RESERVE PRICE EFFECTS IN AUCTIONS: ESTIMATES FROM MULTIPLE RD DESIGNS[*]

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Abstract

We present evidence from 260,000 online auctions of second-hand cars to identify the impact of public reserve prices on auction outcomes. To establish causality, we exploit multiple discontinuities in the relationship between reserve prices and vehicle characteristics to present RD estimates of reserve price effects on auction outcomes. Our first set of results show that, in line with the robust predictions of auction theory, an increase in reserve price decreases the number of bidders, increases the likelihood the object remains unsold, and increases expected revenue conditional on sale. Reserve price effects are found to be larger when there are more entrants, and when the reserve price is lower to begin with. Our second set of results then combine these estimates to calibrate the reserve price effect on the auctioneer's expected revenue. This reveals the auctioneer's reserve price policy to be locally optimal. Our final set of results provide novel evidence on reserve price effects on the composition of bidders. We find that an increase in reserve price: (i) decreases the number of potential bidders as identified through individual web browsing histories; (ii) leads to only more experienced and historically successful bidders still entering the auction; (iii) the characteristics of actual winners are less sensitive to the reserve price than those of the average bidder, suggesting auction winners are not the marginal entrant.

Keywords: auctions, regression discontinuity, reserve price.
JEL Classification: D44, L11, L62.

1 Introduction

Online auctions have become an increasingly important trading mechanism in modern economies. *eBay* alone has 81 million active users worldwide and auctions a billion objects annually [eBay 2009]. As data from auction settings has become accessible, especially from online auction environments, there has been a surge in empirical analysis testing whether the behavior of buyers and sellers is consistent with auction theory [Bajari and Hortacsu 2004].

This paper contributes to this strand of empirical literature by presenting evidence from 260,000 online auctions of second-hand cars that took place between January 2003 and November 2008, to identify the impact of public reserve prices on a rich set of auction outcomes. To establish causality, we present evidence from multiple regression discontinuity (RD) research designs. There has been much recent discussion on the availability and use of credible research designs in industrial organization [Angrist and Pischke 2010, Einav and Levin 2010, Nevo and Whinston 2010]. We contribute to this debate by presenting among the first applications of an RD design in industrial organization in general, and empirical auctions more specifically.[1]

We use a rich data set to identify the impact of reserve prices on various margins of bidder's behavior such as their entry into auctions, bidding behavior within the auction, and ultimately the winning bid. We then utilize these estimates to shed light on whether the reserve prices set by the auctioneer indeed maximize expected revenue.[2]

Our analysis has broad relevance in three regards. First, car sales through auctions are becoming increasingly important: the value of cars sold via auction in the US was \$89bn in 2007, and used car dealers filled over 30% of their inventory via auctions [Roberts 2009]. Second, the auction mechanism used in our setting is an open ascending auction with proxy bidding, widely suggested to be the most prevalent online auction format [Bajari and Hortacsu 2004]. Third, the specific auction design feature we study, reserve prices, is commonly observed in online and o- ine formats. Following the seminal works of Myerson [1981] and Reiley and Samuelson [1981], the wide range of conditions under which it is optimal to use a second-price auction with a reserve price are now well established [Maskin and Reiley 1984, Cremer and McLean 1988, McAfee *et al.* 1989]. On the other hand, alternative classes of model emphasize the circumstances under which higher reserve prices can reduce seller's revenue [Levin and Smith 1994, Bulow and Klemperer 1996]. It may therefore be optimal for auctioneers to set no reserve.[3]

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[1]Imbens and Lemieux [2007], van der Klaauw [2008] and Lee and Lemieux [2009] provide overviews of RD designs and the related literature. Although such designs have become common in economics since the late 1990s, to our knowledge this research design has not previously been employed in the empirical auctions literature. Indeed in over 60 studies using RD designs surveyed in Lee and Lemieux [2009], none were in industrial organization.

[2]The reserve price is the minimum amount the auctioneer will accept for the auction to end with a sale. The auctioneers' strategic choices relate to: (i) determining the level of the reserve, that is the focus of our analysis; (ii) whether to make the reserve public information or not. All the auctions we study have public reserve prices. Vincent [1995] and Rosenkranz and Schmitz [2007] provide theoretical explanations for when reserve prices should be public or secret. Bajari and Hortacsu [2003] and Katkar and Reiley [2006] provide evidence on this.

