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The Market for Used Cars: New Evidence of the Lemons Phenomenon

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Abstract

The lemons model assumes that owners of used cars have an information advantage over potential buyers with respect to the quality of their vehicles. Owners of bad cars try to sell them to ill-informed buyers while owners of good cars hold on to theirs. Consequently, the quality of traded automobiles tends to be sub-average. In contrast to previous empirical work, the following paper investigates both the behavior of buyers and sellers, testing for adverse selection by sellers and for quality uncertainty among buyers with a sample consisting of all 1985 cars registered in the Swiss canton of Basle-City over the period 1985-1991. Our data support both adverse selection and buyer uncertainty suggesting that a lemons problem exists.

Journal of Economic Literature Classification Numbers: C41, D82, L15, L62.
Keywords: adverse selection, used car market, duration models.

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1. Introduction

In AKERLOF's (1970) "lemons" model, buyers cannot distinguish between the qualities of used cars. Consequently, cars of different qualities sell at a common price that reflects the buyers' estimate of average quality. Sellers, on the other hand, know the quality of their vehicles, yet due to the non-observability of car quality to buyers, can only sell their vehicles at the common price reflecting average quality. Hence, owners of automobiles of above-average quality hold on to their cars, while owners of "lemons" attempt to sell theirs to ill-informed buyers. The average quality of traded cars is thus lower than that of the population of cars: good used cars are driven out of the market by bad ones. In the limit this adverse selection phenomenon can even lead to market breakdown.

Empirical tests of the lemons model customarily concentrate on adverse selection. In this approach, the quality of traded goods is often compared with that of the population of goods from which they stem.[1] Examples include BOND (1982, 1984), who compares the maintenance frequency of pickup trucks purchased new and used; LEHN (1984), who finds evidence that free agents that switch teams spend more time on the disabled list than those retained by their clubs; or GREENWALD and GLASSPIEGEL (1983), who discover that the quality of slaves brought to market in pre-Civil War New Orleans was 20-40% below average. These findings are inconclusive, however, as buyers may be fully informed and nevertheless purchase low quality goods because they are more willing than sellers to accept the associated risks and costs of owning them. Thus, adverse selection alone does not necessarily imply information asymmetry.

The following study attempts to correct this shortcoming by testing both for the adverse selection by sellers and the quality uncertainty among buyers. We show that cars put on the market represent a negative selection from the population of registered cars and that the buyers of used cars suffer from quality uncertainty. Taken together, the two results point to the presence of information asymmetry.

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[1] Another common test for adverse selection is to investigate the prices of goods prone to adverse selection. If adverse selection holds then goods subject to negative selection should sell at a discount. This approach has been employed by, among others, GENESOVE (1993), who compares the prices of used cars sold in the wholesale used-car market by used-car dealers and by new-car dealers, respectively; CHEZUM and WIMMER (1997), who compare the auction prices of horses sold by breeders who also race horses with those sold by breeders that do not; and GIBBONS and KATZ (1991), who compare the subsequent wages of workers displaced by plant closings with those of workers laid off. All studies find evidence of adverse selection.

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We apply our test of the lemons model on a sample consisting of all 1985 cars registered in the Swiss canton of Basle-City over the period 1985-1991. Our test of adverse selection is based on the results of vehicle safety-inspection records. Cars in Basle are subject to mandatory safety inspections at fixed time intervals. Under certain conditions, however, vehicles that are sold are required to be inspected ahead of schedule, thus enabling us to discriminate between the quality of sold and non-sold cars. Our results indicate that the probability of a vehicle having a defect increases if the used car was sold privately, supporting the presence of adverse selection. Interestingly, we find that the opposite holds true for used cars sold by dealers. This result conforms with AKERLOF's (1970) conjecture that institutions such as warranties and reputation may develop to offset the effects of asymmetric information.[2]

Our test of quality uncertainty, on the other hand, rests on the following simple idea. The lemons model assumes that buyers of used cars are incompletely informed about the true quality of the vehicles they purchase. With time, however, owners should discover the actual condition of their purchased vehicles. Accordingly, those individuals who bought lemons should become increasingly aware of their mistakes and attempt to unload their cars on other buyers. As a consequence, the probability of a recently acquired car being resold should, after perhaps initially increasing, decline as ever less is left to be learned about the vehicle. We demonstrate this result with a simple model of quality uncertainty and then test the model's prediction by investigating the shape of the hazard function of car ownership. If car buyers suffer from quality uncertainty at the time of purchase, the hazard function should decline with the duration of ownership, reflecting the decreasing likelihood of buyers discovering any further defects that would lead them to resell their vehicles.

Of course in an Akerlof-type of equilibrium buyers expect to purchase low quality goods on average. But they still do not know whether the purchased good is above or below this expected low average. Thus, buyers may be disappointed and try to resell the purchased item. With perfect and symmetric information, on the other hand, sellers may simply prefer better quality than buyers at going prices, also leading to an equilibrium in which goods traded are below average. However in this case, no buyer is disappointed and moved to resell purchased goods.

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[2] In the US all states have "lemon" laws, though they differ as to what they require dealers to do with returned vehicles. It is still possible to sell a car identified in one state as a lemon without warning in another state (see http://www.autopedia.com./html/HotLinks_Lemon.html). In the EU consumers enjoy less protection. A new directive which took effect in 2002 forces dealers to fix defects within two years in a new car or one year in a used car (see http://europa.eu.int/scadplus/leg/en/lvb/-l32022.htm). VAILLANT (2004) presents evidence that screening devices too can provide an effective protection against adverse selection.

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Our hazard function approach has been implemented before in labor market studies that test for the quality uncertainty that underlies job-matching models of labor turnover (JOVANOVIC, 1979).[3] The following study appears to be the first attempt to employ this methodology to the lemons model, however.[4] Using the ownership biographies of all 1985 cars registered in Basle in the sample period, we show that the estimated hazard function of car ownership does indeed decline with the duration of ownership as quality uncertainty implies. In addition, we find that higher quality cars are less likely to be resold shortly after purchase.

The remainder of the paper is organized as follows. Section 2 describes the data of our study in more detail. Section 3 explains our method of testing for adverse selection and gives the results. Section 4 develops our model of buyer uncertainty and presents our empirical findings. The last section summarizes and concludes.

2. Data

Our study is based on two separate data sets. The first one consists of protocols from state vehicle safety inspections, and the other of registration records drawn from the databank of the Department of Motor Vehicles in the canton of Basle-City. All data pertain to cars manufactured in 1985 and registered in Basle at some time during the sample period from 1985 through 1991. We concentrate on a single vintage to avoid possible cohort effects.

The vehicle safety inspection protocols constitute form sheets filled out by the state inspector on the day the car was initially presented for inspection. The inspection protocols record a vehicle's chassis number (unique to each vehicle), the date the vehicle was submitted for inspection, vehicle mileage, the detected defects, the make of the

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3 Job-matching models assume that an employee and employer are not perfectly informed as to whether they meet each other's expectations when entering into an employment contract. In the course of time, however, "mismatches" are discovered and get sorted out by job separations. Hence, the hazard function of job tenure should, after perhaps initially rising, thereafter decrease. BORLAND and LYE (1996), CHAPMAN and SOUTHWICK (1991), HAUTSCH ET AL. (2001), LANCASTER ET AL. (1987), OHTAKE and OHKUSA (1994), and SHELDON (1992) find empirical support for this conjecture.

4 ENGERS, HARTMANN, and STERN (2005) have subsequently used duration data on car ownership in Virginia to test for the lemons problem. Their model predicts a positive relationship between the length of the initial spell of car ownership and all subsequent ones if the lemons problem holds. Instead, they discover a negative relationship. However, their finding may simply result from the finite lives of cars. If a car has a fixed life of, say, roughly 10 years then the second spell of ownership can last only as long as the remaining life left in the car. For example, if the first owner sells after 2 years, the second owner can drive the vehicle for another 8 years; if the first owner sells after 8 years, the second owner can use the car for only another 2 years.

car and the grounds for presenting the vehicle.

The protocols distinguish six different reasons for submitting an automobile for inspection: (i) periodic check up, (ii) private or (iii) dealer sale, (iv) ticketing by police for a safety defect, (v) technical alteration, or (vi) export out of Switzerland. Periodic inspections (i) occur at fixed intervals: roughly every four years in our sample period.[5] Vehicles used for commercial purposes (taxis, rental, driver education), however, have to appear annually. Privately (ii) and dealer-owned (iii) cars sold are subject to inspection if the vehicle is at least four-years old at the time of sale and has not been inspected in the last year prior to purchase. Inspections occur before the sale of the car. In all cases, the authorities carry out the inspections themselves. The inspection protocols record any deficiency discovered when the car is initially presented. If a car does not pass inspection at its initial presentation, the owner must have the defects repaired and re-submit the vehicle until it passes. In all instances, an inspection is mandatory and not left up to the owner. Since the timing of periodic inspections is not affected by the actions of owners, vehicles brought in for a periodic inspection represent a random sample of the population of registered cars.

We use the protocol data to investigate whether cars put up for sale are more or less likely to display a defect than a randomly chosen vehicle (*Section 3*). The unit of observation is an inspection protocol.

Our second sample consists of registration records that document all vehicle registrations, de-registrations and re-registrations of 1985 cars that occurred in Basle in the sample period 1985-91. From these records we construct 3,806 spells of vehicle ownership, 2,645 of which refer to cars bought new and 1,161 to automobiles purchased used.[6] An ownership spell begins with the registration of a car by the current owner and ends with the final de-registration of the vehicle by the same individual. An ended spell is considered complete when a new owner re-registers the same car, which implies that a sale has occurred.[7] Otherwise the spell is considered to be incomplete, or right-censored.

