") did not consider the emission charge a truly incentive–based policy instrument, but rather a limited financial compensation for water use and deterioration (see Thomas, 1995). Another reason worth mentioning is the difficulty for the regulator to evaluate properly the social utility function for abatement or, equivalently, the social disutility function for pollution. When consumers' preferences towards pollution are not known with sufficient accuracy, then the regulator may not be able to design the proper Pigouvian tax scheme (see Baumol and Oates, 1988). As a result, firms facing a uniform emission charge will not find it profitable to abate at a "socially–acceptable" rate, because of the discrepancy between marginal cost of abatement and marginal benefit from abatement.

The problem is complicated further because uniformity of the emission tax does not allow for optimal policies to be achieved in practice. This is because distortions are likely to be important when considering heterogenous polluters, characterized by different efficiency parameters. Theoretically, this could be overcome by letting the tax t depending on θ. However, in most real–world environmental policies, the emission charge is in fact uniform, mainly for ease of implementation and equity grounds. Hence, it is often not possible for the regulator to implement a personalized, firm–specific emission charge.

It is then clear that more flexible policies are called for. A complementary environmental policy instrument which is often used in practice is a contract scheme between the local regulator and the firm; according to this contract, the firm accepts to invest in a treatment plant in order to abate at a given rate, while receiving a transfer $T(\theta)$. The contract–based regulation policy allows for a case-by–case determination of abatement rate (and other possible variables of interest to the regulator) consistent with standard regulatory and juridical procedures. It is therefore interesting as a complementary or alternative policy to the uniform emission charge regulation. As we will see below, the actual performance of contract schemes crucially depends on the ability for the regulator to observe firm's characteristics which are likely to affect the abatement activity (Xepapadeas, 1991; Baron, 1985).

2.3 Regulation under Perfect Information

In the contract–based regulation of the firm, the regulator is assumed to maximize total surplus, i.e. for consumers and the firm, with respect to abatement level, δB. The regulator preferences are summarized in a parameter σ, used as a weight in the surplus function. High values for this parameter indicate that the regulator favors consumers more than the firm. Following Baron (1989), this weight must be in the interval $[0.5, 1]$ for the problem to be consistent[2]. The consumers' utility function for abated pollution is denoted $W(.)$, with $W' > 0$, $W'' \leq 0$. The contract between the regulator and the firm consists in the pair $(\delta(\theta), T(\theta))$, where $T(\theta)$ is the subsidy granted to the firm. Total surplus then reads

$$\sigma \left[W(B\delta(\theta)) - tB\delta(\theta) - T(\theta)\right] + (1-\sigma)\left[tB\delta(\theta) - C(\theta, B, \delta(\theta)) - K + T(\theta)\right],$$

where it is implicitely assumed that consumers' surplus and the regulator's budget can be aggregated. Both transfer $T(\theta)$ and the amount paid to the firm for abatement, $tB\delta(\theta)$, must be paid by consumers through some redistribution (fiscal) mechanism.

Two conditions must be met by the regulation mechanism. First, the abatement rate δ^* must be greater than in the *status quo* for the regulation to be effective. Second, for the firm

[2] It can be shown by a somewhat different exposition of the regulator's problem that values of σ less than 0.5 correspond to a *negative* opportunity cost of public funds.

to accept to participate in the contract relationship, its profit under regulation must be greater than its *status quo* profit, i.e. we must have $\Pi(\theta, \delta^*(\theta)) \geq \Pi(\theta, \delta^0)$. This condition is denoted *Individual Rationality* in the literature. Using the definition (1) of the profit, total surplus can be rewritten

$$\sigma\left[W(B\delta(\theta)) - C(\theta, B, \delta(\theta)) - K\right] + (1 - 2\sigma)\Pi(\theta, \delta(\theta), T(\theta)).$$

Under perfect information, i.e. when the regulator knows the value of parameter θ, the problem is simplified by the fact that the principal is able, through the transfer, to exactly equate both regulation and *status quo* profits. Hence, the second term in total surplus can be omitted and maximizing with respect to the abatement rate yields:

$$W'(B\delta^*(\theta))B = \frac{\partial C(\theta, B, \delta^*(\theta))}{\partial \delta}.$$

The First–Best (perfect information) solution equates marginal utility and marginal cost of abatement. This is the standard result of Pigouvian taxation. But as argued above, it is likely that the actual rate is lower than the optimal level. Hence if we assume that the marginal utility for abatement is constant, and proportional to the actual emission charge t, we can write

$$W'(\cdot) = t^* \equiv \varepsilon t \qquad \varepsilon > 1.$$

The parameter ε reflects the imperfection in the uniform emission tax scheme. With our choice of the cost function, the First–Best optimal abatement rate is, in logarithmic form,

$$\log \delta^* = \frac{1}{\alpha_1 - 1}\left\{\log(\varepsilon / c\alpha_1) + \log t - (\alpha_0 - 1)\log B - \beta \log \theta\right\}. \tag{4}$$

Because $\varepsilon > 1$, the First–Best abatement rate δ^* is always greater than in the *status quo*.

2.4 Regulation under Asymmetric Information

We now consider the case where the principal does not observe the agent's efficiency parameter θ. In theory, the contracting procedure is modelled as follows. First, the firm is asked to report its private information, i.e. its efficiency parameter. Based on the reported $\tilde{\theta}$, the regulator then proposes a contract, i.e. a pair $(\delta(\tilde{\theta}), T(\tilde{\theta}))$, that the firm can accept or not. Nevertheless, in practice it is not necessary to require the agent to reveal his type directly. The regulator offers a *menu* of contracts to the agent who, assuming the contracting scheme is properly designed, selects the contract corresponding to his type.

