APPENDIX (NOT FOR PUBLICATION)
RESERVE PRICE EFFECTS IN AUCTIONS:
ESTIMATES FROM MULTIPLE RD DESIGNS

SYNGJOO CHOI   LARS NESHEIM   IMRAN RASUL*

MARCH 2015

A Appendix

A.1 Credibility Checks on the RD Design

We divide these checks into three types: (i) whether discontinuities in auction outcomes at the cut-off remain *conditional* on observables; (ii) whether the assignment variable is smooth around the discontinuity or appears to have been *manipulated* by the seller; (iii) whether there is differential endogenous *sorting* of bidders either side of the cut-off.

On the first check, to see if the evidence of discontinuities in outcomes remains once we take account of information on covariates Z_i, we follow Lee and Lemieux [2010] and proceed in two steps. We first form predictions of auction outcomes based on regression analysis. We then construct the residuals from the regression model, and then plot the average residual in bin widths of 50 over the range ± 500 of the assignment variable against the mid-point of each bin. We do this for the baseline Cat-C1 regime.

Denote the winning bid in auction j for a vehicle of model m in time period t as w_{jmt}. This corresponds to the maximum of the second highest bid placed in the auction and the reserve price. The vehicle has observable characteristics Z_j, including its model m. A model refers to a specific vehicle manufacturer and vehicle type, so that for example a BMW 316 and BMW 318 are distinct models. As shown at the foot of Table A1, there are 980 unique vehicle models in Cat-C1 auctions. Time t is measured as months since January 2003. We then estimate the correlates of the log of winning bids using the following panel data model,

$$\log w_{jmt} = \alpha_m + \beta_t + \Pi \mathbf{Z} + u_{jmt}, \tag{1}$$

*All authors are at the Department of Economics, University College London, Drayton House, 30 Gordon Street, London WC1E 6BT, United Kingdom. E-mails: syngjoo.choi@ucl.ac.uk; l.nesheim@ucl.ac.uk, i.rasul@ucl.ac.uk.

where α_m and β_t are model and time fixed effects respectively, $\mathbf{Z}$ is the matrix of other observable characteristics of the vehicle including the log of the pre-accident value, log of the indicated mileage, dummies for whether the vehicle uses petrol rather than diesel fuel, whether it is manual transmission, whether the keys are available, whether a service history is available, whether the V5 logbook is available, whether it is an EU import, the log of the number of words describing damage to the vehicle recorded on the auction web page, a series of dummies for each year of manufacture, and dummies for the salvage year at which the vehicle is located. Robust standard errors are calculated. Importantly we do not control for the reserve price in (1).[1]

We also predict the number of bidders expected to enter the auction using a fixed effects Poisson model [Hausman *et al.* 1984], and we use a linear probability model to estimate the probability of the item being unsold at first auction. In both specifications we control for the same set of covariates as described above.

Table A2 reports the results. Column 1 shows that this rich of covariates explains 82% of the variation in the log of the winning bid. Moreover the estimated marginal effects on some of the covariates can also be validated. For example, the marginal effect of having the keys available, evaluated at the mean, corresponds to an increase in the winning bid w_{jmt} of £26.5 for Cat-C1 vehicles. This corresponds closely to the true cost of acquiring keys for such category of vehicle. Finally, as is intuitive we find that many of the covariates have the same signed marginal effect on the winning bid and the number of entrants, and have the opposite signed marginal effects on the probability of the vehicle remaining unsold at first auction.[2]

For winning bids we take the residuals from (1). Figure A1A shows the average residual, and its associated 95% confidence interval, in bins of width 50 either side of zero for the assignment variable over the range ± 500. As with the unconditional descriptive evidence in Figure 1B, this shows a clear discontinuity in the *residuals* precisely at the discontinuity, with no correspondingly similar jumps in average residuals between other adjacent bins. Given that we do not control for R_i in (1) this result is highly suggestive of there being an reserve price effect on winning bids conditional on the rich set of vehicle characteristics embodied in $\mathbf{Z}$ and the model fixed effects α_m.

Figure A1B shows analogous results based on the fixed effects Poisson regression for the number of bidders. For expositional ease we show how the predicted number of bidders varies with the assignment variable. As with the unconditional descriptive evidence in Figure 1C, the data clearly shows, conditional on covariates, there exists a substantial jump in the predicted number of bidders at the cut-off.

The second set of evidence we provide on the credibility of the RD design relates to manipulation of the assignment variable. The econometric concern is whether vehicle PAVs are

[1] In the UK, the V5 Logbook is required to transfer the legal ownership of a vehicle from seller to buyer. The logbook is also required to then register the vehicle in the buyer's name.

[2] We also estimated a specification analogous to (1) using a random effects Tobit model to take account of the dependent variable being censored at the reserve price, where the random effect was the vehicle model. This led to the majority of coefficients having the same sign and significance as those reported.

manipulated to lie on one side of the cut-off or the other. To check for this, Figure A1C shows the kernel density of the assignment variable, $(PAV_i - 1500)$. Two points are of note.[3]

First, from inspection, there is no obvious discontinuity in the assignment variable at zero. Nor is there any obvious bunching of the assignment variable distribution to either side of the cut-off. This provides suggestive evidence that the engineers of the insurance firm that supplies all vehicles to the auctioneer and who determine each vehicles PAV, do not manipulate these assessments to lie to one side of the assignment cut-off.[4]

Second, the distribution of the assignment variable is bunched at multiples of £50. Due to this bunching, when we formally test for whether the assignment variable is smooth at the cut-off value using the test proposed in McCrary [2007], we reject the null. To our knowledge, no test currently exists to check for discontinuities in the assignment variable in the case where the assignment variable is bunched. More reassuringly, when we implement McCrary's test for other covariates in Z_i, that are not bunched at fixed intervals, we accept the null of there being no discontinuity in each covariate at conventional levels of significance.