[3]Public reserve prices can increase revenue both in independent-values setting [Myerson 1981, Reiley and Samuelson 1981] and in affiliated or common-value settings [Milgrom and Webber 1982]. With exogenous entry and no *ex post* renegotiation, this public reserve is set to extract expected surplus from the highest bidder [Haile 2000, Zheng 2002]. With endogenous entry, the public reserve might be set no higher than seller's valuation to encourage

Conditional on a positive reserve price, there are relatively robust theoretical predictions on how reserve prices affect bidder's entry, winning bids, and the sellers' expected revenue. Nevertheless, credible causal evidence on such reserve price effects remains scarce. Much of the previous empirical literature based on reduced form correlations and structural models has suggested reserve prices might be an important determinant of seller revenues. A nascent literature is now emerging that provides credible causal estimates on reserve price effects using natural field experiments [Reiley 2006, Brown and Morgan 2009, Ostrovsky and Schwarz 2009].[4] We build on this literature by providing evidence from multiple RD research designs within the same auction environment to estimate reserve price effects on a rich set of auction outcomes, for high stakes objects.[5]

We exploit discontinuities in the relationship between reserve prices and vehicle characteristics to present RD estimates of the effect of reserve prices on auction outcomes. The discontinuities in reserve prices differ across distinct classes of vehicle, and change over time within vehicle classes. In total, we exploit four discontinuities in reserve price that vary in magnitude and sign.

We estimate the causal impact of public reserve prices on a rich set of auction outcomes. The first set of outcomes relate to winning bids, the number of entrants, and the probability the object is sold. A body of theory now exists that provides unambiguous comparative static effects of reserve prices on these three margins, and indeed, such outcomes have been the focus of much of the previous literature in economics. These comparative statics are robust to assumptions on whether: (i) bidders have private, affiliated or common values for the object;[6] (ii) bidder's entry into an auction is exogenous or is endogenously determined by the object's characteristics. Hence the first contribution of our analysis is to provide credible estimates of the causal impact of reserve prices on previously studied auction outcomes.

Our main results on these margins are as follows. First, in line with the robust theoretical

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efficient levels of entry [McAfee and McMillan 1987, Levin and Smith 1994]. These entry effects are mitigated in common value auctions where it is easier for bidders to determine their willingness to pay. Indeed, in common value settings high reserve prices reduce the information bidders have about the common value by restricting the behavior of potential bidders. This might reduce sales prices overall [Vincent 1995, Horstmann and LaCasse 1997]. In line with this, in online auctions there is some evidence that reserve prices are often set at lowest feasible level [Walley and Fortin 2005].

[4]The evidence on the causal impact of other auction design features reinforces the notion that reserve prices are a relatively important determinant of revenues in *online* auctions [Bajari and Hortacsu 2004]. For example, Brown and Morgan [2009] find that while reserve prices significantly increase winning bids, variation in auction ending rules that allow for late bidding, have no appreciable effect on revenues or the number of entrants. Of course there are other aspects of auction design that have significant effects on revenues. Chief among these is the precise auction format. The online evidence on this is surveyed in Bajari and Hortacsu [2004], and Athey *et al.* [2010] present evidence from o- ine timber auctions on the relative effects of sealed bid and open auctions.

[5]Relative to most other experimental studies of online reserve price effects, the objects we consider are high stakes items. Over our entire sample, the mean value of a vehicle sold is £793 but there is also considerable variation in winning valuations: the 90th (10th) percentile of winning bid distribution is £1680 (£50). Reiley [2006] presents field experiment evidence on reserve prices for collectible trading cards where average winning bids are $100. Brown and Morgan [2009] present evidence on reserve price effects from a field experiment on online coin auctions across auctioneers where average winning bids are around between $40 and $60.