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5 Although three-year intervals were mandatory officially during the sample period, most cars were inspected at four-year intervals due to a lack of personnel.

6 Cars purchased used, unlike those bought new, also include vehicles that were originally registered outside the canton of Basle-City. The registration data pertain solely to periods of ownership in Basle-City, however.

7 The protocol records from the first sample cannot be used to define a sale since not all cars sold are subject to inspection. Furthermore, some cars sold after inspection may have been inspected for reasons not related to a sale.

The spells record the chassis number of a vehicle, its make, its fuel requirement (diesel or gasoline), the beginning and end date of a spell, the current owner's social security number, the license plate number, the vehicle's current use (private or commercial; taxi, rental, or driver education), and whether the spell ended with a sale. We use the ownership spells to analyze the shape of the hazard function, i.e., to investigate how resell probabilities evolve as the length of vehicle ownership increases (*Section 4*). The unit of observation is an ownership spell.

It is important to note that although both samples pertain to the same cohort of cars, the two samples and their sources are different. The first sample consists of the safety inspections conducted on the cohort of vehicles in Basle-City, and the second encompasses their registration records kept in the same canton. Not all cars found in the registration data to have been sold need to have been inspected beforehand and thus to appear in the inspection data. And not all cars presented for inspection due to a change of ownership need to have been traded between residents of Basle-City and thus to appear in the registration data as sales. Hence, the possibilities of merging the two data sets are extremely limited.[8] The main information we were able to merge was whether a vehicle that was sold according to the registration data was inspected three months prior to sale according to the inspection data.

3. Test of Adverse Selection

Our test of adverse selection is based on a comparison of the quality of sold and randomly chosen cars, where the definition of car quality rests on the results of the official vehicle safety inspections.[9] We consider cars that passed inspection at their initial presentation to be of higher quality than those that failed. In other words, we view the results of the initial inspection as an indicator of the overall quality of a car and not just of safety and environmental aspects, which the inspections address. This interpretation finds support in our findings below pertaining to the effect of the brand of a car on its passing inspection.

We investigate whether cars put up for sale are more likely to fail their initial inspec-

[8] To illustrate this point, note that according to *Table 3* below, which pertains to the registration data, 28.8% or 46 of the 160 used cars privately sold in Basle-City were inspected three months prior to sale in Basle-City, whereas according to *Table 1*, which relates to the inspection data, 165 used cars were inspected prior to being put up for private sale.

[9] EMONS and VON HAGEN (1991) use similar safety inspection data to establish weak information efficiency in the German automobile market.

tion than randomly chosen vehicles on the basis of the following probit model

$$P(y_i = 1 \mid \mathbf{x}_i) \quad = \quad \Phi(\alpha' \mathbf{x}_i), \tag{1}$$

where $P(y_i = 1 \mid \mathbf{x}_i)$ represents the probability that a car i with observed profile $\mathbf{x}_i$ fails inspection and Φ denotes the standard normal c.d.f.

The covariate vector **x** contains (i) variables which describe the car and (ii) dummy variables which distinguish between the various grounds for submitting a vehicle for inspection. We measure all descriptive variables in deviations from their respective means and choose vehicles brought in for a periodic inspection as the reference group. Also included in the reference group are seven cars inspected for export and four vehicles for which data on the grounds for inspection were missing. Including these 11 cases should have no effect on the results as they constitute a tiny share of the observations in the reference group (*Table 1*). The reference group also contains any cars possibly sold after having passed a periodic inspection. Including these cases will not affect our results either as the timing of periodic inspections is exogenously determined by the authorities. The presence of cars possibly sold later among the cars presented for a periodic inspection ensures that the reference group is representative of all qualities. Hence, the coefficients of the dummy variables measure the relative chances of a non-periodically inspected, or self-selected car with average attributes passing inspection compared to that of an identical randomly chosen vehicle.

Our sample comprises 5,333 inspections conducted on 4,418 cars. *Table 1* describes the data contained in the inspection protocols. The brand of car, also included in our analysis, is excluded from the table to conserve space. Our sample contains 45 different makes of car. The first column of the table lists the various possible grounds for submitting a car for inspection. "Periodic checks" refers to the regular inspections to which cars in Basle are subject at fixed intervals. The table indicates that the large majority (63 percent) of cars submitted for inspection came in for a periodic check. The second largest group (30 percent) consisted of cars put up for sale or sold by dealers ("dealer sale").

Table 1 about here

The next columns give the share of inspected cars with diesel engines and the average mileage of the vehicles at the time of inspection measured in kilometers. The last columns in the table pertain to the types of defects for which the safety inspections check. "Devices" refer to various minor items like windshield wipers and rearview mirrors. As the table indicates, just over 77 percent of the cars inspected were devoid of defects. The most common faults were linked to lights or the power train (engine and drive shaft). The table also shows that a below-average share (52.7 percent) of privately sold cars and an above-average share (83.3 percent) of dealer-sold vehicles had no technical defects, implying that cars offered for sale by private individuals are of lower quality than those vehicles dealers offer.[10] This evidence is merely suggestive, however, as no control is made for the influence of other factors such as mileage, which may vary systematically across categories. The probit estimates presented in *Table 2* control for such effects.

Table 2 about here

The probit estimates show that greater mileage does indeed raise the chances that a car will have a defect. Nonetheless, even after controlling for mileage, privately sold cars still exhibit an above-average propensity of being defective. In every category, save one ("handbrake"), a privately sold car that went through a safety inspection was more likely to have a defect than a randomly chosen car with the same characteristics. The chances overall are 27 percent higher according to the results appearing in the final column ("None") of *Table 2*. Dealer-sold cars, on the other hand, have a 10 percent lower chance of exhibiting a defect, possibly because dealers have a reputation to lose if they choose to sell lemons. This would conform with AKERLOF's (1970) conjecture that institutions may develop to offset the effects of asymmetric information.

The estimated coefficients of the brand dummies suggest that passing the initial safety inspection is an overall sign of higher vehicle quality. This can be seen in the fact that German (Audi, BMW, Mercedes, Porsche) and Japanese (Honda, Mazda, Mitsubishi, Nissan, Toyota) cars, which German data (Cf. EMONS and VON HAGEN,1991) from the sample period show to be more solid, have a greater chance of passing inspection initially than mileage-equivalent Italian (Alfa, Fiat, Lancia) or French (Citroën, Peugeot, Renault) vehicles, which the same data find to be less dependable. *Section 4*

[10] Cars sold constitute vehicles that had to be submitted for inspection because they changed owners, were at least four-years old at the time of sale, and had not been inspected in the last year prior to sale.

provides further evidence of the existence of these quality differences among car brands.

It is of course possible that whether a car passes an inspection initially depends not only on the basic quality of a vehicle but also on the decision of car owners to have their vehicles checked and repaired before submitting them for inspection. For example, the lower likelihood of cars ticketed by the police for safety reasons ("ticketed") of failing inspection undoubtedly arises from the fact that owners of cars with a ticketed defect have them repaired before presenting them for inspection since the defect is clearly specified and there is no chance that the authorities will miss detecting the problem. Car dealers are another case in point. If one assumes that having a car checked and repaired in advance and submitting it for inspection are both costly undertakings and that dealers have a cost advantage with respect to prior check-ups and repairs, then one should expect dealers to check their vehicles before submitting them for inspection and thus to achieve higher success rates.[11] This argument cannot explain why vehicles presented by private persons due to a sale do worse than those in for a periodic inspection, however, as no obvious cost differential exists between these two groups of non-dealers.[12] It therefore seems that the greater defect rate of privately sold cars vis-à-vis observably identical randomly chosen vehicles arises from lower quality. Furthermore, since the probit estimates indicate that the higher failure rates are not merely due to chance, it would appear that private sellers are generally aware of the sub-average quality of their cars.

How well buyers are informed is a different matter, however. Generally speaking, little information is available to buyers of a used car in Switzerland. The only certain source of information is the vehicle registration, which merely identifies the current owner. Thus a buyer cannot base his quality expectations on the number of previous owners as he can, say, in Germany where a document listing all the previous holders remains with the vehicle. Nor can the buyer know with certainty how long the seller has owned his or her car as the vehicle registration gives only the date of the most recent registration, not when the present owner took possession of the vehicle. In addition, the buyer knows from the vehicle registration when the vehicle last passed in-

[11] Another cause of the higher success rate of dealer-submitted cars could be that inspectors trust dealers more and hence inspect their cars less thoroughly.

[12] Experience shows that garages tend to make more repairs than necessary if told to fix everything that might not pass inspection. Therefore, it is a sensible strategy for private persons to present their cars for inspection first and then to have any detected defects repaired. The duplication of inspection costs with this strategy is less than the costs of superfluous repairs arising from the “fix everything” strategy. This explains why private individuals customarily do not have their cars checked by a garage before submitting them for inspection.

spection, but not why the car was presented for inspection or whether the car passed inspection initially or had to be re-submitted after having the detected defects repaired. In short, the buyer does not have access to the inspection protocols which served as our database in this section.

Instead of theorizing about what used-car buyers might know or not know prior to purchase, we examine the resell behavior of buyers in the first months after purchase.

4. Test of Quality Uncertainty

Our test of quality uncertainty among car buyers is based on the shape of the hazard function h(t) in the *initial* periods of car ownership. Roughly speaking, a hazard function gives the probability of an event (car resale) occurring at time t, given that it has not occurred up to this point.[13] If car buyers suffer from quality uncertainty, the first months of ownership will consist of a learning process in which buyers discover the hidden characteristics of their newly purchased vehicles. Assuming that at least some buyers react to any dissatisfaction with their purchases by reselling their vehicles, we should observe that the probability of a newly purchased car being resold generally decreases with the duration of ownership (negative duration dependence), reflecting the decline in the discovery of new hidden negative attributes of the vehicle.