The third set of evidence we provide on the credibility of the RD design relates to differential endogenous sorting by bidders into auctions either side of the cut-off. The econometric concern is that if experienced bidders are aware of the discontinuity between PAV_i and R_i then such bidders might be more likely to enter auctions just below the discontinuity where reserve prices are generally set to be low in nearly all the RD regimes we consider. Such selective entry would confound the RD estimates that are evaluated at the discontinuity.

This concern is ameliorated because PAV_i is nowhere reported on the auction website, and even within a vehicle category, the mapping between PAV_i and R_i changes over time. To provide further evidence, Figure A1D shows the average win rate of auction entrants in regime Cat-C1 auctions, in bin widths of 50 over the range ± 500 of the assignment variable against the mid-point of each bin. Just to the left of the discontinuity, there is no evidence of a bunching of higher win rates among bidders. Rather win rates are falling as PAV_i rises. The discontinuity in win rates among bidders occurs precisely at the discontinuity, not to its immediate left.

A.2 Robustness Checks on the Baseline RD Estimates

Table A3 presents a series of robustness checks on the baseline RD estimates of the reserve price effects in auctions from regime Cat-C1. These are divided into two types relating to: (i) samples and placebo discontinuities (Panel A); (ii) bandwidth and kernel choices (Panel B).

[3] The bandwidth chosen is Silverman's [1986] optimal bandwidth that is equal to $1.06n^{-\frac{1}{5}}\min(s, \frac{IQR}{1.34})$ where n is the sample size, s is the standard deviation of PAV, and IQR is the interquartile range of PAV.

[4] While our analysis focuses exclusively on the 90% of auctioned vehicles that originate from one large insurer, the remaining vehicles auctioned by the same auctioneer are actually supplied by private sellers. Private sellers can choose whether to set a reserve price and whether to publicly announce the reserve. Conditional on vehicle characteristics, we find reported pre-accident values to not be significantly different between vehicles supplied by the insurer and vehicles supplied by private sellers who also use a public reserve price.

Column 1 of Panel A restricts the sample to auctions with strictly more than one bidder. We find that in such auctions the reserve price effect on winning bids is larger and the effect on the number of bidders is smaller than in the baseline estimates. Both estimates remain significant at the 1% level. Column 2 restricts the baseline sample to a narrower window around the cut-off using values of the assignment variable between the median above and below the cut-off value. The baseline results are robust to using this more restricted sample that does not utilize information from vehicles with PAV_i far away from the discontinuity, and that arguably better captures the spirit of RD designs [Lemieux and Milligan 2008]. Columns 3 and 4 consider placebo cut-offs at the median quantile above and below the true cut-off, respectively. Reassuringly we find no evidence of a change in auction outcomes around these points.

In Columns 5 and 6 of Panel B we present RD estimates based on bandwidths that are half of, and double the size used for the baseline estimates respectively. For both outcomes, the baseline results are robust to these alternative bandwidth choices. Column 7 shows the baseline results to be robust to using a rectangular kernel. For both outcomes the standard errors are smaller than those reported in the baseline estimates using a triangular kernel.[5] Finally, Column 8 follows the suggestion in Lee and Card [2008] in the case of a discrete assignment variable, of block bootstrapping the standard errors by the value of the assignment variable. Doing so, as expected the standard errors rise relative to the baseline specification for both outcomes, although the estimated effects remain significant at the 1% level.

A.3 External Validity

A limitation of RD designs is that they effectively identify a *weighted* average treatment effect of W_i, where the weight is proportional to the *ex ante* likelihood that an individual realization of PAV_i will be close to the cut-off [Lee and Lemieux 2010]. In our setting there is no particular economic significance to basing our RD estimates around the $PAV_i = £1500$ cut-off. We therefore bolster the external validity of our findings using two strategies: (i) we exploit the variation over time within a vehicle category to present difference-in-difference estimates of the impact of changes in reserve price on auction outcomes; (ii) we exploit data from Category-C auctions that have taken place between December 2008 and June 2010, in which all aspects of the auction environments are unchanged except that the discontinuity between PAV_i and R_i occurs at $PAV_i = £2000$.

A.3.1 Difference-in-Difference Estimates

We exploit the variation over time within a vehicle category to present difference-in-difference (DD) estimates of the impact of changes in reserve price on auction outcomes. For example, the

[5] This result is replicated if we use alternative kernels such as an Epanechnikov kernel or use Silverman's [1986] rule-of-thumb bandwidth selection formula which is the optimal bandwidth choice assuming the actual density and kernel are Gaussian.

switch from regime Cat-C3 to Cat-C2 has the properties that: (i) for vehicles with $PAV_i < £1500$, over time $\Delta R_{it} = (.08 \times PAV_i) - 5$; (ii) for vehicles with $PAV_i \geq £1500$, $\Delta R_{it} = 0$. This allows us to infer the same marginal effect of reserve prices on auction outcomes as in the RD design, but exploiting time variation in R_{it} that occurs for vehicles over the entire range of auctions in which $PAV_i < £1500$, rather than a specific jump in R_i around the $PAV_i = £1500$ cut-off. We focus on estimating reserve price effects on winning bids, the number of bidders, and the probability the vehicle remains unsold. We do so considering three switches of regime: from Cat-C2 to Cat-C1, from Cat-C3 to Cat-C2, and from Cat-B2 to Cat-B1.