[6]As in most auction settings, it is *a priori* unclear whether a private or common values model provides a better description of the market. On the one hand, individual buyers might have a particular need for a particular set of parts or may have idiosyncratic business opportunities. On the other hand, the overall quality of the resale market is common to all buyers and information about market quality may very well be dispersed amongst buyers. Given these issues, we focus on theoretical predictions that are robust to assuming common or private values.

predictions, we find an increase in reserve price: (i) decreases the number of actual bidders; (ii) decreases the likelihood the object is sold; (iii) increases expected revenue conditional on the object being sold. Second, exploiting the full set of discontinuities in reserve prices, we find the impact of reserve prices is greater when: (i) there are more auction entrants; (ii) the reserve price is lower to begin with. These results build on existing evidence from the field on reserve price effects.

Our second set of results bring together our various estimates to calibrate the overall impact of reserve prices on the auctioneer's expected revenue. As explained in more detail later, seller revenues correspond closely to her profits in this setting as most costs are fixed. To then understand whether reserve prices are set optimally, we combine our quasi-experimental estimates of reserve price effects with non-experimental estimates of the seller's revenue in case the object is not sold at first auction. These reveal that the reserve price policy followed by the auctioneer is locally optimal in that a small change in reserve price would not significantly change the seller's expected revenue or profit.

Our final contribution is to exploit some unique aspects of our data to estimate the impact of reserve prices on two sets of outcomes relating to the composition of bidders. First, using web browsing histories of individuals on the auction website we determine the impact on the number of *potential* bidders, namely those individuals who would find it optimal to enter the auction absent any transaction or search costs of doing so.

Second, exploiting data from bidder registration forms and bidder histories with the auctioneer dating back to January 2003, we study how bidder *characteristics* change with reserve prices. For instance, we construct individual histories of the number of auctions a bidder has previously entered, the bidders' historic probability of winning an auction they enter and so forth. Over the study period, there are around 6200 bidders actively participating in auctions. They are mostly professional bidders that own their own firms.

On these more novel margins of behavior, our main results are as follows. First, as reserve prices rise the number of potential bidders falls. This effect is however far smaller in magnitude than the reserve price effect on the number of actual entrants. Second, averaging across all entrants, only more experienced and historically more successful bidders remain in the auction at higher reserve prices. If bidder valuations correlate to bidder characteristics, this result suggests that entry into auctions is endogenous. In consequence, the valuation of bidders that enter the auction differ from those that could have potentially entered the auction. Along both margins – bidder experience and winning histories – the characteristics of actual winners are less sensitive to the reserve price than the average bidder. Hence as is intuitive, the evidence suggests auction winners are not the marginal entrant, which again might be indicative of endogenous entry. Taken together, these margins are informative for the development of future theory, and provide a basis from which, in future work, to construct and estimate a structural model of bidder's behavior in this setting.

The paper is organized as follows. Section 2 discusses the auction environment, data sources, descriptive evidence, and the RD design. Section 3 presents our RD estimates on standard margins of behavior. Section 4 focuses on seller's behavior and calibrates her first order condition for expected revenue maximization to shed light on whether reserve prices are set at the locally optimal

level. Section 5 estimates reserve price effects on more novel margins of bidder behavior. Section 6 concludes. The Appendix provides evidence on the credibility of the RD design, robustness checks on our baseline results, and present difference-in-difference estimates of the same reserve price effects that exploit the time variation in how reserve prices are set. This allows us provide greater external validity to our results by estimating reserve price effects over a wide range of reserve prices, not just those local to the discontinuities.

2 Setting, Data and Descriptives

2.1 The Setting

We analyze data from a UK based auctioneer, on 260,000 online auctions that occurred between January 2003 and November 2008. The objects for auction are second-hand vehicles that have been salvaged from an insurance firm many after having been involved in an accident. The auction mechanism used is an open ascending auction with proxy bidding, that is similar to an ascending second price auction.[7] Potential bidders need to register with the auctioneer to browse the inventory of auctions and enter any specific auction. Most bidders are professional buyers and have much experience with the auction format and the use of reserve prices. We focus on identifying the causal impact of reserve prices on auction outcomes holding constant all other auction design features.[8]

Many of the vehicles in our sample had been involved in an accident. The nature of the accidents varies, ranging from very minor accidents for vehicles that are ready to go back on the road, to vehicles that are written-off and can only be utilized for spare parts or scrap. In the UK automobile salvage market, vehicles are grouped into four categories based on the degree of damage. The categories are defined by the Association of British Insurers (ABI) and standards for classification are published.[9] Our dataset contains information on auctions of cars in three of the four categories, referred to as Categories B, C and D. Two steps are taken to classify each vehicle into a category. First, the pre-accident value for the vehicle (PAV) is independently assessed by