Obviously, the contracting scheme has to satisfy the participation constraint previously described, namely that profit under regulation has to be greater than or equal to the *status* *quo* profit. Moreover, another constraint is relative to the revelating property of the contract scheme. The regulator is willing to enforce truthful reporting of characteristic θ by the firm, in order to avoid strategic behavior. Indeed, as the contract is indexed on the reported parameter $\tilde{\theta}$, a firm with a "good type" (i.e. a high efficiency parameter θ) may report itself as a "bad type." In so doing, the firm may be assigned a reasonable objective in terms of abatement, while receiving a more profitable lumpsum transfer. The constraint associated to truthful revelation is denoted *Incentive Compatibility* in the literature. It states that the firm must be better off when reporting the true type value, as it is when reporting any other value. A major difference with the First–Best solution is that now the regulator has to grant an *information rent* to the firm in return for its truthful report. Such a rent is supported by the transfer $T(\cdot)$; because of the cost of public funds, the regulator may experience a significant financial burden for this.

Therefore, the regulator is not able to implement the First–Best solution and in particular is unable to determine the transfer which would achieve equality between profits under *status quo* and regulation. He has nevertheless prior information on the firm's characteristic, which enables him to maximize total surplus *ex ante*, over the definition domain for θ. Such information is available to the principal through past contracts with similar firms, or technical data on abatement activity on a sector–by–sector basis. Prior information to the regulator is traditionally represented by a probability distribution function $F(\theta)$ with associated density function $f(\theta)$, defined on the domain $[\underline{\theta}, \overline{\theta}]$. Total expected surplus then reads

$$\max \int \{\sigma [W(B\delta(\theta)) - C(\theta, B, \delta(\theta)) - K] + (1 - 2\sigma)\Pi(\theta, \delta(\theta), T(\theta))\} f(\theta) d\theta. \tag{5}$$

The menu of contracts $(\delta^{**}(\cdot), T(\cdot))$ is chosen so as to maximize (5), taking into account the three constraints

$$\Pi(\theta, \delta(\theta), T(\theta)) \geq \Pi(\theta, \delta(\tilde{\theta}), T(\tilde{\theta})) \quad \forall \theta, \tilde{\theta} \qquad \text{(Incentive Compatibility)}, \tag{6}$$

$$\Pi(\theta, \delta(\theta), T(\theta)) \geq \Pi(\theta, \delta^0, 0) \quad \forall \theta \qquad \text{(Individual Rationality)}, \tag{7}$$

and

$$\delta^{**}(\theta) \geq \delta^0(\theta) \quad \forall \theta \qquad \text{(Increased Abatement)}, \tag{8}$$

where θ is the true parameter value and $\tilde{\theta}$ is the report of the type by the firm. As shown in the Appendix, the equilibrium solution under asymmetric information is given by:

$$\log \delta^{**} = \begin{cases} \frac{1}{\alpha_1 - 1} \{\log(\varepsilon / c\alpha_1) + \log t - (\alpha_0 - 1)\log B - H(\theta)\} & \text{for } \theta \geq \theta_c, \\ \frac{1}{\alpha_1 - 1} \{-\log(c\alpha_1) + \log t - (\alpha_0 - 1)\log B - \beta \log \theta\} & \text{for } \theta < \theta_c, \end{cases} \tag{9}$$

where

$$H(\theta) = -\beta \log \theta + \log \left[1 - \beta \frac{2\sigma - 1}{\sigma} \frac{1 - F(\theta)}{f(\theta)} \frac{1}{\theta} \right], \tag{10}$$

and θ_c is the solution to

$$\varepsilon - 1 = -\frac{2\sigma - 1}{\sigma} \frac{1 - F(\theta_c)}{f(\theta_c)} \frac{\beta}{\theta_c}. \tag{11}$$

Only firms with efficiency parameter *greater than* θ_c will be regulated by means of contracts. This comes from two competing effects. On the one hand, it is socially more profitable to regulate efficient firms so as to promote overall emission reduction. On the other hand, it is more costly to regulate efficient firms since the information rent is increasing in θ (see Appendix). The principal therefore concentrates only upon a fringe of firms above the threshold value θ_c, so as to reduce overall information rents. Interestingly, the threshold value crucially depends on the discrepancy between the Pigouvian tax level and the actual emission charge. In other words, when the inefficiency in the emission tax system is important, the threshold value θ_c decreases, and more firms are regulated (see Thomas, 1995, for a similar result). On the other hand, firms below the threshold value will not be regulated, and will be left at the *status quo* level, namely they will be characterized by the abatement rate δ^0 defined in Equation (3). Figure 1 presents the different solutions for the abatement rate in function of parameter θ. It is easily seen that the abatement rate solutions can be ranked as follows: $\delta^{**}(\theta) \leq \delta^*(\theta)\,\forall\,\theta$, $\delta^0(\theta) \leq \delta^*(\theta)\,\forall\,\theta$ and $\delta^{**}(\theta) \geq \delta^0(\theta)$ for $\theta \geq \theta_c$.