Denote the outcome in auction j for a vehicle of model m on date t as y_{jmt}. Z_i and Z_t denote vehicle and time varying characteristics. Z_i refers to the set of observables controlled for in (1). Consider then estimating reserve price effects using the switch from Cat-C2 to Cat-C1. We then define C_t^j to be a dummy variable equal to one if regime Cat-C1 is in place on date t, and zero if regime Cat-C2 is in place. Whether and how reserve prices change between the regimes depends on whether the pre-accident value for the vehicle, PAV_{jmt}, is above or below the £1500 cut-off. We therefore define a dummy variable $DPAV_{jmt}$ set equal to one if $PAV_{jmt} < £1500$, and zero if $PAV_{jmt} \geq £1500$. We then estimate the following panel data specification,

$$\log y_{jmt} = \alpha_m + \beta_0 C_t^j + \beta_1 DPAV_{jmt} + \beta_2 \left[C_t^j \times DPAV_{jmt}\right] + \Gamma_j \mathbf{Z}_j + \Gamma_t Z_t + u_{jmt}, \qquad (2)$$

where α_m are model fixed effects, and $\mathbf{Z}_j$ is a matrix of characteristics of vehicle j, and monthly UK scrap metal prices are in Z_t. To reduce concerns that we pick up time trends, we restrict the sample to a six month window, split equally either side of the date of the regime switch. β_0 captures any time effects on $\log y_{jmt}$ over this narrow window switching from Cat-C2 to Cat-C1. β_1 captures the differential effect on the outcome of the vehicle being above or below the $PAV_{jmt} = £1500$ cut-off. The parameter of interest is β_2, that measures the difference-in-difference effect of the vehicle being above or below the $PAV_{jmt} = £1500$ cut-off with the switch from one reserve price regime to the other, ΔR_{it}.[6]

For outcomes on winning amounts and the probability the vehicle remains unsold we estimate (2) using OLS. On the number of bidders, a specification analogous to (2) is estimated using a Poisson fixed effects model. In the OLS specifications, u_{jmt} is clustered by auction closing date to allow for unobserved factors that are contemporaneously correlated across auctions.

Table A4 presents the results. The first three columns show auction outcomes as we move from the Cat-C2 to Cat-C1 regimes. This change corresponds to an increase in the reserve price of £35 for all vehicles with $PAV_{jmt} < 1500$, and the reserve price is unchanged for all other vehicles. In Column 1 we then see that: (i) there is a naturally declining time trend in winning amounts as we move from the Cat-C2 to Cat-C1 regimes ($\widehat{\beta}_0 < 0$); (ii) vehicles with $PAV_{jmt} < 1500$ and

[6] As $DPAV_{jmt}$ is a dummy variable, it is possible to also control for PAV_{jmt}. The reported results are robust to doing so as well as also including higher order polynomials in PAV_{jmt}.

lower reserve prices have lower winning bids ($\widehat{\beta}_1 < 0$); (iii) most importantly, there is a differential time trend in winning amounts with the change in regime for vehicles for which there is change in reserve price ($\widehat{\beta}_2 > 0$). At the foot of the table we report the implied marginal change in winning bid with respect to a £1 change in reserve price, evaluated at the mean PAV_{jmt} conditional on $PAV_{jmt} < £1500$. This implied marginal reserve price effect, £1.65, evaluated at this lower PAV_{jmt} is far larger than that implied by the RD estimate reported in Table 4 that is evaluated at $PAV_i = 1500$. Taken together, this suggests the marginal effect of the reserve price on winning amounts is decreasing in the underlying valuation of the vehicle.

On the other margins of behavior, Column 2 shows that there is a significant fall in the number of bidders as the reserve price rises. The marginal effect reported at the foot of Table A4 and which is evaluated at a relatively low mean reserve price – that corresponds to the average reserve conditional on $PAV_{jmt} < £1500$ – is actually almost identical to the marginal effect derived from the RD estimates. Column 3 shows a very similar pattern of results on the likelihood the vehicle remains unsold at first auction and again the sign, magnitude and significance of the implied marginal effect lines up well with the RD estimates.

The remaining Columns of Table A4 focus on the two other changes in regime. Columns 4 to 6 show the difference-in-difference estimates based on the switch from Cat-C3 to Cat-C2 in which $\Delta R_i = -£62$ for all vehicles with $PAV_i < £1500$, and $\Delta R_i = 0$ for all vehicles with $PAV_i \geq £1500$. Note that for vehicles with $PAV_i < £1500$, the sign of the change in reserve prices exploited for the DD estimates is negative. In contrast, the sign of the change in reserve prices exploited for the RD estimates was positive. The results are broadly in line with the DD estimates from the regime switch from Cat-C2 to Cat-C1. We again find that relative to the RD estimates, the implied marginal reserve price effect on the winning bid to be larger when evaluated at this lower reserve, but that the marginal effects on the number of bidders and likelihood the vehicle remains unsold to be almost identical across DD and RD estimates.