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[7]Bajari and Hortacsu [2003] describe proxy bidding in *eBay* auctions for coins. Borrowing from their description, when a bidder submits a proxy bid, she is asked by the auctioneer to state the maximum amount she is willing to pay for the object. Suppose the reserve price is £10, the bid increment is £5, and the first bidder, bidder A, places a proxy bid of £100. The highest bid of bidder A is then initially set to the reserve price. If a new bidder enters with a proxy bid of £25, i.e. above the reserve and below £100, the highest bid of bidder A is re-set to £30 (£25 plus the bid increment). If the highest bid reaches above bidder A's proxy bid, she can always place a new proxy bid. At the auction close, the highest bidder wins and pays the second-highest proxy bid plus one bid increment.

[8]In our sample period 79% of winning bidders are professionals, namely sole traders, companies or partnerships that predominantly purchase vehicles for resale. The remaining winners are private buyers. The median bidder has been registered with the auctioneer for three years. Such bidders are unlikely to suffer from the winner's curse, as has been found for more inexperienced bidders in online common value settings. Other auction design features, such as the auction length, bid increments, and whether late-bidding automatically extends the auction, do not vary discontinuously with the reserve price discontinuities we exploit, nor do they vary at the same time as exploited for the DD estimates.

[9]Salvage categories were developed by the ABI, vehicle recyclers, the UK Driver and Vehicle Licensing Agency (DVLA) and the UK police force in an effort to curb vehicle crime in the UK. See Association of British Insurers [2007].

engineers from the insurance firm supplying the vehicles. These correspond closely to published secondhand vehicle values from the main UK sources (e.g. Parker's Car Price Guide or Glass's Guide to Car Values) and so are not subject to manipulation.

Cars are then categorized as follows. Category-B (Cat-B) cars are so structurally damaged or devoid of parts that it is not possible to repair the car economically or safely. Such cars are purchased essentially for their scrap metal value. Category-C (Cat-C) cars are damaged to the extent that the retail cost of repair to the car is estimated to exceed the retail PAV. Hence it is not economically viable to repair the car and return it to the road. Such cars are purchased for the value of their spare parts. Finally, Category-D (Cat-D) cars have suffered minor or no damage and the retail cost of repair to the vehicle does not exceed the retail PAV. Such cars are mostly bought by professional dealers or private buyers, to go back on the road.

This categorization opens up the possibility of measuring the impact of reserve prices on auction outcomes across distinct car markets for each vehicle category that significantly differ in: (i) the expected number of entrants; (ii) the underlying value of the item to the seller; (iii) resale possibilities and hence whether bidder valuations are best thought of as being private or common.

2.2 Data Sources

We combine various data sources for our analysis. The first provides details of all auctions between January 2003 and November 2008. This contains information on: (i) vehicle characteristics such as make and model, transmission, engine size, shape, mileage, whether the keys are available, a detailed description of any damage etc.; (ii) auction characteristics such as the date of the auction, the bid increment, the salvage yard at which the vehicle is held and can be viewed etc. Each vehicle has a unique identifier that allows us to trace whether it has been auctioned multiple times. As detailed below, in an OLS regression framework for first time auctions, these observable vehicle and auction characteristics are sufficiently rich to explain 65% of the variation in winning bids in Cat-B auctions, and over 80% of the variation in Cat-C and Cat-D auctions.

Our second data source is at the bid-bidder-auction level. For each auction we observe the sequence of bids placed by *all* bidders, not just the winner. We observe the bid value, the time at which it was placed, whether it was a proxy bid and so forth. Each bidder has a unique identifier that we match with our third data source, bidder registration data. This details when each bidder first registered with the auctioneer and the type of bidder (partnership, company, private buyer etc.). We use this to construct bidder histories with the auctioneer based on their behavior since January 2003. For example, for bidder j on date t we define her 'win-rate' as,

$$w_{jt} = \frac{\#\text{auctions won between January 2003 and } t}{\#\text{auctions entered since January 2003}}. \tag{1}$$

We define analogous win-rates for specific categories of vehicles, as bidders tend to specialize by category. We use these bidder histories to construct proxies for bidder heterogeneity in any given auction and to estimate how the composition of all bidders in general, and winners in particular,

changes with (discontinuous) changes in the reserve price.