3 Estimation and Testing

3.1 Estimation of the Competing Models

The perfect information solution is theoretically characterized by the equation

$$\log \delta = X'\lambda + \beta \log(\theta),$$

where $X = (1, \log t, \log B)$, and (λ, β) are structural parameters. However, the efficiency parameters are unknown to the practitioner. As usual in econometrics, we consider that we have at hand some observable variables W related to θ through a known parameterized function $k(\cdot, \gamma)$. Then we consider

$$\begin{aligned} E[\log \delta | X, W] &= X'\lambda + \beta E[\log \theta | W] \\ &= X'\lambda + \beta k(W, \gamma). \end{aligned}$$

Hence, we get the perfect information econometric model

$$\log \delta = X'\lambda + \beta k(W, \gamma) + U, \quad E[U|X, W] = 0. \tag{12}$$

Note that all parameters may not be indentified, and specifically we may not be able to get separate estimates of β and γ.

The asymmetric information solution is theoretically characterized by Equation (9). For using this formula for econometric estimation, we must take into account that under adverse selection we observe only industrials that contract with the agency. Therefore, we consider

$$\begin{aligned} E_\theta[\log \delta | \theta \geq \theta_c, X, W] &= X'\lambda + E\left\{ \int_{\theta_c}^{+\infty} H(\theta) \frac{f(\theta)}{1 - F(\theta_c)}\, d\theta \middle| W \right\} \\ &= X'\lambda + g(W). \end{aligned}$$

From its definition, the function $g(\cdot)$ is generally a highly non-linear function. Moreover, even if we model θ through a known function of some explanatory variables W, $g(\cdot)$ remains unknown, as $H(\theta)$ depends not only on θ, but on the whole unknown distribution function of the firms' types $F(\cdot)$. Previous work deals with this problem by specifying a particular form for $F(\cdot)$ and deriving the corresponding $g(\cdot)$, whose parameters are subsequently estimated by numerical algorithms. In this work, we let the types' distribution, and then the function $g(\cdot)$ unspecified, and we apply a semiparametric procedure for estimating the parameters λ. Specifically, we use the semiparametric estimation procedure proposed by Robinson (1988), that we briefly recall.

Our econometric model writes

$$\log \delta = X'\lambda + g(W) + V, \quad E[V|X, W] = 0. \tag{13}$$

By taking conditional expectation with respect to W, we get

$$g(W) = E[\log \delta | W] - E[X'|W]\lambda$$

and by difference of the two previous equations, we end up with

$$\log \delta - E[\log \delta | W] = [X - E(X|W)]'\, \lambda + V.$$

The estimation procedure consists in inserting nonparametric (kernel) estimates $E_n[\log \delta | W]$ and $E_n[X|W]$ in place of the unknown conditional expectations and estimating λ by a standard no-intercept OLS rule. The resulting parameter estimate $\widehat{\lambda}$ is consistent and asymptotically normally distributed with a $\sqrt{n}$ rate of convergence. Moreover Robinson (1989) suggests use of $\widehat{\lambda}$ to form estimators of $g(\cdot)$ as $E_n[\log \delta | W] - E_n[X'|W]\widehat{\lambda}$.

3.2 Testing for Asymmetric Information

The two assumptions that the specification of the cost function implies separation between the influence of the type and of other factors and that $\log(\theta)$ can be approximated through a known function of observable variables allows for a simple test of asymmetric information. Indeed, from the two theoretical models of Section 2, we have built two competing econometric models

$$\begin{cases} \log\delta = X'\lambda + k(W,\gamma) + U & \text{(Perfect Information)},\\ \log\delta = X'\lambda + g(W) + V & \text{(Adverse Selection)}. \end{cases}$$

Therefore, in our setting, the perfect information model corresponds to the asymmetric information model in which the unknown function $g(\cdot)$ equals $k(\cdot,\gamma)$ for some value of γ. One possibility for testing for neglected asymmetric information could be to entertain a test of equality of $g(\cdot)$ and $k(\cdot,\gamma)$, based on nonparametric and parametric estimators respectively. Another one could be to compare estimators of λ in the two models through a Hausman-type test. A third solution is simply to test if the conditional expectation of the residual is zero in the perfect information model. The advantage of this method is threefold. First, we need only to estimate the simpler model. Second, the testing procedure will be robust against possible misspecifications of the parametric part of the model. Third, this procedure is applicable in other problems where the parametric assumptions on the function of interest (cost functions, production functions, ...) are different.

Several procedures for testing a parametric specification against a nonparametric one exist in the literature. In the sequel, we will use the one developped by Zheng (1996), which is implemented as follows. First we compute residuals $\hat{U}_i$ from the parametric model of perfect information. Then we compute the statistic

$$V_n = \frac{2}{n(n-1)}\sum_{i<j}\hat{U}_i\hat{U}_j\frac{1}{h^p}K\left(\frac{X_i - X_j}{h}, \frac{W_i - W_j}{h}\right),$$

where h is a bandwidth, p is the dimension of (X,W) and $K(\cdot,\cdot)$ is a kernel from $\mathbb{R}^p$ to $\mathbb{R}$. Under the null hypothesis

$$H_0 : E[U|X,W] = 0,$$

the statistic V_n is such that $nh^{p/2}V_n \xrightarrow{d} N(0,\omega^2)$. Under any alternative to the null, i.e. under any misspecification of the parametric regression model, $nh^{p/2}V_n \xrightarrow{p} +\infty$. Hence a one-sided normal test can be based on $nh^{p/2}V_n/\omega_n$, where ω_n^2 is a consistent estimator of ω^2, see Zheng (1996) for details.