Finally, Columns 7 to 9 show the difference-in-difference estimates based on the switch from Cat-B2 to Cat-B1 in which $\Delta R_i = £35$ for all vehicles with $PAV_i < £1500$, and $\Delta R_i = 0$ for all vehicles with $PAV_i \geq £1500$. In contrast to the RD estimates in Table 4, we see that the change in reserve price at evaluated at such a low reserve price for Cat-B vehicles does have a significant impact on the winning bid. In line with the RD estimates, the reserve price effect significantly reduces the number of bidders, and the marginal effect is larger in absolute value than the RD estimates. Finally, the DD estimates, like the RD estimates, show there to be no reserve price impact on the likelihood the vehicle remains unsold for such low value Cat-B vehicles.

A.3.2 Exploiting a Discontinuity in Reserve Price at a Different PAV

From December 2008 onwards, the reserve price algorithm for Category-C vehicles has been such that: (i) $R_i = £5$ if $PAV_i < £2000$; (ii) $R_i = .08PAV_i$ if $PAV_i \geq £2000$. Hence there exists a discontinuous jump in R_i from £5 to £160 at $PAV_i = £2000$. 21% of auctions in this period are of vehicles with $PAV_i \geq £2000$. Table A5 reports the estimated reserve price effects on winning bids, the number of entrants, and the likelihood the vehicle remains unsold using this discontinuity. As a point of comparison, Column 1 shows the previous baseline estimates from the Cat-C1 RD regime. Column 2 shows that when the discontinuity occurs at the higher PAV_i of £2000, there still exists a significant reserve price effect on winning bids. The magnitude of the implied marginal effect is larger than the baseline estimate. This is in line with the previous evidence that reserve price effects are larger when the reserve price is lower to begin with. However, this effect is estimated less precisely than the baseline amounts both because of the smaller sample size, and the fact that the bulk of the distribution of PAV in this regime (80%) lies predominantly below the cut-off at £2000. On the other margins, the reserve price effects are of the anticipated sign, although neither is estimated precisely. As a further falsification check on the earlier results, Column 3 presents evidence of there being jumps in outcome in this latest Cat-C around $PAV_i = £1500$ that was previously exploited for the baseline estimates in Table 3. Reassuringly, the evidence suggests there is no natural jump in outcomes at this threshold on any margin.

A.4 Re-auctions

To estimate the last component of (5) requires using data from second auctions. In our data each vehicle has a unique identifier and so we can track when a vehicle comes up for second, or higher, auction. The median time to second auction is four days for Cat-C1 vehicles, and the vast majority of second time auctions have a reserve price set of £5. Table A6 presents descriptive evidence on first and second time auctions for the Cat-C1 regime. Around 4% of cars are unsold at first auction. At second auction, 99% of them are sold. As expected, given the lower reserve price, winning amounts are significantly lower in second auctions. Given the short time frame between first and second auctions, and the lower reserve price in the second auction, bidders might have an incentive to delay their participation in the original auction [McAfee and Vincent 1997]. A dynamic analysis of bidding behavior across auctions lies outside the scope of this paper, but we note that as shown in Table A6: (i) only slightly fewer bidders enter second auctions relative to first auctions; (ii) there are significantly fewer second auctions in which only one bidder enters; (iii) the win rate among bidders does not significantly differ across first or second auctions.

Denote the winning bid in a second-time auction j for a vehicle of model m in time period t as w_{2jmt}. The vehicle has observable characteristics Z_j, including its model m. We then estimate how the winning bid in the re-auction is correlated to the reserve price for the same vehicle in its first time auction, R_{1jmt}, using the following panel data model,

$$\log w_{2jmt} = \alpha_m + \beta_t + \Pi \mathbf{Z} + \gamma R_{1jmt} + u_{jmt}, \tag{3}$$

where α_m and β_t are model and time fixed effects respectively, $\mathbf{Z}$ is the matrix of other observable characteristics of the vehicle. Robust standard errors clustered by auction closing date are calculated. The parameter of interest is the elasticity γ, which maps back to $\frac{\Delta E[\pi|PAV=PAV_c,S=0]}{\Delta R_i}$.[7]

The results are presented in Table A7. Column 1 shows that the unconditional correlation between the first-time reserve price and the second time winning bid is .343, and this is significantly different from zero. Column 2 shows this correlation to be almost the same magnitude, and estimated more precisely when the full set of covariates is controlled for. Column 3 shows $\widehat{\gamma}$ not to be significantly different between vehicles whose PAV is above or below the £1500 cut-off used for the RD estimates. In conclusion, the baseline estimate from Column 2 implies the marginal effect of a £1 increase in the reserve price at first auction corresponds to an increased winning bid of £.24 at first re-auction. This estimate of $\frac{\Delta E[\pi|PAV=PAV_c,S=0]}{\Delta R_i}$ is then used to calibrate (5).

[7] The controls include the log of the pre-accident value, log of the indicated mileage, dummies for whether the vehicle uses petrol rather than diesel fuel, whether it is manual transmission, whether the keys are available, whether a service history is available, whether the V5 logbook is available, whether it is an EU import, the log of the number of words describing damage to the vehicle recorded on the auction web page, a series of dummies for each year of manufacture, and dummies for the salvage year at which the vehicle is located.