Our fourth data source relates to the web browsing histories of all bidders since January 2007. This allows us to track which auctions each registered bidder views, the number of times they view a given auction's web page, and the time at which they viewed. We use this to construct measures of the number of *potential* bidders in an auction. Finally, we have collated UK time series on monthly scrap metal prices. Our working sample covers 258,068 first time auctions, 55% of which are for Cat-C vehicles. There are 6200 registered and active bidders over this period.

2.3 Reserve Price Regimes

All the auctions we analyze have public reserve prices, denoted R_i in auction i. The precise algorithm to set R_i is based (discontinuously) on the car's pre-accident value, PAV_i. Three points are of note. First, PAV_i is determined by engineers from the insurance firm that supplies the vehicle to the auctioneer. These correspond closely to published values from sources such as Glass's Guide to Car Values. Importantly for the RD design, this value is not subject to manipulation, and moreover the engineers have no incentives to attempt such manipulation as their payoffs do not depend on the PAV_i nor on the revenues raised from vehicle auction. In the Appendix we provide further evidence in support of this assertion.

Second, the PAV_i is *not* revealed to potential bidders, nor is the algorithm mapping PAV_i to R_i. When potential bidders browse the auction website they first observe the set of auctions active on that date. The median number of active auctions on a given day is 189. At this stage, potential bidders know only the vehicle model being auctioned and its salvage category. If a potential bidder then chooses to view a specific auction web page, they observe three types of information: (i) detailed vehicle characteristics, but excluding PAV_i ; (ii) auction characteristics such as start and close times, and the reserve price; (iii) the current highest bid and the entire history of highest bids and when they were placed. No information is provided on bidder identities or the number of bidders.[10]

Third, the relationship between R_i and PAV_i differs across vehicle categories B, C and D. Within a category, the mapping between R_i and PAV_i also varies over time. Between 2003 and 2008 we observe six distinct reserve price regimes across car category and time, as summarized in Table 1. Column 1 shows that for Cat-C cars, from 10th July 2006 to 17th November 2008, the reserve price was a discontinuous function of PAV_i. In particular, $R_i = \pounds 40$ if $PAV_i < \pounds 1500$, and $R_i = .08 \times PAV_i$ if $PAV_i \geq \pounds 1500$. This induces a discontinuity in R_i from $\pounds 40$ to $\pounds 120$ for at $PAV_i = \pounds 1500$, as shown in Figure 1A. There are 60,000 auctions within this regime and we focus on this sub-sample to establish our baseline results on the reserve price effects. We refer to this as the Cat-C1 reserve price regime.[11]

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[10] The design of the website does not therefore differ radically from other online auction formats for vehicles in both the UK and US. Given that the vehicles are supplied by a single insurance firm, there is no notion of the seller's reputation in this setting, and bidders do not operate on both sides of the online market.

[11] This raises three issues: why does the auctioneer find it optimal to have a discontinuity in R_i, why is it a discontinuous function of PAV_i, and why does it vary over time? On the first issue, auction theory usually predicts

Columns 2 and 3 detail the other reserve price regimes for Cat-C cars, that we refer to as the Cat-C2 and Cat-C3 regimes. In Cat-C2 R_i discontinuously jumps at $PAV_i = £1500$, but the magnitude of the jump varies from that in Cat-C1. We use this regime to check whether the implied marginal effect of the reserve price on outcomes from the baseline Cat-C1 regime, also apply when we exploit this larger jump in R_i in the Cat-C2 regime. A comparison of results from Cat-C1 and Cat-C2 regimes also helps shed light on how reserve price effects vary with the level of the reserve price to begin with. In particular in Cat-C2 the reserve price is almost at its lowest feasible level ($R_i = £5$ if $PAV_i < £1500$) and so this sheds light on whether it might be optimal for the auctioneer to set a zero reserve in this setting.