3.3 Testing for Parametric Specification

The separation between the type θ and other factors in the profit function is central for our analysis. This hypothesis, together with the specification of the cost function, allows estimation of structural parameters of interest. Moreover, we may reject the whole perfect information model only because of misspecification of the parametric cost function. Therefore, it seems important to check if the parametric specification of the economic model is acceptable in view of the evidence provided by the data. In our analysis, this is the Cobb-Douglas specification that entails separability. Moreover, it implies that the expectation of $\log \delta$ is linear in $\log t$ and $\log B$, either in the perfect information model or in the adverse selection one. To check this linearity, we apply the nonparametric conditional moment test developped by Delgado, Dominguez and Lavergne (1997), which is an extension of Zheng's test. From the residuals $\hat{U}_i$ (of either the parametric or the semiparametric model), we can compute

$$V_n^* = \frac{2}{n(n-1)} \sum_{i<j} \hat{U}_i \hat{U}_j \frac{1}{h^q} L\left(\frac{X_i - X_j}{h}\right),$$

where h is a bandwidth, q is the dimension of X and $L(\cdot)$ is a kernel from $I\!R^q$ to $I\!R$. This statistic has a behavior similar to V_n, i.e. $nh^{p/2}V_n^* \xrightarrow{d} N(0, \omega^{*2})$ under the null hypothesis

$$H_0 : E[U|X] = 0,$$

and $nh^{p/2}V_n^* \xrightarrow{p} +\infty$ under any alternative. As before, a one-sided normal test is built upon $nh^{p/2}V_n^*/\omega_n^*$, where ω_n^{*2} is a consistent estimator of ω^{*2}, see Delgado, Dominguez and Lavergne (1997) for details.

3.4 Computing P-values

It is now well-known that for tests such as Zheng's one, the asymptotic normal approximation does not provide an adequate approximation for usual sample sizes. The test statistic behaves like a centered and rescaled chi-square with degrees of freedom converging to infinity, in an asymptotic sense, and accordingly the finite sample distribution is typically right-skewed. Hence, in testing for asymmetric information and separability, it can be misleading to use p-values coming from the asymptotic normal approximations.

Two solutions can be thought of. A wild bootstrap procedure, such as studied by Härdle and Mammen (1993) and Li and Wang (1995), can be applied to compute more accurate p-values. This roughly comes to generate residuals from a distribution that has the same conditional third moments than the residuals from the (parametric or semiparametric) model under test, and then to recover a bootstrap sample by adding the estimated parametric function to these generated residuals. This method is used in testing for asymmetric information.

Unfortunately, we cannot apply wild bootstrap in testing for parametric specification. Indeed, we are testing for the nullity of a conditional expectation involving only part of the explanatory variables, i.e. only X. In this case, a bootstrap procedure would need to generate values of W that mimic the dependence with the other variables, which is not possible in our framework. Instead, we use an approximation based on a centered-rescaled chi-square with degrees of freedom estimated from the data, as proposed by Chen (1994) and Lavergne and Vuong (1995) in different contexts.

4 Empirical Application

4.1 Data Description

We use plant–level data on abatement activity of industrials located in three French hydrographical basins: Adour–Garonne (Southwest), Rhin–Meuse (Northeast) and Seine–Normandie (Paris and North). The number of observations is 320 and the sample period is 1985-1992. Contracts are recorded between industrials and local Water Agencies, concerning external abatement plants only. This is because they do not modify the production process and allow to recover abatement variables, which would not be possible with internal abatement. An industrial is represented only once in the sample, so that our static framework can be applied to this set of data. There are some cases in which the contract covers several successive operations, mostly because of the technical complexity and the high construction cost of the abatement plant. Abatement rates are then computed after complete setting up of the plant, taking into account the one–year delay for the equipment to become fully operative.

Effluent emission data are available on five categories of pollutants: Biological Oxygen Demand (BOD), Total Suspended Solids, Nitrogen, Phosphates, and Inhibitory Matters. We choose BOD as the pollution index, as it is good indicator for overall pollution, accounting for more than 75% of total emission fees[3]. B is then defined as the *gross* (i.e. before treatment) emission level, in kg per day. In the following, the level of emission B, the abatement rate δ, and the unit emission charge t will therefore correspond to BOD.

There exist three possible steps in wastewater abatement. The first step, denoted primary

[3]BOD is a conventional, degradable pollutant defined as the quantity of oxygen absorbed by the effluent, measured on a 5-day period at a temperature of 20°C. BOD is a good measure of microbiological activity, particularly when the effluent is severely polluted. See McConnell and Schwarz (1992) for details.

treatment, deals with organic matters essentially, while secondary and tertiary treatments are required when effluents are more complex in nature. A firm will be more efficient in the abatement activity when effluents can be abated with primary treatment only. Considering exogenous variables entering the conditional expectation of $\log(\theta)$, we select an indicator of organicity of effluent emissions, denoted $PART$, with $PART \in [0,1]$. A value of that index close to one indicates that effluents are mostly organic, and therefore require limited additional treatment, hence reducing the cost of abatement. The motivation for this choice is that abatement of BOD is likely to be more difficult, and hence will require more know-how and ability from the industrial, when that effluent comes jointly with other, more toxic pollutants.