Table A1: Vehicle Characteristics by Reserve Price Regime

Means, standard deviation in parentheses

	Category C Vehicles			Category B Vehicles		Category D Vehicles
	(1) Regime 1 (Baseline)	**(2) Regime 2**	**(3) Regime 3**	**(4) Regime 1**	**(5) Regime 2**	**(6) Regime 1**
Form of Discontinuity in Reserve Price:	**Jumps up from 40 to 120 at PAV=1500**	**Jumps up from 5 to 120 at PAV=1500**	**No jump at PAV=1500**	**Jumps down from 40 to 5 at PAV=1500**	**No jump at PAV=1500, R=5**	**No jump at PAV=1500**
Time Period	10 July 2006 - 17 Nov 2008	1 Feb 2005 - 7 July 2006	2 Jan 2003 - 31 Jan 2005	8 Aug 2006 - 17 Nov 2008	27 Sept 2004 - 7 Aug 2006	2 Jan 2003 - 17 Nov 2008
Number of First Time Auctions	60061	44734	45066	21296	22631	64280
Pre-accident Value	2442	2272	2325	2389	2389	4833
	(2988)	(2818)	(2763)	(3398)	(3112)	(5739)
Indicated Mileage	77534	76652	75469	74677	71975	59109
	(40351)	(40097)	(41340)	(44006)	(42577)	(39133)
Petrol [Yes=1]	.848	.864	.856	.841	.847	.828
	(.359)	(.343)	(.351)	(.366)	(.360)	(.377)
Manual Transmission [Yes=1]	.878	.897	.875	.884	.895	.859
	(.328)	(.303)	(.331)	(.320)	(.307)	(.348)
Keys Available [Yes=1]	.940	.871	.575	.874	.764	.833
	(.237)	(.335)	(.494)	(.332)	(.425)	(.373)
Service History Available [Yes=1]	.170	.038	.013	.124	.033	.116
	(.376)	(.192)	(.114)	(.330)	(.177)	(.320)
V5 Logbook Available [Yes=1]	.582	.243	.178	.539	.237	.444
	(.493)	(.429)	(.382)	(.499)	(.425)	(.497)
EU Import [Yes=1]	.007	0	0	.006	0	.002
	(.085)	(0)	(0)	(.076)	(0)	(.047)
Number of Words Describing Damage	5.71	5.08	4.66	6.53	6.11	5.10
	(4.47)	(4.06)	(4.29)	(5.21)	(4.78)	(4.23)
Unique Types of Vehicle Make	49	48	48	48	49	49
Unique Types of Vehicle Model	980	972	922	780	868	1123

Notes: All statistics refer to vehicles that are being auctioned for the first time. A Category B Vehicle is a Salvaged Vehicle which is so structurally damaged or devoid of parts that it is not possible to repair it economically or safely. A Category C Vehicle is a Salvaged Vehicle which is damaged to the extent that the retail cost of repair to the vehicle exceeds the retail pre-accident value thereof. A Category D Vehicle is a Salvaged Vehicle which is damaged to the extent that the retail cost of repair to the vehicle does not exceed the retail pre-accident value thereof. Each Column represents a different regime in which the relationship between the pre-accident value (PAV) and the public reserve price (R) varies. The time period refers to the dates on which this regime is in place. The number of bids placed included proxy bids. The pre-accident value refers to an engineer's valuation of the vehicle prior to it being involved in any accident.

Table A2: Correlates of Auction Outcomes

Robust standard errors in parentheses

	Category C, Regime 1			Category B, Regime 1	Category D
Dependent Variable:	(1a) OLS: Log (Winning Bid)	(1b) FE Poisson: Number of Bidders	(1c) Vehicle Unsold	(2) OLS: Log (Winning Amount)	(3) OLS: Log (Winning Amount)
Log (Pre-accident Value)	.442***	.030***	.062***	.188***	.474***
	(.018)	(.006)	(.003)	(.017)	(.021)
Log (Indicated Mileage)	-.004**	.007***	-.002***	.011***	-.010***
	(.002)	(.001)	(.001)	(.002)	(.002)
Petrol [Yes=1]	-.218***	-.215***	.023***	-.205***	-.181***
	(.007)	(.006)	(.002)	(.015)	(.006)
Manual Transmission [Yes=1]	-.056***	-.016**	.006**	-.022	-.018***
	(.007)	(.007)	(.003)	(.015)	(.007)
Keys Available [Yes=1]	.054***	.076***	-.018***	.094***	.047***
	(.009)	(.009)	(.004)	(.014)	(.006)
Service History Available [Yes=1]	.019***	-.011**	.001	.022	.033***
	(.005)	(.005)	(.002)	(.014)	(.006)
V5 Logbook Available [Yes=1]	-.002	.002	-.006***	-.039***	.004
	(.004)	(.004)	(.002)	(.009)	(.005)
EU Import [Yes=1]	.065**	.046*	-.005	-.019	.105**
	(.029)	(.026)	(.011)	(.090)	(.047)
Log (Number of Words Describing Damage)	-.062***	-.084***	.010***	.006	-.063***
	(.003)	(.003)	(.027)	(.006)	(.003)
Month of Auction Dummies (39)	Yes	Yes	Yes	Yes	Yes
Year of Manufacture Dummies (29)	Yes	Yes	Yes	Yes	Yes
Salvage Yard Dummies (14)	Yes	Yes	Yes	Yes	Yes
Model Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	.820	-	.078	.649	.859
Number of Auctions	55079	54911	57462	19368	54673

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. All observations relate to auctions of category C Vehicles in Regime 1, where there is at least one bidder. The number of observations drops in Column 1b because for 168 model types there is insufficient variation in the number of bidders across auctions. In Column 3 we include all first time auctions. The dependent variable is a dummy variable equal to one if no bids are placed in the auction so the vehicle remains unsold, and zero otherwise.