Finally, Column 3 shows that in Cat-C3 there is no discontinuity in reserve prices at $PAV_i = £1500$. In this regime $R_i = .08 \times PAV_i$ for *all* PAV_i. We use this regime to provide a falsification check that auction outcomes do not naturally change around $PAV_i = £1500$ even in the absence of a discontinuity in R_i.

Columns 4 and 5 show there are two regimes to consider for Cat-B vehicles. In the more recent regime, Cat-B1, R_i jumps down from £40 to £5 at $PAV_i = £1500$. We can use this regime to test whether the effects of reserve prices on auction outcomes are of opposite sign to those documented in the baseline regime Cat-C1. Column 5 shows that in the Cat-B2 regime, in place between 27th September 2004 and 7th August 2006, $R_i = £5$ for all PAV_i. This can again be used as a falsification check that auction outcomes do not naturally jump at $PAV_i = £1500$ for category C vehicles. The final column shows that for Category D, over the entire period, $R_i = .1 \times PAV_i$ for all PAV_i so this regime is used as a further falsification check on auction outcomes at $PAV_i = £1500$.

Table 1 also presents information for each regime on the percentage of auctions that have $PAV_i < £1500$ and so lie to one side of any discontinuity in reserve prices. Across Cat-C and Cat-B regimes there is a fairly even split of vehicles either side of the cut-off. As expected a far smaller share of Cat-D vehicles have $PAV_i < £1500$.

All of this discussion relates to how reserve prices are set in the *first* time vehicle auctions we focus on. As shown below, the vast majority of vehicles are sold at first auction. For those that are not, they usually come up for re-auction with the same auctioneer within a week. We observe such re-auctions in our data. The default reserve price for re-auctioned vehicles is £5 for all salvage categories.[12]

that reserve prices are increasing in the seller's valuation and depend on the distribution of bidder valuations. Calculating the optimal reserve price for every car is potentially costly as it requires the seller to calculate the precise degree of damage and evaluate the distribution of bidder evaluations. By definition, the benefits of such calculations are lower for low-value cars. In the face of such costs, the observed reserve price policy might be a good rule-of-thumb approximation to an optimal reserve policy. In terms of expected revenues, we later document that the reserve price is set at its locally optimal level. On the second issue, we note that PAV_i is correlated with winning amounts, and that the ratio of winning amounts to PAV_i is less than 0.2 in all vehicle categories. Using a reserve price rule based on the ex ante PAV_i is relatively costless for the seller, rather than having to form an independent assessment of any potential damage to the vehicle and bidders' behavior. Finally, the use of reserve price rules that vary over time or induce quasi-experimental variation allows the auctioneer to receive feedback on and learn what might be the optimal reserve price policy.

[12]The marginal cost of holding onto a vehicle is approximately zero for the auctioneer. This cost is borne by the salvage yard where the vehicle is physically located. However, the reserve price in re-auctions is set at its lowest possible value because the auctioneer faces competitive pressure to ensure the salvage yards it works with do not

2.4 Vehicle Characteristics by Reserve Price Regime

Table A1 presents descriptives on vehicles by reserve price regime. This highlights that PAV_i is highest for Cat-D vehicles as expected. There is actually not much difference in PAV_i between Cat-B and Cat-C vehicles, confirming that the extent of damage incurred in the accident is not much correlated to the *ex ante* value of the vehicle. Table A1 also highlights the detailed list of vehicle characteristics available in the auction database. These fall into three types of characteristic. First, we observe a rich set of standard vehicle features such as mileage, transmission etc. Second, we code information relating to the damage the vehicle has suffered. For example we code the number of words in the auction data base that describes the vehicle damage. The third class of characteristic are the make and model of the vehicle – the auctions cover 49 vehicle makes (Audi, BMW, Ford etc.) and around 1200 specific vehicle models, where for example, BMW 316 and BMW 318 are considered to be two different models etc.