Table 1 presents descriptive statistics for variables in the sample. Variability in the unit emission charge originates both from yearly variation and from regional differences in the design of the emission fees.[4] Additional exogenous variables are needed as instruments in the IV procedure: as candidates, we use dummy variables for the industry sector of the firm (SIC). The definition of the sectors is the following, with the number of firms in each sector: $COD1$: Food and drinks (73 firms); $COD2$: Dairy products (50 firms); $COD3$: Chemicals (41 firms); $COD4$: Iron and steel (103 firms); $COD5$: Paper and wood (36 firms).

4.2 Estimation and Testing of the Perfect Information Model

Two versions of the model (12) corresponding to different forms of $k(\cdot,\gamma)$ are estimated. Model I assumes that the conditional expectation of $\log(\theta)$ is linear in $\log(PART)$; in Model II, the expectation of $\log(\theta)$ is linear in $PART$. In a preliminary step, we check for exogeneity of B and do not reject this hypothesis. Hence this validates our assumption of separability between production and abatement (see Section 2.1). We subsequently consider models in which $\log PART$ and $PART$ are possibly endogeneous, so as to take into account possible misspecifications due for instance to omission of variables. Instrumental Variable estimation results based on the set $(X, COD1, COD2)$ are presented in Table 2, for both model specifications. From Pesaran and Smith's (1994) R^2, both models fit equally. Parameters associated with $\log(t)$ and $\log(\theta)$ are significantly different from 0 at the 0.05 level, but only the parameter values of $\log\theta$ are significantly different between models. Moreover, the estimated parameter of $\log\theta$ is coherent with the assumption that the abatement cost is decreasing in the efficiency parameter. Parameter associated to B is significant in Model II only. From these estimates, we can retrieve structural

[4]On the period considered, emission charges designed by local Water Agencies were fairly stable before the 1992 French Law on Water induced a significant increase in unit emission fees from 1992 to 1996.

parameters α_0 and α_1 with their estimated standard errors. These values imply that the cost function is actually increasing in B and δ, and convex in δ.

For both specifications, we entertain a battery of standard tests presented in Table 3. White's test strongly rejects homoscedasticity in both cases, so that standard errors given in Table 2 are computed by means of a robust consistent variance-covariance matrix. Hausman's test rejects exogeneity of $\log PART$ in Model I. This may indicate possible misspecification in $k(\cdot, \gamma)$ or neglected asymmetric information. In contrast, this test does not reject exogeneity of $PART$ in Model II, so that one may conclude that asymmetric information is not present. We also compute a pure significance test as suggested by Godfrey (1988) that does not reject either of the models at a 5% level; this test may be also interpreted as an overidentifying restriction test. Lastly, Pagan and Hall's (1983) test (with the whole set of instrumental variables) leads to confirm the correctness of our specifications. Consequently, we consider our IV estimation results as a valid base for subsequent analysis.

For checking the specification of the Cobb-Douglas cost function, we apply the testing procedure detailled in Section 3.3. We compute an individual bandwidth for each variable (i.e. $\log t$ and $\log B$). The choice of the bandwidth parameters uses the rule-of-thumb $h = 0.79In^{-1/5}$, where I is the interquartile range of the variable, i.e. the difference between the 0.75 and the 0.25 quantiles (see Härdle, 1993). In order to investigate the sensitivity of the test to the choice of the bandwidths, we introduce a multiplicative factor c in the formulae for h, which varies from 0.5 to 1.5. The results for this test in Table 4 show that the Cobb-Douglas specification is not rejected in either case. The p-values are quite large for Model I, with negative values of the test statistics that asymptotically occur only under the null. For Model II, the p-values are always superior to 0.2, indicating the non-rejection of our specification.

Considering now testing for asymmetric information, we apply the procedure detailled in Section 3.2. We use a similar method for the choice of the bandwidth parameters, now including the variable $PART$ in addition to $\log t$ and $\log B$. We report p-values from both the χ^2 approximation and from the bootstrap procedure based on 200 samples. For Model I, the values of the test statistics are quite large for any choice of the bandwidths, leading to p-values that are always less than 0.05. This is in accordance with Hausman's test outcome and clearly indicates that we cannot accept the parametric Model I derived under perfect information. For Model II, the issue of the testing procedure depends on the chosen bandwidths. For the base case where $c = 1$, the p-value is a mere 7 percent when using the χ^2 approximation and 12.5 percent with the bootstrap procedure. Moreover, as we smooth further, the test rejects the null with greater probability. Hence, the conclusions from these nonparametric specification tests differ from what we obtain using standard parametric tests. In particular, Hausman's test does not allow to reject the parametric model. In contrast, the outcome of the nonparametric specification tests lets us suspect that further investigation is required. In particular, it is worth considering the asymmetric information assumption within a semiparametric model.

4.3 Estimation and Testing of the Asymmetric Information Model

We estimate the econometric model (13) derived under the assumption of asymmetric information by Robinson's (1988) method. This method requires a bandwidth that asymptotically undersmoothes with respect to the theoretical optimal bandwidth in nonparametric regression estimation.[5] Thus, we choose bandwidth parameters proportional to $n^{-0.3}$. Further analysis (whose results are not reported) shows that the estimation results are not very sensitive to variation of these parameters. Table 6 reports our estimation results. The two parameters related to $\log t$ and $\log B$ are significant and their standard errors are not higher than in parametric modelling. Note that we have taken into account possible heteroscedasticity in their computation as suggested by Robinson (1988). For $\log t$, the obtained value is notably below the ones obtained in the parametric models, while for $\log B$, we have the reverse effect. Concerning the structural parameters, α_0 has significantly decreased with a similar standard error, while α_1 has a larger estimated value than in the parametric estimation.