Table A3: Robustness Checks on the Baseline Results

Non Parametric Regression Discontinuity Results

Bootstrapped standard errors in parentheses, based on 50 replications

	A. Samples and Placebos				B. Bandwidth, Kernels and Standard Errors			
Outcome Variable	**(1) More Than One Bidder**	**(2) Narrow Window**	**(3) Placebo Cut-off at Median Quantile Above True Cut-off**	**(4) Placebo Cut-off at Median Quantile Below True Cut-off**	**(5) Half Bandwidth**	**(6) Double Bandwidth**	**(7) Rectangular Kernel**	**(8) Clustering Standard Errors**
Winning Bid	54.3***	59.5***	-16.1	-.492	34.0***	45.0***	32.8***	33.6***
	(3.92)	(.387)	(10.6)	(16.7)	(5.53)	(2.50)	(3.61)	(6.30)
Number of Bidders	-.888***	-.804***	-.141	-.053	-1.23***	-1.22***	-1.35***	-1.33***
	(.064)	(.388)	(.107)	(.480)	(.124)	(.052)	(.069)	(.085)
Number of Auctions	52963	28885	31184	25570	56959	56959	56872	56959

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. All observations relate to auctions of category C Vehicles in Regime 1, where there is at least one bidder. Each coefficient is estimated from a separate non parametric regression using a triangular kernel, where the bandwidth is set is chosen to give positive weight to at least 30 observations on each side of the discontinuity when estimating the conditional mean at the cut-off. Bootstrapped standard errors based on 50 replications are shown. In Column 1 we restrict the sample to auctions with strictly more than one bidder. In Column 2 the narrow window is defined as using values of the assignment variable between the median above and below the cut-off value. The bandwidths in Columns 5 and 6 are set to half and double the value that gives positive weight to at least 30 observations on each side of the discontinuity when estimating the conditional mean at the cut-off. In Column 7 a rectangular kernel is used. In Column 8 the standard errors are block bootstrapped by the value of the assignment variable.

Table A4: Difference in Difference Specifications

Robust standard errors in parentheses clustered by auction closing date in all columns except for number of bidders

RD Regime Change:	Category C RD Regime 2 to RD Regime 1 (ΔR=£35)			Category C RD Regime 3 to RD Regime 2 (ΔR=-£62)			Category B RD Regime 2 to RD Regime 1 (ΔR=£35)		
Dependent Variable:	(1) Winning Bid	(2) Number of Bidders	(3) Vehicle Unsold	(4) Winning Bid	(5) Number of Bidders	(6) Vehicle Unsold	(7) Winning Bid	(8) Number of Bidders	(9) Vehicle Unsold
Category C RD Regime 1	-.271***	-.042***	-.018***						
	(.010)	(.005)	(.006)						
Pre-accident Value<£1500	-.958***	.318***	-.183***	-.566***	-.153***	.138***	-.529***	-.151***	.011***
	(.015)	(.007)	(.004)	(.013)	(.009)	(.006)	(.020)	(.011)	(.004)
Category C RD Regime 1 x Pre-accident Value<£1500	.536***	-.160***	.045***						
[ΔR=£35]	(.016)	(.007)	(.003)						
Category C RD Regime 2				-.421***	-.121***	.050***			
				(.011)	(.005)	(.004)			
Category C RD Regime 2 x Pre-accident Value<£1500				-.262***	.444***	-.371***			
[mean ΔR=-£62]				(.019)	(.009)	(.006)			
Category B RD Regime 1							-.058***	-.035***	-.011***
							(.016)	(.009)	(.004)
Category B RD Regime 1 x Pre-accident Value<£1500							.500***	-.091***	-.003
[ΔR=£35]							(.021)	(.012)	(.004)
Implied ΔOutcome/ΔR, evaluated at mean PAV<1500	1.65***	-.018***	.000***	.502***	-.017***	.002***	.952***	-.007***	-.000
	[1.56, 1.75]	[-.019, -.016]	[.000, .000]	[.430, .574]	[-.018, -.016]	[.002, .002]	[.872, 1.03]	[-.008, -.005]	[-.000, .000]
Vehicle Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	.790	-	.125	.762	-	.231	.608	-	.038
Number of Auctions (clusters)	91996 (976)	91892	97701 (978)	65129 (876)	65024	78121 (877)	37662 (1059)	37518	39022 (1063)

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Robust standard errors that allow for clustering by the auction opening data are reported throughout, except in Column 5, where robust standard errors are reported. OLS estimates are reported in all Columns except 5 where a fixed effects Poisson model is estimated. All observations relate to auctions of salvage category C Vehicles in Regime 1 or 2, in a window around the change from Regime 2 to Regime 1 which took place on July 7th 2006. In all Columns except 4, the window runs from April 3rd April to September 29th 2006. In Column 4 a narrower window running from May 1st to August 31st is used instead. In all Columns except 3 and 7, we restrict attention to auctions in which there is at least one bidder. In Column 3 there are at least two bidders, and Column 7 includes auctions in which there are no bidders and the vehicle is left unsold. In Columns 2 to 7 the following additional controls are included - the log of the engineers pre accident value, the log of the indicated mileage, dummies for whether the vehicle uses petrol fuel, is a manual transmission, whether the keys are available, whether a full service history is available, whether the V5 logbook is available, whether the vehicle is an EU import, the log of the number of words describing damage to the vehicle, dummies for each year of vehicle manufacturer, dummies for each salvage yard holding the vehicle, and the price of scrap metal per month.