If buyers instead do not suffer from quality uncertainty, then any observed resales should result from subsequent shocks in buyers' tastes or constraints,[14] which do not imply any particular pattern of duration dependence for the hazard function in the short run. In fact if these shocks follow a Poisson process, the hazard function of resell will be horizontal (Cf. LANCASTER,1990, p. 86). Depreciation or aging, which in principal could also serve as a motive for reselling (albeit hardly over the short term considered here), do not imply a falling hazard rate either. In fact, if the optimal age for a heterogenous population of car owners to trade in their cars happened to be normally distributed, the hazard function would be monotonically increasing.[15]

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13 Strictly speaking, the probability p(t) of selling one's car in a given interval t to t+dt, given that one has not done so by time t, equals h(t)·dt, where dt represents a small increase in time. In the following, we also term p(t) the hazard rate.

14 Other possibilities such as buyer heterogeneity are considered below.

15 In this case the hazard function of resell would equal $\phi(t)/[1-\Phi(t)]$, where ϕ and Φ represent the normal density and c.d.f., respectively. This expression is monotonically increasing in ownership duration t.

4.1. Theoretical Model

The intuition behind our reasoning can be captured by the following simple model.[16] We develop the model in two steps: we first view the hazard function of a single spell of car ownership and then focus on the aggregate hazard function of a group of cars of a given average observable quality $\bar{\lambda}$. Our empirical model applies to the aggregate hazard function.

Single-Spell Hazard Function

To start, suppose owners take the expected number of defects λ a vehicle will suffer per period as an indicator of its quality. The consumer does not know λ at the time of purchase but discovers its value by driving the vehicle. Let $\bar{\lambda}$ be the consumer's belief about the average value of λ for *traded* cars of a given observable quality.[17] $\bar{\lambda}$ equals the actual average expected number of defects of vehicles of this category so that expectations are unbiased.

Now consider a consumer who has bought a car with an unobserved mean defect rate λ from the class of traded vehicles with expected quality $\bar{\lambda}$. We assume that the actual number of defects x_t the car has in period t (t=1,2,…) follows a Poisson process with expectation λ, i.e., $P\{x_t = k\} = (\lambda^k / k!)e^{-\lambda}$ for k=0,1,2,…. For the sake of simplicity, define defects broadly enough so that $\lambda \geq 9$. Then x_t can be sufficiently well approximated by the normal distribution so that $x_t \sim N(\lambda, \lambda)$.[18]

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[16] It is important to stress from the outset that our model does not purport to provide an equilibrium model of the market for used cars. Our model focuses only on the short-run motives for selling vehicles. In the long run other considerations come into play, such as depreciation, which lead to increased sales in the longer term. Based on this intuition, PORTER and SATTLER (1999) construct a model in which durable goods deteriorate over time and owners sell to update to their preferred quality. Similarly, HENDEL and LIZZERI (1999) model car owners as selling their used vehicles to enjoy the higher quality offered by a new car. They show that despite adverse selection an equilibrium exists in which the average quality of used cars is positive. These models pertain to the long-term motives for reselling cars and predict initially low resell rates that then increase with the age and mileage of a vehicle. STOLYAROV (2002) finds evidence in the US car market consistent with this prediction. See GILLIGAN (2004) for a further test. To our knowledge, no model currently exists to explain the phenomenon our paper addresses, i.e., the behavior of buyers when their purchased cars do not meet expectations.

[17] $\bar{\lambda}$ is a conditional mean. It pertains to the average quality of traded cars, which according to the lemons model should be below the mean quality of the population of observably identical cars.

[18] The Poisson assumption implies that quality uncertainty, as measured by the variance, decreases with mean quality: the lower the mean quality of a vehicle (high λ), the more the number of defects per period will vary about the mean. We find this assumption attractive as it seems reasonable to expect that the number of defects to vary less among, say, new (i.e. higher quality) cars than used (i.e. lower quality) ones since the reliability of used cars depends on a myriad of additional factors such as care and maintenance which increases defect uncertainty.

In each period t the consumer observes x_t and computes as an estimator of λ the average number of defects experienced so far $\hat{\lambda}_t = (1/t)\sum_{\tau=1}^{t} x_\tau$. If $\hat{\lambda}_t$ lies with some given statistical significance α above some unreliability threshold $z \geq \bar{\lambda}$, the consumer will be dissatisfied with the quality of the purchased car to such an extent that he or she will resell it. The choice of the level of statistical significance α should depend on the buyer's costs of erring, and the selection of the minimum acceptable quality z on his or her preferences and on the transaction costs of selling a recently purchased car. The threshold z will lie above $\bar{\lambda}$ as the buyer expects to have bought quality $\bar{\lambda}$.

In each period the consumer tests whether $\hat{\lambda}_t$ is still compatible with the null hypothesis $\lambda \leq z$. To do so the consumer computes the test statistic $(\hat{\lambda}_t - z)/\sqrt{z/t}$ and sells his vehicle if $(\hat{\lambda}_t - z)/\sqrt{z/t} > \Phi^{-1}(1-\alpha)$. For a car with an expected defect rate λ, $\hat{\lambda}_t \sim N(\lambda, \lambda/t)$. Since the test statistic is a linear transformation of $\hat{\lambda}_t$, we have $\frac{\hat{\lambda}_t - z}{\sqrt{z/t}} \sim N\left(\frac{\lambda - z}{\sqrt{z/t}}, \frac{\lambda}{z}\right)$. Accordingly, the conditional probability that the consumer sells his car in t given he has not done so up to this point, i.e., the *hazard rate*, is

$$p(t,\lambda,z,\alpha) := \text{Prob}\left(\frac{\hat{\lambda}_t - z}{\sqrt{z/t}} > \Phi^{-1}(1-\alpha)\right) = 1 - \Phi\left(\frac{\Phi^{-1}(1-\alpha) - \frac{\lambda - z}{\sqrt{z/t}}}{\sqrt{\lambda/z}}\right).$$

Having derived the hazard function of resell, we now investigate its duration dependence. Here one has to distinguish between three possible drawings of the unobserved quality λ vis-à-vis z: (i) a more than acceptable quality ($\lambda < z$), (ii) a just acceptable quality ($\lambda = z$) and an unacceptable quality ($\lambda > z$).[19] Among the cars in the first category the hazard rate is decreasing since $\partial p / \partial t < 0$ in this case. Sales of these cars result from Type I errors: although in reality the cars fulfill an owner's minimum quality requirements z, they are sold by mistake due to an unusually high number of observed defects x_t in the first periods of ownership. The hazard rate, or the probability of committing a Type I error, declines over time, however, as the precision of the test statistic increases with the length of ownership. In the limit, the hazard rate goes to zero, i.e., $\lim_{t \to \infty} p(t, \lambda, z, \alpha) = 0$.

The hazard rates of cars that are just acceptable ($\lambda = z$), on the other hand, are con-

[19] Note that by choosing a minimum acceptable quality z, the consumer subdivides the class of cars with expected quality $\bar{\lambda}$ into these three categories.

stant and equal to α, the chosen level of statistical significance. Finally, vehicles that do not meet minimum quality requirements ($\lambda > z$) exhibit an increasing hazard rate $\partial p / \partial t > 0$. In this case, the error lies in holding on to unacceptable cars for any length of time, which represents a Type II error. In time, however, the precision of the test statistic again increases so that all unacceptable cars are eventually resold, i.e., $\lim_{t \to \infty} p(t, \lambda, z, \alpha) = 1$.

In short, our model likens the learning process of buyers to the consistency property of sampling statistics: the more observations, the greater the certainty. The latter is true no matter how good the buyer's statistical abilities happen to be.

The formula for the hazard rate indicates in addition that increasing the mean number of defects λ a given car will generate (or, equivalently, increasing the quality uncertainty associated with it) shifts the hazard function of resale upwards since $\partial p / \partial \lambda > 0$. In other words, the hazard functions of cars of unobservably lower quality lie above those of otherwise comparable vehicles. Our model also implies that $\partial^2 p / \partial \lambda \partial t > 0$ so that the hazard functions of cars with a common observed expected quality $\bar{\lambda}$ increasingly diverge as the length of car ownership increases, i.e., they fan out about α, the constant hazard rate of just acceptable cars.

Aggregate Hazard Function

Our results to this point pertain to the hazard function of a single car with unobserved quality λ drawn from a set of cars with the observed mean quality $\bar{\lambda}$. Our empirical model, however, applies to the aggregate hazard function of all vehicles with a common observed mean quality $\bar{\lambda}$.[20] The aggregate hazard function is a weighted average of the cars of this mean quality not yet resold at any given time t. Since lower quality cars in this group are resold faster ($\partial^2 p / \partial \lambda \partial t > 0$), acceptable cars make up an ever larger share of those vehicles not yet resold as the duration of ownership increases. Therefore, the aggregate hazard function increasingly adopts the shape of the hazard functions of the acceptable cars in the group of cars with observed mean quality $\bar{\lambda}$. In the limit ($t \to \infty$), the aggregate hazard function converges to the hazard function of the vehicle with the highest unobservable quality in the group and, hence, with the lowest hazard function. Consequently, after perhaps initially increasing as a result of the high sell off of unacceptable cars in the first periods of car ownership, the aggregate hazard function will eventually decrease and converge to zero. *Figure 1* presents

[20] $\bar{\lambda}$ is captured by the regressors.

simulations based on $\bar{\lambda}$ = 13 (23), z = 14 (24), α = 0.05, and uniformly distributed λ with support [10,16] ([20,26]) to illustrate this point.[21]

Figure 1 about here

The final issue with regard to our model pertains to the effect of an increase in the observed mean quality $\bar{\lambda}$ on the aggregate hazard function. The answer depends on the effect the observed difference has on the car owner's choice of threshold z vis-à-vis $\bar{\lambda}$ (i.e. z - $\bar{\lambda}$) and on the distribution of the unobserved quality differences λ about $\bar{\lambda}$. To start, let us assume that z - $\bar{\lambda}$ increases and/or that the distribution of the unobserved quality differences about $\bar{\lambda}$ decreases as observed mean quality rises (i.e. $\bar{\lambda}$ falls). In this case the aggregate hazard function shifts downwards because increasing z - $\bar{\lambda}$ or decreasing the variation of unobserved quality differences about $\bar{\lambda}$ increases the share of acceptable cars (λ < z) and hence those with decreasing hazard functions. Neither of these two assumptions seems unreasonable. For example, with regard to the first assumption, new cars, which are generally of higher quality than used vehicles, tend to suffer a disproportionately higher loss of value in their first year. This should increase the transactions costs of reselling them and, in turn, raise their relative resell thresholds z - $\bar{\lambda}$. And the second assumption, that the distribution of unobserved vehicle heterogeneity about $\bar{\lambda}$ increases with $\bar{\lambda}$, merely extends the Poisson property of an inverse relationship between mean quality and quality uncertainty.