We also perform the nonparametric specification tests on the semiparametric model in the same way as for the parametric case, see Table 7. When checking for the Cobb-Douglas specification, we obtain p-values that are always higher than 0.23, leading to the non-rejection of this assumption. The test using all three variables $\log t$, $\log B$ and $PART$ as conditioning variables checks for the whole specification of the regression model (see Fan and Li [1996]). We obtain results indicating that the semiparametric model is a valid candidate for modelling the abatement equation in the asymmetric information case.

For comparing goodness-of-fit in parametric and semiparametric modelling, we compute the sum of squared differences between actual and fitted values. Model I leads to a value of 304.57, Model II to a value of 229.18, while the semiparametric model attains a value of 228.80. Hence the semiparametric model fits similarly to Model II, while taking into account the adverse selection problem. Finally, Figure 2 shows the estimated function $g(\cdot)$ from the semiparametric model. It is mostly increasing on its domain, with an exception for extreme low values of $PART$.

[5] This is also a requirement for testing the whole specification of the model as done subsequently, see Fan and Li (1996).

But, as easily seen, it departs from a simple linear specification.

These results have important policy implications. First, the coefficient associated with $\log t$ is the elasticity of abatement with respect to the emission tax. Overestimating this parameter as in the parametric models of perfect information can therefore lead to erroneous conclusions in evaluating the effect of a change in the tax level. Second, neglecting possible asymmetric information may lead to bias in estimation of economies of scale in the cost function. Specifically, in our application, the economies of scale are underestimated. The parametric models I and II lead us to accept with great probability the hypothesis $\alpha_0 = 1$, i.e. the assumption of constant returns to scale in the abatement activity. In contrast, the semiparametric results reveal potential increasing returns to scale. Therefore, while fitting as well as the parametric Model II. the semiparametric model allows for more flexibility in the $g(\cdot)$ function and allows robust estimation of the structural parameters.

5 Conclusion

As clearly shown in our application, semiparametric methods give us great flexibility in estimating and testing models with possible adverse selection. First, when considering a perfect information model, nonparametric testing procedures allow to assess the presence of adverse selection, without requiring estimation of the general model by costly numerical methods. Moreover, these procedures can also be used to validate the parametric assumptions of the economic model. This point is crucial because one may falsely conclude in favor of asymmetric information only because of erroneous assumptions in the economic model. For instance in our application, we check the Cobb-Douglas specification of the abatement cost function, that leads us to a tractable model. Second, when considering an adverse selection model, semiparametric modelling prevents us from possible misspecification errors related to the type's distribution, while allowing estimation of structural parameters that are of central interest for policy analysis. We can also check the parametric part of the model by means of consistent testing specification procedures as done in the perfect information model.

As pointed out in the paper, this framework can prove very useful in a wide variety of problems where adverse selection can be present. In most applications, practioners must assume that effects of the private information parameter can be disentangled from other effects, in order to get a workable model. In this case, our framework is applicable with possibly slight adjustments.

References

Baron, D.P. (1985) "Regulation of prices and pollution under incomplete information," *Journal of Public Economics*, 28, pp. 211–231.

Baron, D.P. (1989) "Design of regulatory mechanisms and institutions," in *Handbook of Industrial Organization*, ed. by R. Schmalensee and R. Willig, North-Holland, pp. 1347–1448.

Baumol, W.J. and W.E. Oates (1988) *The theory of environmental policy*, Cambridge University Press, Cambridge.

Chen, J.C. (1994) "Testing for no effect in nonparametric regression via spline smoothing techniques," *Annals of the Institute of Statistical Mathematics*, 46(2), pp. 251–265.

Chiappori, P.A. and B. Salanié (1997) "Empirical contract theory : the case of insurance data," *European Economic Review*, 41, 943–950.

Dalen, D.M. and A. Gomez-Lobo (1997) "Estimating cost functions in regulated industries characterized by asymmetric information," *European Economic Review*, 41, 935–942.

Delgado, M., M. Dominguez and P. Lavergne (1997) "Consistent specification testing of nonlinear econometric models," Universidad Carlos III (work in progress).

Fan, Y. and Q. Li (1996) "Consistent model specification tests: omitted variables and semiparametric functional forms," *Econometrica*, 64 (4), pp. 865–890.

Gasmi, F., J.J. Laffont and W. Sharkey (1997) "Empirical evaluation of regulatory regimes in local telecommunications markets," IDEI, Toulouse.

Godfrey, L.G. (1988) *Misspecification tests in econometrics*, Cambridge University Press, Cambridge.

Härdle, W. and E. Mammen (1993) "Comparing nonparametric versus parametric regression fits," *Annals of Statistics*, 21 (4), pp. 1926–1947.

Ivaldi, M. and D. Martimort (1994) "Competition under nonlinear pricing," *Annales d'Economie et de Statistique*, 34, pp. 71–114.

Laffont, J.J. and J. Tirole (1994) *A Theory of incentives in procurement and regulation*, MIT Press, Harvard.

Laffont, J.J., H. Ossard and Q.H. Vuong (1995) "Econometrics of first–price auctions," *Econometrica*, 63, pp. 953–980.

Lavergne, P. and Q. Vuong (1995) "Nonparametric significance testing," INRA-ESR, Toulouse.

Li, Q. and S. Wang (1995) "A simple consistent bootstrap test for a parametric regression function," University of Guelph.