Table A5: External Validity

Non Parametric Regression Discontinuity Results

Bootstrapped standard errors in parentheses, based on 50 replications

	Cat-C, Regime 1 Jumps up from 40 to 120 at PAV=1500	Last Regime Jumps up from 5 to 160 at PAV=2000	
	(1) Comparison	(2) Baseline	(3) Assume RD at PAV=1500
Outcome Variable			
A. Winning Amount	33.6***	138.8*	3.46
	(3.80)	(82.6)	(9.96)
Implied ∆Outcome/∆R	.420***	.888*	
	[.336, .504]	[-.156, 1.93]	
B. Number of Bidders	-1.33***	-.805	-.013
	(.081)	(.804)	(.152)
Implied ∆Outcome/∆R	-.017***		
	[-.018, -.016]		
C. Vehicle Unsold [Yes =1]	.104***	.039	.0001
	(.006)	(.013)	(.0001)
Implied ∆Outcome/∆R	.003***		
	[.003, .003]		
Number of Auctions	56959	17410	17410

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. All observations relate to auctions where there is at least one bidder. Each coefficient is estimated from a separate non parametric regression using a triangular kernel, where the bandwidth is set is chosen to give positive weight to at least 30 observations on each side of the discontinuity when estimating the conditional mean at the cut-off. Bootstrapped standard errors based on 50 replications are shown. A Category B Vehicle is a Salvaged Vehicle which is so structurally damaged or devoid of parts that it is not possible to repair it economically or safely. A Category C Vehicle is a Salvaged Vehicle which is damaged to the extent that the retail cost of repair to the vehicle exceeds the retail pre-accident value thereof. A Category D Vehicle is a Salvaged Vehicle which is damaged to the extent that the retail cost of repair to the vehicle does not exceed the retail pre-accident value thereof. Each Column represents a different regime in which the relationship between the pre-accident value (PAV) and the public reserve price (R) varies.

Table A6: Auction Outcome Descriptives, by Auction Number

Category C Vehicles, Regime 1

Means, standard deviation in parentheses

	First Time Auction		Second Time Auction		t-test: Column 1=3	t-test: Column 2=4
	(1) Vehicle Sold	(2) Vehicle Unsold	(3) Vehicle Sold	(5) Vehicle Unsold	(5) p-value	(6) p-value
Number of Auctions (% of First/Second Time Auctions)	56904 (95.9)	2439 (4.11)	1938 (99.1)	17 (.009)		
Reserve Price in First Time Auction	178	211	226	188	[.000]	[.000]
	(243)	(287)	(250)	(144)		
Reserve Price in Second Time Auction	-		5	5		
			(0)	(0)		
Winning Amount	495	-	149	-		[.000]
	(1037)		(192)			
Number of Bidders	4.67		4.54	-	[.061]	
	(3.05)		(1.92)			
Percentage of Auctions With One Bidder	.070		.010		[.000]	
	(.254)		(.099)			
Win Rate Among Bidders	.223		.221		[.519]	
	(.082)		(.063)			

Notes: All auctions refer to Category C vehicles during regime 1. A Category C Vehicle is a Salvaged Vehicle which is damaged to the extent that the retail cost of repair to the vehicle exceeds the retail pre-accident value thereof. The number of bids placed included proxy bids. In Columns 5 and 6 we report the p-value on a two-sided test of the null hypothesis that the means are equal across first and second time auctions. The win rate for any given bidder is the percentage of auctions they have entered and won. This is averaged across all bidders in the auction to obtain the win rate among bidders.