If one assumes instead that z - $\bar{\lambda}$ and the variation of unobserved quality about $\bar{\lambda}$ remain unchanged when observed mean quality changes (as modeled in *Figure 1*), then the aggregate hazard function of cars of higher observed mean quality will start higher and, after perhaps initially increasing, decrease more rapidly then the aggregate hazard function of cars with a lower observed mean quality. To see this, let $z_d < z_p$. Now take an unacceptable car out of each sample, i.e., $\lambda_d > z_d$ and $\lambda_p > z_p$. Furthermore, let $\lambda_d - z_d = \lambda_p - z_p$. We thus compare two cars out of each set whose expected

[21] The value of 13 for $\bar{\lambda}$ was chosen to ensure that a normal distribution provides a good approximation to a Poisson process. It was then increased to 23 to provide enough change to make the differences in the hazard functions in *Figure 1* clearly visible. The values for z were selected such that $\bar{\lambda}$ < z, as our decision model assumes, and so that the difference z-$\bar{\lambda}$ remained constant. Otherwise the values are arbitrary. Note that buyer heterogeneity with respect to the resell threshold z or the significance level α has no effect on this result. The choice of z merely determines the initial share of increasing, decreasing, and constant hazard functions in a given observable category of cars at time 0, and the choice of α simply slows or accelerates individual resell hazards, leaving the sorting process that drives our result unaffected.

defect rate exceeds the corresponding threshold by the same amount. Then we have

$$p(t,\lambda_p,z_p,\alpha) < p(t,\lambda_d,z_d,\alpha) \Leftrightarrow$$

$$\Phi^{-1}(1-\alpha)\sqrt{z_p/\lambda_p}-(\lambda_p-z_p)\sqrt{t/\lambda_p} > \Phi^{-1}(1-\alpha)\sqrt{z_d/\lambda_d}-(\lambda_d-z_d)\sqrt{t/\lambda_d} ,$$

which holds as $z_p/\lambda_p > z_d/\lambda_d$ for $\lambda_d > z_d$ and $\lambda_p > z_p$. A similar argument shows that $p(t,\lambda_p,z_p,\alpha) > p(t,\lambda_d,z_d,\alpha)$ for $\lambda_d < z_d$, $\lambda_p < z_p$, and $\lambda_d - z_d = \lambda_p - z_p$. This means that cars of higher observed quality will initially be resold at a higher rate than the others. Yet eventually the aggregate hazard rate for cars of higher observed quality will, as in the case of our previous assumptions, come to rest below the hazard rate of the others, as *Figure 1* illustrates. Put differently, the probability of a Type I or Type II error is lower for cars of higher observed mean quality under this set of circumstances.

In summary, our model predicts that the aggregate hazard function, after possibly increasing during an initial phase of vehicle testing, declines with the duration of ownership. Furthermore, cars of high observable quality eventually have lower hazard rates than cars of low observable quality, if not from the outset.

Note that the quality uncertainty, which our model is intended to test, could also capture uncertainty with regard to car characteristics. For example, a buyer could discover after purchasing a vehicle that it did not have any technical defects but that it nevertheless did not really fit his or her unchanged needs. Characteristic uncertainty is not interesting in the present context as it does not imply asymmetric information. To control for characteristic uncertainty we also investigate the resell probabilities of cars bought new. Our reasoning is that quality uncertainty should be lower among new cars because of their higher mean quality λ and because of possible new-car warranties[22], whereas characteristics uncertainty should be higher since consumers know far less about the characteristics of a car of a given vintage in the year of its production as they have no track record to fall back on. This is particularly true of newly introduced models. Thus if characteristics uncertainty were to dominate we would expect the resell probabilities of cars purchased new to lie above those of otherwise identical vehicles bought used.

Regardless of which form of uncertainty dominates, our test nevertheless requires that

[22] New-car warranties were fairly uncommon in Europe in 1985. Where they did exist they never held for longer than a year.

at least some buyers express any unexpected dissatisfaction by reselling their cars. Since the transaction costs of reselling a newly purchased vehicle may be high, buyers could be poorly informed at the time of purchase and yet not resell vehicles that turn out to be unpleasant surprises. Hence, a perhaps initially rising but lastly falling hazard function is a sufficient[23] but not a necessary implication of the presence of buyer uncertainty.

4.2. Empirical Methodology

Our empirical investigation focuses on the shape and locus of the aggregate hazard function of car ownership for vehicles of a given observed mean quality. Observable quality is captured by the covariates of our regression analysis.

Our analysis is based on the ownership biographies of all 1985 cars registered in the canton of Basle-City between 1985 and 1991. The car histories were constructed from the records of the Basle-City Department of Motor Vehicles. Our observations consist of all spells of *non-dealer* ownership these cars generated in Basle. The social security number of the car owner, included in the registration data, allows us to sort out any cars registered to dealers. We restrict our study to non dealer-owned cars since the resell behavior of dealers probably does not reflect quality uncertainty. In other words, periods in which a vehicle is registered to a dealer, say, as a demonstration car are not counted as ownership spells and thus excluded from our sample. An ownership spell begins with the purchase of a car and ends with its being resold, where a sale is defined as a situation in which a car with a given chassis number is re-registered to a person with a different social security number. Ownership spells need not end in a sale, however. They could still be in progress at the end of the sample period, or owners could junk their cars or move to another canton before the sample period ends. Spells of this sort are right censored and treated appropriately in the estimation. Spells of ownership begun outside the canton, on the other hand, are left censored and excluded from the sample. In total, our sample consists of 1,161 spells of non-dealer ownership pertaining to used cars and 2,645 spells applying to new cars. We concentrate on the ownership spells of used cars, employing the ownership spells of new vehicles for purposes of comparison.

We apply both semi-parametric and parametric duration models. Semi-parametric ap-

[23] The issue of unobserved heterogeneity, which could call the sufficiency aspect into question, is discussed below in conjunction with equation 6.

proaches restrict the covariate structure, whereas parametric approaches also constrain the shape of the hazard function. We employ both approaches in the hope of obtaining more robust results.

Our semi-parametric approach is based on grouped durations. The model assumes that the hazard rate, or probability, $p_i(t)$ that an ownership spell i that has lasted to at least time t-1 will end in a sale in the interval [t-1, t) can be sufficiently approximated by the following function (cf. CAMERON and TRIVEDI, 2005, pp. 600-603 for a survey of alternative grouped duration approaches)

$$p_i(t) \;=\; \Phi(\alpha_t + \boldsymbol{\beta}'\mathbf{x}_i + \boldsymbol{\gamma}'\mathbf{z}_{it}) \quad , \tag{2}$$

where $\Phi(.)$ = standard normal cumulative density function,

α_t = interval-specific constant or, alternatively,

= $\sum_{j=0}^{J} \alpha_j \cdot t^j$,

$\mathbf{x}_i$ = vector of constant characteristics describing the vehicle at the time of purchase (t = 0)

$\mathbf{z}_{it}$ = vector of time-varying characteristics describing the vehicle at ownership time t

t = 1, ..., T.

The α parameters define the underlying or baseline hazard function and provide a basis for testing its shape.

We estimate the parameters of the model with the maximum likelihood procedure. To keep data handling manageable, we group the ownership spell durations, which are measured in days, into 26 (= T) equal-length intervals of 90 days, or one quarter. For convenience, we assume that right censoring occurs at the end of an interval. These assumptions lead to the following likelihood function

$$L = \prod_{t=1}^{T} \prod_{i=1}^{I_{t-1}} p_i\left(t\right)^{d_{it}} \left(1 - p_i(t)\right)^{1-d_{it}} \quad , \tag{3}$$

where I_{t-1} represents the number of spells of car ownership still in progress at the beginning of the duration interval [t-1, t) and d_{it} is a dummy variable indicating whether spell i ended in a resale in this interval (d_{it} = 1) or not (d_{it} = 0). Note that each spell contributes several observations to (3), the number of observations per spell equaling the number of time intervals the spell enters. Applying (3) necessitates splitting each spell into a corresponding number of sub-spells.

We measure the explanatory variables in (2) as deviations from their respective means[24] so that $\Phi(\alpha_t)$ represents the hazard function of an average spell of ownership in the interval [t-1, t), holding the value of all variables constant. The unknown parameter vectors β and γ do not vary across spell intervals, i.e., we do not estimate separate probit models for each quarter. This restriction is necessitated by the fact that many of the cars resold in a given time interval are unique with regard to one or more of the right-hand variables in (3). In this case, specifying interval-specific coefficients would lead to a breakdown of the maximum likelihood estimation procedure (cf. GREENE, 2000, p. 832).