McConnell, V.D. and G.E. Schwarz (1992) "The supply and demand for pollution control: evidence from wastewater treatment," *Journal of Environmental Economics and Management*, 23, pp. 54–77.

Miravette, E. (1997) "Estimating demand for local telephone service with asymmetric information and optional calling plans," INSEAD, Paris.

Pagan, A.R. and A.D. Hall (1983) "Diagnostic tests as residual analysis," *Econometric Reviews*, 2, pp. 159–218.

Pesaran, M.H. and R.J. Smith (1994) "A generalized R^2 criterion for regression models estimated by the instrumental variables method," *Econometrica*, 62(3), 705–710.

Thomas, A. (1995) "Regulating pollution under asymmetric information: the case of industrial wastewater treatment," *Journal of Environmental Economics and Management*, 28, pp. 357–373.

Wolak, F.A. (1994) "An econometric analysis of the asymmetric information regulator–utility interaction," *Annales d'Economie et de Statistique*, 34, pp. 13–69.

Xepapadeas, A.P. (1991) "Environmental policy under imperfect information: incentives and moral hazard," *Journal of Environmental Economics and Management*, 20, pp. 113–126.

Zheng, J.X. (1996) "A consistent test of functional form via nonparametric estimation techniques," *Journal of Econometrics*, 75, pp. 263–289.

Appendix. Derivation of the Asymmetric Information Solution

We present here the resolution of the principal's problem, using standard techniques in the literature on regulation under asymmetric information. The interested reader may consult e.g. Baron (1989) or Laffont and Tirole (1994) for more details.

We first consider the condition for truthful revelation of the agent's type, i.e.

$$\Pi(\theta,\theta) \geq \Pi(\theta,\tilde{\theta}) \qquad \forall\, \theta, \tilde{\theta}$$

which is equivalent to $\frac{\partial \Pi(\theta,\tilde{\theta})}{\partial \tilde{\theta}} = 0$. Differentiating profit totally and using condition (8) (Increased Abatement) yields $\dot{\Pi} = \frac{d\Pi(\theta,\tilde{\theta})}{d\theta} = -\frac{\partial C(\theta,B,\delta)}{\partial \theta}$. In our case, we then have

$$\dot{\Pi} = -c\beta\theta^{\beta-1}B^{\alpha_0}\delta^{\alpha_1} \quad > 0.$$

Because we must have that $\delta \geq \delta^0$ under regulation, this condition is equivalent to the slope of Π being higher in absolute value than the slope of Π^0. Hence, the profit function $\Pi(\theta)$ is always above the *status quo* profit $\Pi^0(\theta)$, and both coincide at $\theta = \theta_c$, as shown in Figure 1. The firm with parameter θ_c receives a zero rent, and the information rent is increasing in the agent's type. Furthermore, firms below θ_c are left in the *status quo* case with abatement rate $\delta^0(\theta)$. Consequently, θ_c is the threshold value defined by the equality between Second–Best (asymmetric information) abatement rate and the *status quo* abatement rate.

Integrating by parts the expectation of profit yields

$$\int_{\theta_c}^{\overline{\theta}} \Pi(\theta)dF(\theta) = \Pi(\theta_c) + \int_{\theta_c}^{\overline{\theta}} \frac{\partial \Pi(\theta)}{\partial \theta}(1 - F(\theta))d\theta = \Pi^0(\theta_c) - \int_{\theta_c}^{\overline{\theta}} \frac{\partial C}{\partial \theta}(1 - F(\theta))d\theta.$$

Total expected surplus now reads

$$\int_{\theta_c}^{\overline{\theta}} \left\{\sigma\left[W(B\delta) - C(B,\delta,\theta) - K\right] + (1-2\sigma)\frac{1}{f(\theta)}\left[\Pi^0(\theta_c) + (1-F(\theta))\frac{\partial C}{\partial \theta}\right]\right\} f(\theta)d\theta.$$

Maximizing with respect to δ and using the cost function specification given in (2) yields

$$t^* = \varepsilon t = c\alpha_1\theta^{\beta}\delta^{\alpha_1-1}B^{\alpha_0-1}\left[1 - \frac{2\sigma-1}{\sigma}\frac{1-F(\theta)}{f(\theta)}\frac{\beta}{\theta}\right].$$

Thus the Second–Best (asymmetric information) solution for the abatement rate is, in logarithmic form

$$\log(\delta^{**}) = (\alpha_1 - 1)^{-1}\{\log(\varepsilon) + \log(t) - \log(c) - \log(\alpha_1) - \beta\log(\theta)$$
$$-(\alpha_0 - 1)\log(B) - \log\left[1 - \beta\frac{2\sigma-1}{\sigma}\frac{1-F(\theta)}{f(\theta)}\frac{1}{\theta}\right]\right\}.$$

This equilibrium solution under asymmetric information is valid for firms with characteristics in the interval $[\theta_c, \overline{\theta}]$. Thus, θ_c is the value of θ such that $\delta^{**} = \delta^0$, i.e. θ_c is solution to

$$\varepsilon - 1 = -\frac{2\sigma-1}{\sigma}\frac{1-F(\theta_c)}{f(\theta_c)}\frac{\beta}{\theta_c}.$$

Figure 1. Abatement rates under *status quo*, perfect information, and asymmetric information.