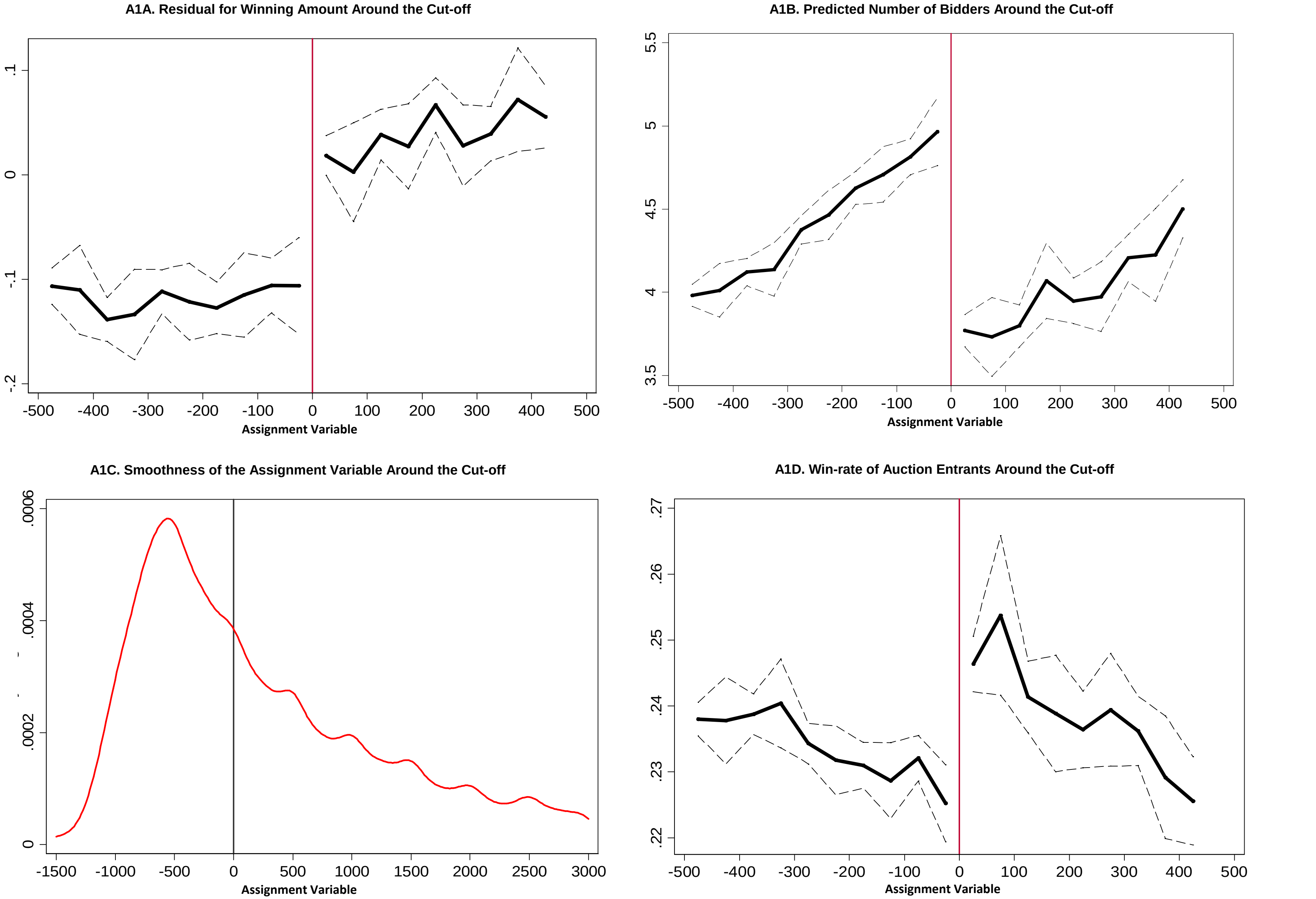
Table A7: Re-auction Outcomes

Dependent Variable: Winning Amounts in Re-auctions of Category C Regime 1 Vehicles
Robust standard errors in parentheses clustered by auction closing date

	(1) Unconditional	(2) Baseline	(3) Heterogeneous Effects of PAV
Reserve Price in First Time Auction	.343***	.359***	.335***
	(.125)	(.077)	(.070)
Log (Pre-accident Value)		.031	.024
		(.087)	(.300)
Log (Pre-accident Value) x I[PAV>=1500]			-.005
			(.288)
Implied Marginal Effect (on level of winning bid)		.238***	.222***
		(.051)	(.046)
Other Vehicle Characteristics	No	Yes	Yes
Month of Auction Dummies (39)	No	Yes	Yes
Year of Manufacture Dummies (29)	No	Yes	Yes
Salvage Yard Dummies (14)	No	Yes	Yes
Model Fixed Effects	No	Yes	Yes
Adjusted R-squared	.197	.572	.573
Number of Auctions	1826	1826	1826

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. All observations relate to second auctions of category C Vehicles in Regime 1, where there is at least one bidder. The other vehicle characteristics controlled for in Columns 2 onwards are the number of days since the first auction, the indicated mileage, whether it runs on petrol, whether it is manual transmission, whether the keys are available, whether a service history is available, whether a V5 logbook is available, whether the vehicle is a EU import, the number of words describing vehicle damage, and a series of dummies for the year of manufacture, the salvage yard holding the vehicle, month of auction, and vehicle model effects. In Columns 2 and 3 all continuous variables are in logs. Robust standard errors that are clustered by auction opening date are estimated throughout. The marginal effect reported at the foot of the table is the implied effect on the level of the winning bid (not in logs).

Figure A1: Regression Discontinuity Specification Checks



Notes: All figures use auction data from Category C vehicle auctions during regime 1, which is in place from July 10th 2006 until November 17th 2008. Figure 1A shows evidence related to the residual from having estimated the log of the winning bid on vehicle characteristics. The figure shows the average residual, and its associated 95% confidence interval, in bins of width 50 either side of zero for the assignment variable over the range ±500. Figure A1B shows analogous results based on the fixed effects Poisson regression for the number of bidders. Figure A1C shows the kernel density of the assignment variable, (PAVi-500). The bandwidth chosen is Silverman's [1986] optimal bandwidth. Figure A1D shows the average win rate of auction entrants, and its associated 95% confidence interval, in bins of width 50 either side of zero for the assignment variable over the range +/-500.