Our parametric approach uses non-grouped durations and is based on the following specification

$$h_i(\tau) = h_0(\tau)\exp(\delta'\mathbf{x}_i) \quad , \tag{4}$$

where τ represents continuous time measured in days. $h_0(.)$ is a baseline hazard function of a given parametric form. In contrast to (2), (4) assumes that the effect of covariates is multiplicatively separable from the baseline hazard function (proportional hazard model). Accordingly, δ does not contain a constant term. We also exclude time-varying covariates in the parametric approach.

We assume the following Weibull specification for the baseline hazard function $h_0(\tau)$

$$h_0(\tau) = \eta r(\eta\tau)^{r-1} \quad . \tag{5}$$

η is a location parameter, and r a scaling parameter. The hazard function is monotone decreasing for $0 < r < 1$, constant for $r = 1$, and monotone increasing for $r > 1$. Estimates of r thus provide an alternative means of testing the shape of the hazard function.

As is well known (see, e.g., KIEFER,1988), an aggregate hazard function can decline monotonically although the individual hazard functions making up the aggregate are constant, yet different. For example, car buyers may not suffer from quality uncertainty but instead differ with respect to their constant propensities to sell their cars (owner heterogeneity). In this case the hazard function would also display negative duration in the aggregate although no quality uncertainty exists. In contrast to this problem of so-called unobserved spell heterogeneity, our model implies that individual hazard

[24] The means are based on all ownership spells, both those of cars bought new and used.

functions are not constant, except in the special case where λ = z. To test for the presence of unobserved spell heterogeneity, which could bias our results, we follow common practice and condition the baseline survivor function $S_0(\tau)$ of the Weibull model on a random variable ν intended to capture the unobserved heterogeneity. We choose a very flexible parameterization for ν by assuming that it has a gamma distribution with mean 1 and variance θ. This leads to the following unconditional baseline hazard function[25]

$$h_0(\tau) = \eta r(\eta\tau)^{r-1}[S_0(\tau)]^{\theta}. \quad (6)$$

As is easily seen, (6) reverts to (5) when unobserved heterogeneity is not present (θ = 0).

We also employ maximum likelihood to estimate the parametric model. In contrast to (3) each spell contributes just one observation to the likelihood function.

4.3. Results

Table 3 reports the means of the ownership spells in our sample, distinguishing between uncensored ("resold") and right-censored ("not resold") spells. Ownership duration measures the length of time (in quarters) that a vehicle had been held on average at the time the ownership spell ended, either through a sale or right-censoring. The remaining variables constitute the right-hand variables (**x**, **z**) in our model. With the exception of "age at purchase", all right-hand variables represent dummy variables. In the semi-parametric split-spell model, we replace "age at purchase" with the age of the car at the beginning of each time interval, which results in a time-varying variable (z), the sole regressor of this kind in the study.

Table 3 about here

The inspection variables indicate whether a car was submitted to a safety inspection in the last three months prior to purchase, i.e., before the new ownership spell began,

[25] See GREENE (2000), p. 947 for a derivation of (6). HECKMAN and SINGER (1984) note that (6) may over parameterize the survivor function leading to serious errors in inference.

implying that any defects discovered were repaired.[26] Our model implies that the improved quality associated with having passed inspection should lead to lower resell hazard rates. Indeed this is what *Table 3* suggests as a smaller share of the used cars resold had been inspected up to three months prior to purchase: 28.8 percent compared to 32.9 percent for cars not resold.

The dummy variable "company owned" indicates whether a car was registered to a firm rather than to a person during a particular spell of ownership. As can be seen, no firm purchased a used car in our sample. "Commercially used" denotes that the automobile was being used as a rental car, a taxi, or for driver education during the observed spell. The brands listed in the table are those for which dummy variables were created and appear in their order of prominence in our sample.

Table 3 suggests that resold cars (uncensored spells) are held for shorter periods of time prior to resale on average and tend to be somewhat newer, not in commercial use, and gasoline fueled. The table further indicates that automobiles from Alfa, Fiat, Mitsubishi, Nissan, Renault and Toyota are generally more likely to be traded, whether bought new or used, while German cars (Audi, BMW, Ford, Mercedes, Opel, Porsche, VW) are often more likely to be held back from the market.

We begin the presentation of our regression results with a histogram (*Figure 2*) showing the hazard function that the coefficient estimates of the semi-parametric model imply. The hazard rates are based on separate estimates for new and used cars employing interval-specific constants for the baseline hazard instead of a polynomial trend as in *Table 4*. The regression results underlying *Figure 2* are not presented to conserve space, but all interval-specific constants were statistically significant at the 1% level. Since all covariates were measured in absolute deviations from their respective overall (used and new car combined) sample means, both sets of hazard rates pertain to the same constant average profile of characteristics and can thus be directly compared.[27]

Figure 2 about here

[26] Inspected cars are those inspected for any of the reasons listed in *Section 2*. We do not distinguish between the various reasons for having to present a vehicle for inspection as we assume that passing an inspection places otherwise observably homogeneous vehicles on a common *mean* quality level.

[27] The hazard rates are equivalent to life-table estimates where right censoring is assumed to occur at the end of an interval and the effects of observed heterogeneity have been eliminated. Life-table estimates subdivide the time line into fixed intervals, whereas Kaplan-Meier estimates allow the interval length to vary according to the distribution of spell lengths.

As can be seen, the resell hazard rates for used cars exhibit a roughly declining trend over the 14 quarters of used-car ownership that our sample covers. By contrast, the conditional resell probabilities of new cars first increase for two quarters of ownership, then decline over the next six quarters before rising again after about two years. Note too that the resell probabilities of new cars lie far below those of used cars in the first quarters of car ownership, implying on the basis of our reasoning presented above that quality uncertainty and not characteristic uncertainty is driving our results.

The evolution of the hazard rates over the first two years of car ownership suggests that buyers of both new and used cars suffer from quality uncertainty. The increase in hazard rates thereafter, however, is undoubtedly due to vehicle depreciation and has nothing to do with quality uncertainty. It is nevertheless interesting to note that the resell probability pattern for new and used cars is roughly similar from the 9th to 14th quarter of ownership, suggesting that owners are equally likely to resell new or used cars once differences in quality uncertainty have been eliminated.[28]

The hazard rate pattern appearing in *Figure 2* moves us to estimate separate models for three time lengths of car ownership: (i) the first five quarters, where both new and used cars were resold, (ii) the first eight quarters, covering the first two years of used-car ownership, and (iii) the first 14 quarters, in which all resales of used cars in our sample occurred.[29] The results appear in *Table 4*. We turn first to the results pertaining to the shape of the underlying hazard function and then focus on the results concerning the effect of observable quality differences.

Table 4 about here

With regard to used cars, our findings are quite clear. Both the semi-parametric and the parametric models point to a monotonically decreasing hazard function, irrespec-

[28] The hazard rates of the cars in our sample purchased new conform roughly to the pattern that STOLYAROV (2002) discovered in a study of the US car market. He finds that resell rates there are very low for young cars and peak when vehicles are 4 years old. Thereafter resell rates stay low for several years and then increase again when the vehicle is about 10 years old.

[29] In the parametric model this is achieved by treating all spells of greater length as right-censored, and in the semi-parametric model by dropping split-spells pertaining to longer ownership durations from the sample.

tive of the time interval chosen.[30] The estimate of the Weibull parameter r is always significantly less than one, and the estimated coefficient of the trend variable significantly less than zero at high confidence levels.[31] We also considered higher order polynomial terms, which allow for a non-monotonic shape, but they proved to be statistically insignificant. The parameter estimates presented in *Table 4* imply a decline in the conditional probability of reselling one's car between 30% (semi-parametric model) and 40% (Weibull model) over the first year of car ownership. Based on the predictions of our theoretical model, these results clearly suggest that the buyers of used cars suffer from quality uncertainty.

In the case of new cars, the evidence is less clear. The estimated coefficients of the trend variable in the semi-parametric model imply that the hazard function has a cubic shape, first increasing, then decreasing and then increasing again. However the data failed to support polynomials of a higher or lower order, which does not speak for the robustness of the result. In contrast, the Weibull model suggests that the hazard function is horizontal, the estimate of the parameter r not differing significantly from one.[32] The lack of clarity is undoubtedly due to the fact that few new cars were resold shortly after purchase: only 10 vehicles or 0.4% of the 2645 new cars in our sample were resold within five quarters after their initial purchase compared to 10.6% of the used cars (cf. *Table 4*). Hence the data base is probably too narrow to determine the true shape of the short-term hazard function for new cars.

As mentioned before, a declining hazard function could result from constant yet differing hazard functions across owners (owner heterogeneity). Unfortunately, our attempts to control for this unobserved heterogeneity on the basis of model (6) met with limited success. We were only able to obtain an estimate of the heterogeneity parameter θ for the entire 14 quarters of used-car ownership our sample covers, and according to this result unobserved heterogeneity is not a problem. Controlling for unobserved heterogeneity is admittedly a daunting task so that our results can hardly be viewed as final.

We come to the second issue: the effects of observed car quality on the hazard func-

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[30] The fact that the Weibull model, which is based on continuous time, and the semi-parametric model, which rests on grouped durations, yield the same results indicates that grouping durations in discrete time intervals does not bias our measurement of duration dependence.

[31] Note that the asterisks in *Table 4* pertain to two-tailed tests. The level of significance rises to at least 5% if the null is one-sided as in our model.