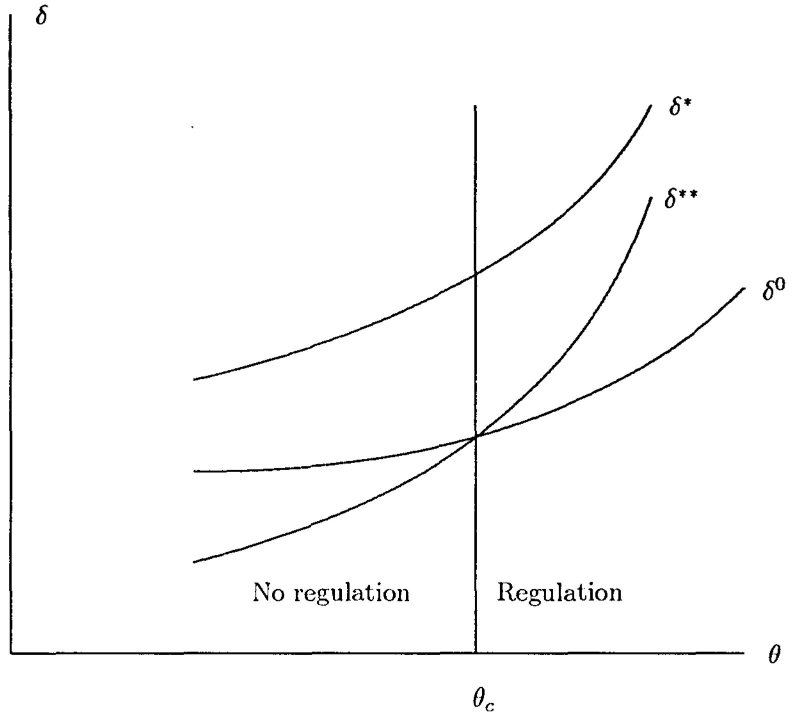

Table 1: Descriptive statistics (320 observations)

Variable	Mean	St. deviation	Minimum	Maximum
δ	0.5793	0.3023	0.0024	0.9960
B	3278.1	9962.1	4.0000	112286
t	225.4	63.2	91.0097	561.06
$PART$	0.5995	0.2996	0.0018	0.9963

δ: abatement rate (in %); B: gross Biological Oxygen Demand (BOD) emission level, in kg. per day; t: BOD emission charge (in French Francs); $PART$: indicator of emissions organicity (in %).

Table 2: IV Estimation results

	Model I		Model II	
Variable	Estimate	Standard error	Estimate	Standard error
Intercept	-3.8303	0.8264	-5.6787	0.9178
$\log t$	0.6500	0.1693	0.6288	0.1619
$\log B$	0.0204	0.0337	0.0586	0.0277
$\log \theta$	0.7318	0.1267	1.8691	0.2965
α_0	0.9686	0.0832	0.9068	0.0811
α_1	2.5385	0.2605	2.5904	0.2575
	R^2 0.176		R^2 0.179	

Model I: $\log \theta$ is linear in $\log PART$; Model II: $\log \theta$ is linear in $PART$.

Instruments used in both models: $\log t$, $\log B$, $COD1$, $COD2$.

Table 3: Tests on IV models

	Model I		Model II	
Test	Statistic	P-value	Statistic	P-value
White's test (χ^2_{10})	68.4788	0.0000	63.7540	0.0000
Hausman's test (χ^2_3)	11.2641	0.0238	5.2925	0.2586
Pure sign. test (χ^2_1)	3.3701	0.0664	3.4706	0.0625
Pagan-Hall's test (χ^2_4)	3.4240	0.6349	3.4782	0.6267

Table 4: Test for parametric specification

	Model I		Model II	
c	Test statistic	P-value	Test statistic	P-value
0.50	-0.7798	0.7791	0.5417	0.2917
0.75	-0.4172	0.6561	0.7866	0.2147
1.00	-0.4853	0.6831	0.7927	0.2129
1.25	-0.5252	0.6986	0.7859	0.2150
1.50	-0.5635	0.7127	0.7004	0.2406

Table 5: Test for asymmetric information

	Model I			Model II		
c	Test statistic	P-value		Test statistic	P-value	
		χ^2 app.	Bootstrap		χ^2 app.	Bootstrap
0.50	1.9098	0.0401	0.0250	0.6446	0.2563	0.2900
0.75	3.0455	0.0031	0.0050	1.0553	0.1457	0.2150
1.00	3.7830	0.0003	0.0000	1.4731	0.0709	0.1250
1.25	3.9973	0.0001	0.0000	1.8644	0.0313	0.0600
1.50	4.3703	0.0000	0.0000	2.5049	0.0063	0.0020

χ^2 app. refers to p-values based on a centered-rescaled chi-square approximation.

Table 6: Semiparametric regression

Variable	Estimate	Standard error
$\log t$	0.5644	0.1640
$\log B$	0.0986	0.0231
α_0	0.8253	0.0976
α_1	2.7718	0.2907

Table 7: Tests for the semiparametric model

	Parametric specification		Whole specification		
c	Test statistic	P-value	Test statistic	P-value	
				χ^2 app.	Bootstrap
0.50	0.6825	0.2442	0.2759	0.3859	0.3550
0.75	0.7300	0.2304	0.1941	0.4230	0.4400
1.00	0.5244	0.2960	0.1737	0.4304	0.4850
1.25	0.4974	0.3057	0.3833	0.3501	0.4000
1.50	0.4301	0.3298	0.8835	0.1883	0.2100

χ^2 app. refers to p-values based on a centered-rescaled chi-square approximation.

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