[32] The Weibull model is of course unable to capture non-monotonic duration dependence. However, estimates of a log-logistic model, which allows for a first increasing and then increasing hazard function, also pointed towards a constant hazard rate.

tion of car ownership. Our model predicts that higher observable vehicle quality or, equivalently, lower quality uncertainty should lower the hazard function of resell. Our findings support this prediction clearly with respect to new versus used cars (*Figure 2*) and to a somewhat lesser extent in regard to inspected and non-inspected used cars (*Table 4*). The qualification pertains to the estimates based on the first five months of car ownership where the sign of the inspection coefficient is correct but not statistically significant. In general, the coefficient estimates imply that a prior inspection lowers resell hazard rates by about 30% over the first year of car ownership.

The estimated coefficients of the brand dummies also point in the direction of the predictions of our model: brands that are more likely to pass inspection (*Table 2*) and thus to be of better quality also have lower resell hazard rates. This is illustrated in *Figures 3* and *4*, which cross plot the estimated brand coefficients from the last column in *Table 2* with those in the first (*Figure 3*) and third columns (*Figure 4*) in *Table 4*. The correlation coefficients ("rho") are not statistically significant, however, so the results are merely indicative.

Figures 3 and 4 about here

Overall our results appear to confirm the predictions of our model: the hazard function of car ownership is clearly decreasing over the short term for used cars, and higher average observable quality (i.e., greater quality certainty) tends to lower resell hazard rates.

Combined with the findings of the previous section, our current results suggest that sellers of used cars enjoy an information advantage over buyers. Our reasoning is as follows. In the previous section we found that the privately sold cars that were required to be inspected because of a change of ownership were more likely to exhibit a defect than a randomly selected vehicle with the same set of observable characteristics. Our test rules out the possibility that the higher defect rate could be due to chance, thus implying that sellers were aware of the sub-average quality of their vehicles. We assume that this result also applies in instances in which the sold used vehicles did not have to be inspected due to a change of ownership or had to be inspected for other reasons. In other words, we assume that the cars inspected due to a sale are representative of all used cars sold. Our data do not permit us to confirm this, however. Secondly, the results in this section clearly suggest that buyers suffer from quality uncertainty: for one, the hazard function of resell appears to decline with the duration of ownership; and, for another, the hazard function shifts downwards when quality uncertainty decreases, as our theoretical model implies. Taken together these findings imply that buyers of used cars are at an information disadvantage vis-à-vis sellers.

Although present, the lemons problem does not appear to be widespread, however. Only 160 or 13.8 percent (cf. *Table 4*) of the used cars in our sample were resold after purchase, and of these 123 or roughly 77 percent were resold within five quarters. Hence, perhaps as few as 10.6 percent (*Table 4*) of the used-car purchases involved situations in which buyers were at an informational disadvantage. On the other hand, there may have been other dissatisfied purchasers for whom the transaction costs of reselling their cars were too high. Hence, informational asymmetry may be more prevalent than the frequency of resales indicates.

5. Conclusions

This paper has attempted to extend previous empirical work on the lemons model by not only testing for adverse selection among goods sellers choose to trade, as in the previous literature, but also investigating the presence of quality uncertainty among buyers of these goods. In the latter endeavor the paper broke new ground methodologically by applying hazard function analysis to spells of consumer-goods ownership.

Our results pertaining to adverse selection indicated that cars sold privately are indeed more likely to have a defect than a randomly chosen vehicle. This suggests that owners of poorer quality cars knowingly put them up for sale. At the same time, our estimates relating to the quality uncertainty of purchasers indicate that buyers are not fully aware of what they are purchasing. This is evidenced by our finding that the probability that buyers will resell their vehicles is higher in the first months of ownership than later. This holds true whether a car was bought new or used, or whether it was inspected before purchase or not. However, the higher the mean quality of a car and thus the lower the degree of quality uncertainty, the less likely the vehicle will be quickly resold, further supporting our conjecture that quality uncertainty lies behind buyers' propensity to resell their vehicles shortly after purchase.

Admittedly, some of our observations can be explained using alternative stories. For example, the lower defect rate of dealer-submitted cars may be the result of the cost advantage of dealers in repairing cars. Yet this argument cannot explain the higher defect rate of cars put up for sale by non-dealers in comparison to the defect rate of randomly chosen cars. In addition, the falling hazard rate could also be due to unobserved consumer heterogeneity or car-characteristic uncertainty. However, our findings point in the opposite direction. All other theories we are aware of predict either constant or increasing hazard rates over the short run. Thus the lemons model seems to provide the best explanation for our results when viewed in their entirety.

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Table 1: Sample Mean of Vehicle Inspections

				Type of Defect:								
Grounds	Cases	Diesel	Kilometers	Lights	Devices	Frame	Suspension	Steering	Power Train	Brakes	Handbrake	None
Periodic Check	3363	0.050	61020	0.132	0.077	0.051	0.047	0.026	0.115	0.023	0.007	0.751
Private Sale	165	0.133	66924	0.248	0.255	0.152	0.103	0.042	0.218	0.042	0.006	0.527
Dealer Sale	1626	0.018	51954	0.073	0.033	0.021	0.037	0.020	0.077	0.017	0.005	0.833
Ticketed	54	0.093	61752	0.056	0.000	0.056	0.056	0.019	0.037	0.019	0.000	0.852
Vehicle Altered	114	0.123	49727	0.053	0.070	0.079	0.079	0.018	0.026	0.009	0.000	0.789
Export	7	0.143	78896	0.000	0.000	0.000	0.000	0.000	0.143	0.000	0.000	0.857
Unknown	4	0.250	80071	0.000	0.250	0.000	0.000	0.250	0.000	0.000	0.000	0.500
Total	5333	0.045	58242	0.115	0.068	0.046	0.046	0.024	0.104	0.021	0.006	0.771

Table 2: Probit Estimates of the Probability of a Vehicle Defect

	Type of Defect:								
Explanatory Variable	**Lights**	**Devices**	**Frame**	**Suspension**	**Steering**	**Power Train**	**Brakes**	**Handbrake**	**None**
Constant	-1.163***	-1.473***	-1.690***	-1.729***	-2.036***	-1.294***	-2.127***	-2.601***	0.715***
	(0.029)	(0.033)	(0.039)	(0.040)	(0.051)	(0.031)	(0.057)	(0.090)	(0.024)
Private Sale	0.404***	0.743***	0.577***	0.404***	0.171	0.391***	0.275	-0.052	-0.563***
	(0.112)	(0.113)	(0.127)	(0.141)	(0.187)	(0.117)	(0.188)	(0.380)	(0.102)
Dealer Sale	-0.342***	-0.407***	-0.408***	-0.109	-0.094	-0.189***	-0.099	-0.115	0.270***
	(0.057)	(0.071)	(0.083)	(0.072)	(0.091)	(0.057)	(0.096)	(0.154)	(0.046)
Ticketed	-0.566**	--	-0.028	-0.014	-0.251	-0.637**	-0.242	--	0.484**
	(0.290)		(0.289)	(0.294)	(0.437)	(0.325)	(0.438)		(0.219)
Vehicle Altered	-0.460**	-0.010	0.270	0.307*	-0.192	-0.671***	-0.316	--	0.076
	(0.198)	(0.184)	(0.179)	(0.180)	(0.306)	(0.253)	(0.387)		(0.136)
Mileage (km x 10^{-3})	0.356***	0.243***	0.194**	0.275***	0.419***	0.470***	0.262***	0.299***	-0.463***
	(0.052)	(0.060)	(0.070)	(0.066)	(0.071)	(0.053)	(0.086)	(0.116)	(0.047)
Diesel	-0.017	0.232*	0.058	-0.213	0.177	-0.158	0.270	0.182	-0.104
	(0.116)	(0.123)	(0.144)	(0.160)	(0.176)	(0.128)	(0.186)	(0.290)	(0.097)
ALFA	0.128	-0.202	-0.112	0.370*	0.420**	0.065	0.509*	0.529	0.016
	(0.160)	(0.185)	(0.211)	(0.199)	(0.197)	(0.152)	(0.290)	(0.352)	(0.136)
AUDI	-0.217	-0.383**	-0.836***	-0.143	-0.450	-0.410***	0.582**	0.597*	0.473***
	(0.161)	(0.184)	(0.293)	(0.223)	(0.292)	(0.160)	(0.265)	(0.316)	(0.138)
BMW	-0.182	-0.423**	-0.222	-0.014	0.069	-0.346**	0.141	--	0.383***
	(0.166)	(0.191)	(0.212)	(0.220)	(0.219)	(0.164)	(0.338)		(0.142)
CITROEN	-0.102	-0.425**	0.176	-0.006	0.225	-0.111	0.408	0.928***	0.234*
	(0.162)	(0.192)	(0.188)	(0.219)	(0.204)	(0.153)	(0.293)	(0.287)	(0.136)
FIAT	0.160	-0.049	0.197	0.546***	0.196	0.328**	1.050***	0.168	-0.233*
	(0.150)	(0.166)	(0.180)	(0.185)	(0.197)	(0.138)	(0.236)	(0.407)	(0.128)
FORD	-0.353**	-0.389**	-0.266	0.031	-0.164	-0.253*	0.087	0.162	0.341***
	(0.161)	(0.177)	(0.201)	(0.203)	(0.228)	(0.148)	(0.323)	(0.398)	(0.132)
HONDA	-0.715***	-0.580***	-0.351*	-0.122	-0.473*	-0.943	--	0.184	0.774***
	(0.185)	(0.194)	(0.214)	(0.217)	(0.292)	(0.196)		(0.402)	(0.143)
LANCIA	0.442*	-0.006	-0.352	-0.134	0.776**	0.161	--	--	-0.041
	(0.252)	(0.306)	(0.457)	(0.457)	(0.306)	(0.263)			(0.238)
MAZDA	-0.599***	-0.920***	-0.553**	-0.012	--	-0.962***	0.590**	--	0.743***
	(0.202)	(0.268)	(0.274)	(0.237)		(0.238)	(0.291)		(0.163)
MERCEDES	-0.260	-0.584***	-0.489**	0.058	-0.179	-0.612***	-0.460	0.104	0.485***
	(0.165)	(0.189)	(0.221)	(0.210)	(0.232)	(0.171)	(0.425)	(0.403)	(0.140)
MITSUBISHI	-0.343**	-0.628***	-0.250	-0.394	-0.067	-0.787***	0.500*	0.679**	0.489***
	(0.178)	(0.215)	(0.222)	(0.274)	(0.248)	(0.206)	(0.290)	(0.324)	(0.147)
NISSAN	-0.487***	-0.439**	-0.259	-0.500*	-0.265	-0.657***	0.293	--	0.640***
	(0.193)	(0.207)	(0.232)	(0.312)	(0.300)	(0.200)	(0.337)		(0.158)
OPEL	-0.344***	-0.403***	-0.207	-0.150	-0.096	-0.163	0.365	0.346	0.341***
	(0.141)	(0.154)	(0.170)	(0.186)	(0.181)	(0.128)	(0.244)	(0.292)	(0.117)
PEUGEOT	-0.159	-0.204	-0.216	0.157	-0.087	-0.093	0.571**	0.594**	0.237*
	(0.161)	(0.176)	(0.207)	(0.204)	(0.231)	(0.150)	(0.269)	(0.319)	(0.135)
PORSCHE	-0.373	-0.412	--	--	--	--	--	--	0.776***
	(0.326)	(0.367)							(0.294)
RENAULT	0.161	-0.112	0.119	0.207	0.159	-0.178	0.850***	0.131	-0.017
	(0.147)	(0.164)	(0.179)	(0.192)	(0.192)	(0.144)	(0.239)	(0.402)	(0.126)
SAAB	-0.106	-0.449	-0.410	-0.156	--	-0.235	--	--	0.443*
	(0.295)	(0.371)	(0.462)	(0.459)		(0.301)			(0.267)
SEAT	0.269	-0.566	0.206	--	--	0.256	1.455***	--	0.027
	(0.318)	(0.494)	(0.400)			(0.318)	(0.391)		(0.298)
SUBARU	0.129	-0.040	0.467**	-0.083	-0.185	-0.127	1.022***	--	-0.062
	(0.220)	(0.247)	(0.243)	(0.344)	(0.426)	(0.230)	(0.320)		(0.191)
SUZUKI	-0.010	0.047	-0.237	-0.013	0.041	-0.253	1.020***	0.606	0.108
	(0.208)	(0.220)	(0.298)	(0.297)	(0.323)	(0.217)	(0.296)	(0.446)	(0.176)
TOYOTA	-0.404***	-0.483***	-0.471**	0.176	0.072	-0.701***	0.224	0.032	0.541***
	(0.152)	(0.169)	(0.201)	(0.183)	(0.185)	(0.156)	(0.276)	(0.399)	(0.125)
VOLVO	-0.118	-0.441**	-0.495**	-0.126	-0.229	-0.436***	0.261	0.143	0.398***
	(0.163)	(0.194)	(0.244)	(0.227)	(0.246)	(0.164)	(0.309)	(0.422)	(0.141)
VW	-0.301**	-0.370***	-0.083	0.181	-0.388**	-0.236*	0.505**	-0.158	0.346***
	(0.138)	(0.151)	(0.164)	(0.172)	(0.197)	(0.126)	(0.230)	(0.384)	(0.114)
Sample Size	5333	5333	5333	5333	5333	5333	5333	5333	5333
$\ln L_0$	-1900.40	-1323.22	-990.95	-997.02	-611.24	-1778.71	-547.33	-200.71	-2871.62
$\ln L^*$	-1790.83	-1240.03	-926.34	-956.57	-571.84	-1645.16	-506.14	-185.72	-2694.48
$-2(\ln L_0 - \ln L^*)$	219.15***	166.37***	129.22***	80.90***	78.79***	267.09***	82.38***	29.97*	354.26***
LRI $(1 - \ln L^*/\ln L_0)$	0.058	0.063	0.065	0.041	0.064	0.075	0.075	0.075	0.062

Asterisks denote statistical significance at the 10% (*), 5% (**), or 1% (***) level. Estimated standard errors appear in parentheses.

Figure 1: Aggregate Hazard Functions

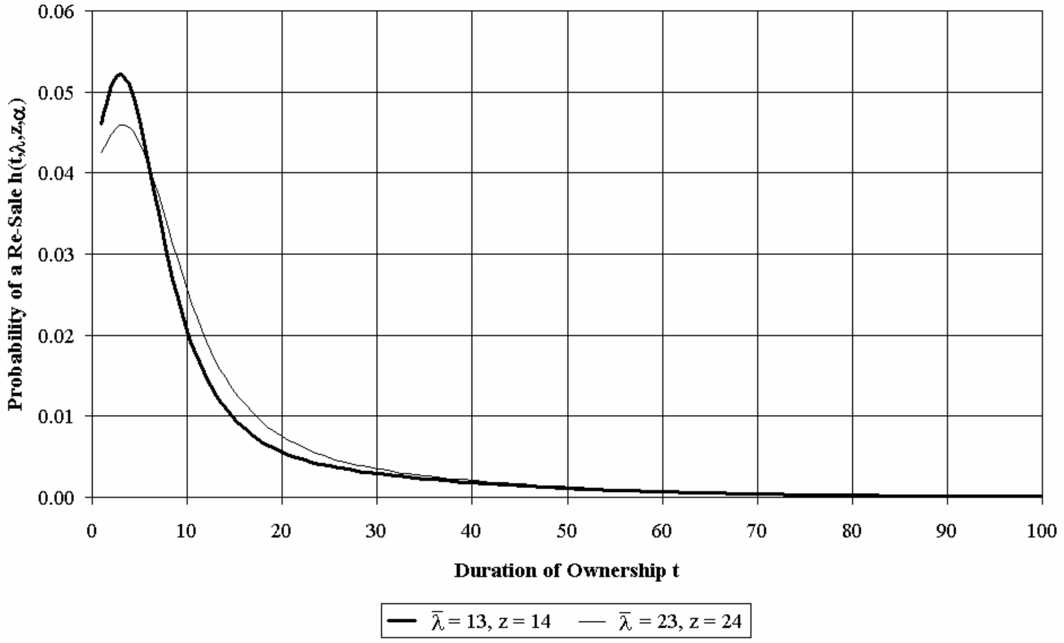

Table 3: Sample Means of Ownership Spells

Variable	Used Cars Resold	Used Cars Not Resold	New Cars Resold	New Cars Not Resold
Total Number of Spells	160	1001	465	2180
Ownership Duration (in quarters)	3.644	5.907	16.98	22.48
Age at Purchase (in quarters)	18.05	19.99	0.000	0.000
Inspected up to 3 Mo. before Purchase	0.288	0.329	--	--
Company Owned	0.000	0.000	0.002	0.002
Commercially Used	0.013	0.015	0.009	0.010
Diesel Engine	0.013	0.030	0.024	0.036
44 Brands in total:				
Opel	0.088	0.113	0.101	0.154
VW	0.063	0.092	0.086	0.128
Toyota	0.138	0.084	0.112	0.094
Renault	0.075	0.073	0.065	0.047
Ford	0.038	0.061	0.071	0.050
Fiat	0.069	0.058	0.067	0.039
Honda	0.044	0.040	0.043	0.053
Audi	0.038	0.043	0.054	0.048
Citroen	0.019	0.044	0.052	0.040
BMW	0.019	0.046	0.039	0.042
Peugeot	0.031	0.040	0.034	0.042
Alfa	0.069	0.056	0.047	0.026
Nissan	0.063	0.029	0.041	0.038
Mitsubishi	0.063	0.036	0.043	0.033
Mazda	0.025	0.029	0.026	0.035
Mercedes	0.031	0.036	0.019	0.032
Volvo	0.013	0.026	0.022	0.020
Suzuki	0.050	0.021	0.013	0.013
Subaru	0.031	0.011	0.006	0.018
Lancia	0.013	0.020	0.026	0.011
Saab	0.000	0.005	0.006	0.007
Porsche	0.006	0.005	0.004	0.005
Seat	0.000	0.003	0.004	0.005
Other	0.019	0.030	0.019	0.019

Figure 2: Hazard Function of New and Used-Car Ownership Based on Semi-Parametric Estimates Controlling for Observable Heterogeneity

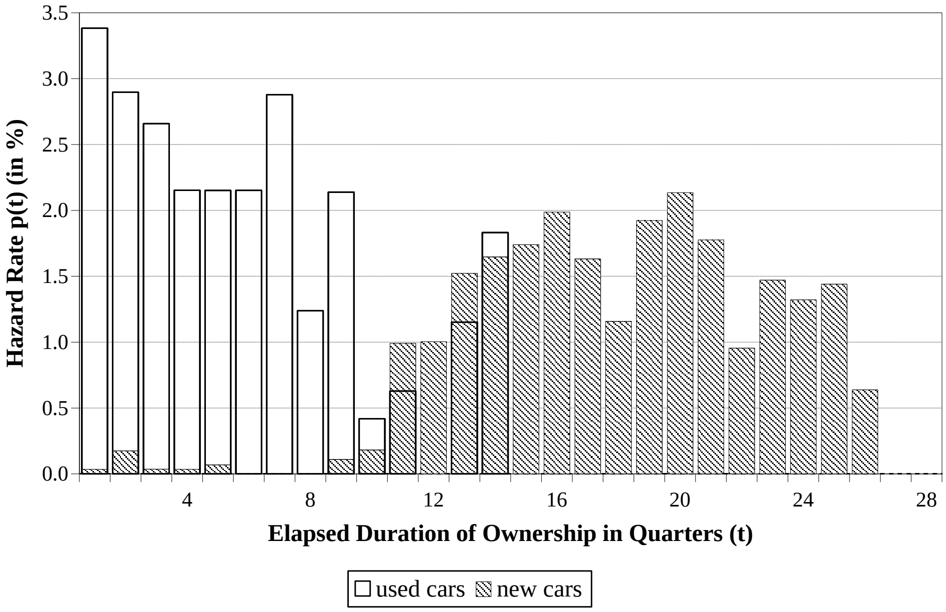

Table 4: (Semi-)Parametric Estimates of the Hazard Function of Car Ownership

Explanatory Variable	Resale within 5 Quarters after Purchase				Resale within 8 Quarters after Purchase		Resale within 14 Quarters after Purchase	
	New Cars		Used Cars		Used Cars		Used Cars	
	Semi-Param.	**Weibull**	**Semi-Param.**	**Weibull**	**Semi-Param.**	**Weibull**	**Semi-Param.**	**Weibull**
Constant	-3.540*** (0.304)	--	-1.791*** (0.152)	--	-1.823*** (0.142)	--	-1.776*** (0.138)	--
t	1.034* (0.612)	--	-0.050* (0.030)	--	-0.036** (0.018)	--	-0.038*** (0.013)	--
t^2	-0.714* (0.389)	--	--	--	--	--	--	--
t^3	0.117* (0.065)	--	--	--	--	--	--	--
$\eta \times 10^2$	--	0.002 (0.007)	--	0.018*** (0.005)	--	0.020*** (0.005)	--	0.019*** (0.008)
r	--	1.258 (1.009)	--	0.814*** (0.072)	--	0.828*** (0.064)	--	0.800*** (0.090)
θ	--	--	--	--	--	--	--	0.083 (1.549)
Prior Inspection	--	--	-0.078 (0.089)	-0.210 (0.265)	-0.142* (0.080)	-0.382* (0.241)	-0.145* (0.077)	-0.432* (0.245)
Vehicle Age	--	--	-0.004 (0.010)	0.005 (0.031)	-0.001 (0.009)	0.014 (0.029)	-0.003 (0.009)	0.021 (0.028)
Commercial Use	1.041*** (0.397)	2.602 (4.276)	-0.287 (0.430)	-0.718* (1.414)	-0.332 (0.417)	-0.862 (1.341)	-0.033 (0.305)	-0.202 (1.065)
Diesel	--	--	-0.428 (0.407)	-1.146* (1.367)	-0.492 (0.394)	-1.366 (1.309)	-0.214 (0.291)	-0.652 (1.073)
ALFA	0.696* (0.390)	1.993 (1.231)	0.841*** (0.285)	2.649*** (0.978)	0.397 (0.265)	1.186 (0.811)	0.440* (0.258)	1.410* (0.833)
AUDI	--	--	0.614*** (0.313)	2.019** (1.030)	0.263 (0.285)	0.818 (0.864)	0.281 (0.281)	0.957 (0.889)
BMW	--	--	0.242 (0.364)	0.884 (1.243)	-0.044 (0.316)	-0.114 (1.015)	-0.034 (0.312)	-0.064 (1.046)
CITROEN	--	--	0.439 (0.338)	1.490 (1.128)	-0.012 (0.318)	-0.005 (0.997)	-0.024 (0.312)	-0.027 (1.028)
FIAT	--	--	0.650** (0.295)	2.097** (0.999)	0.404 (0.262)	1.172 (0.809)	0.398 (0.258)	1.268 (0.836)
FORD	--	--	0.431 (0.318)	1.488 (1.089)	0.068 (0.287)	0.259 (0.909)	0.146 (0.276)	0.552 (0.911)
HONDA	--	--	0.699** (0.305)	2.250** (1.003)	0.311 (0.278)	0.944 (0.842)	0.300 (0.273)	0.990 (0.866)
LANCIA	1.236*** (0.341)	3.184 (2.211)	--	--	-0.213 (0.424)	-0.699 (1.439)	0.069 (0.348)	0.195 (1.185)
MAZDA	--	--	0.551* (0.344)	1.775 (1.154)	0.226 (0.308)	0.671 (0.956)	0.231 (0.303)	0.738 (0.981)
MERCEDES	--	--	0.550 (0.345)	1.790 (1.149)	0.101 (0.326)	0.330 (1.009)	0.305 (0.293)	0.928 (0.959)
MITSUBISHI	--	--	0.726** (0.306)	2.300** (1.025)	0.515** (0.269)	1.456* (0.827)	0.517** (0.264)	1.578* (0.861)
NISSAN	0.863*** (0.314)	2.334** (1.192)	1.015*** (0.295)	2.997*** (1.029)	0.595** (0.271)	1.639** (0.840)	0.555** (0.266)	1.674** (0.860)
OPEL	0.117 (0.375)	0.613 (3.856)	0.567** (0.274)	1.875** (0.947)	0.181 (0.251)	0.579 (0.790)	0.187 (0.247)	0.665 (0.813)
PEUGEOT	--	--	0.551* (0.324)	1.828* (1.070)	0.093 (0.304)	0.333 (0.942)	0.191 (0.287)	0.657 (0.936)
PORSCHE	--	--	0.923* (0.544)	2.828* (1.504)	0.479 (0.522)	1.408 (1.369)	0.517 (0.521)	1.623 (1.428)
RENAULT	--	--	0.715** (0.283)	2.319** (0.960)	0.327 (0.261)	0.999 (0.803)	0.364 (0.254)	1.191 (0.822)
SUBARU	--	--	1.065*** (0.354)	3.138*** (1.119)	0.579* (0.331)	1.601* (0.943)	0.676** (0.311)	1.966** (0.981)
SUZUKI	--	--	1.124*** (0.306)	3.316*** (0.998)	0.704** (0.287)	1.952** (0.830)	0.730*** (0.284)	2.165*** (0.869)
TOYOTA	0.291 (0.360)	0.886 (0.978)	0.755*** (0.271)	2.350*** (0.947)	0.429* (0.246)	1.221 (0.771)	0.470** (0.240)	1.438* (0.800)
VOLVO	--	--	--	--	0.050 (0.353)	0.090 (1.141)	0.057 (0.348)	0.163 (1.174)
VW	0.207 (0.356)	0.640 (1.022)	0.552** (0.282)	1.832* (0.968)	0.141 (0.259)	0.459 (0.812)	0.136 (0.255)	0.489 (0.835)
(Split) Spells	13164	2645	4245	1161	5497	1161	6301	1161
% Cars Resold	0.004	0.004	0.106	0.106	0.129	0.129	0.138	0.138
$\ln L_0$	-81.823	-73.519	-556.78	-532.42	-688.13	-611.23	-745.68	-645.06
$\ln L^*$	-70.285	-63.865	-536.69	-514.65	-666.56	-592.80	-721.35	-627.10
$-2(\ln L_0 - \ln L^*)$	23.075***	19.307**	40.191**	35.552*	43.141**	36.850*	48.665***	35.906
LRI $(1-\ln L^*/\ln L_0)$	0.141	0.131	0.036	0.033	0.031	0.030	0.033	0.028

Asterisks denote statistical significance at the 10% (*), 5% (**), and 1% (***) level, respectively. Estimated standard errors appear in parentheses.

Figure 3: Cross Plot of the Brand Coefficients for No Defects (Table 2) and Resell Hazards (Table 4), New Cars Only

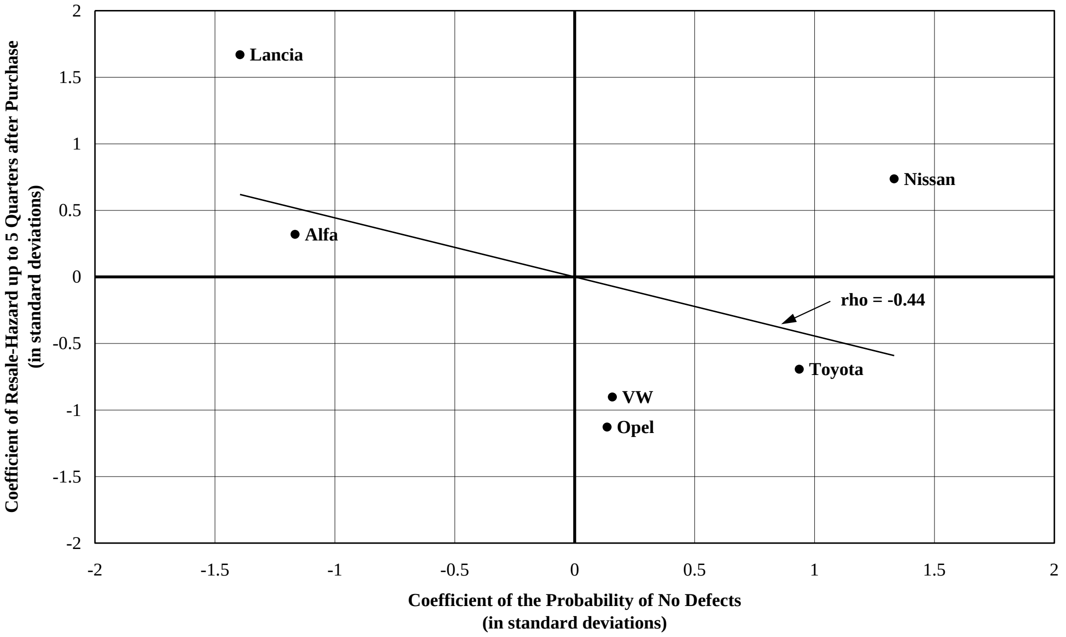

Figure 4: Cross Plot of the Brand Coefficients for No Defects (Table 2) and Resell Hazards (Table 4), Used Cars Only