2.5 Auction Outcomes by Reserve Price Regime

Table 2 provides descriptive evidence on auction outcomes by reserve price regime. Panel A shows those outcomes that have been focused on in the literature. As expected, winning bids are highest for Cat-D vehicles, followed by Cat-C and Cat-B vehicles. Relative to previous studies using online auctions data, the objects considered in our setting are high stakes items. Even in the lowest value Cat-B class, the average winning bid is £229 in regime Cat-B1 and £183 in regime Cat-B2. Moreover, we note that winning bids are typically well above the reserve prices in each category. The fact that reserve prices are not binding in this sense ensures that any discontinuities in reserve prices do not mechanically lead to similar discontinuities in winning bids.[13]

The number of entrants varies across categories. Cat-D auctions attract an average of 6.9 bidders, while for the most recent Cat-C regime, Cat-C1, on average 4.5 bidders enter. For the lower valuation Cat-B auctions, less than 4 bidders enter. Across regimes, the vast majority of auctions attract more than one bidder. Finally, we note that less than 4% of vehicles remain unsold, except in the older Cat-C3 regime when nearly a quarter of vehicles remained unsold. Most vehicles that are unsold come up for re-auction with the same auctioneer, and usually within a week of the original auction. The vast majority of these are then sold at second auction.

Panel B presents descriptive evidence on bidder characteristics and behavior within the auction, by RD regime. Around two thirds of auction participants have won at least once. For example of the 4862 bidders that have entered at least on Cat-C1 auction, 3156 have won at least once. This ratio of winners to bidders is almost the same in Cat-C1 and Cat-D auctions, and is higher in Cat-B auctions. Across regimes, auction winners have win rates around 4-6% higher than the average bidder. Using information on self-reported bidder types, we note that private buyers are

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bear significant costs from unsold vehicles. In this paper we focus predominantly on first time auctions and leave a detailed analysis of the dynamic effects across auctions for future research.

[13]The winning amount is, on average, between 2.7 times the reserve price (Cat-C1, Cat-C3, Cat-D1) and over 35 times the reserve price in both Cat-B regimes.

far more likely to enter Cat-D auctions, which recall comprise vehicles that require minor or no repairs to return to their original condition. In Cat-B and Cat-C auctions, the vast majority of bidders are professionals.

Panel C presents descriptive evidence from web viewing data that is available for the most recent regimes. There are clearly a number of possible ways to use this information to define potential bidders. At one extreme one could think of search and other entry costs as being zero and so any of the thousands of bidder registered with the auctioneer on auction day are potential bidders. Alternatively, entry might be endogenously determined by the object's characteristics as well as entry costs. The web viewing data reveals that although there are a very large number of bidders that view an auction web page at least once, the number of potential bidders might be better approximated by the number of bidders that then choose to view the auction website a number of times. In doing so, such bidders acquire more detailed information on the history of bids placed in the auction, but no information on the identity of bidders is revealed.

More precisely, in Cat-C1 auctions we see that defining potential bidders as those that view the auction web page at least five times, implies that there are on average 6.64 potential bidders, which is around 50% more than the actual number of bidders (4.49). For Cat-D vehicles using the same definition of a potential bidder as someone that have viewed the auction web page at least five times, we find there to be 10.2 potential bidders, which implies an almost identical ratio of potential to actual bidders as in Cat-C auctions. In contrast, for lower value Cat-B vehicles, we see that very few bidders view the auction website five times. Indeed, there are fewer individuals that do this than actually bid in such auctions. This suggests that for low valued vehicles that are predominantly bought for scrap, bidders need to view the auction web page only once or maximally twice before deciding whether to enter.[14]

2.6 RD Design

To identify the causal impact of reserve prices on any given auction outcome, such as the winning bid, we cannot simply compare winning bids in auctions with different reserve prices. As the theory of optimal reserve price setting makes precise, sellers choose reserve prices based on their own valuations and based on the distribution of bidder valuations. Both are likely to be correlated with potentially unobserved vehicle characteristics.[15] To isolate the pure causal effect of reserve prices on winning bids we exploit the previously documented discontinuities in the relationship between the pre-accident value (PAV_i) and the reserve price (R_i).

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[14]These ratios of potential to actual bidders for Cat-C and Cat-D are of similar magnitude to those implied by the structural estimates in Bajari and Hortacsu [2003].

[15]In our case, reserve prices are a function of PAV which is only imperfectly known to bidders. Our primary analysis focuses on the 90% of auctioned vehicles that originate from one large insurer. In a separate of analysis of the remaining vehicles auctioned by the same auctioneer, vehicles supplied by private sellers, we also find reserve values to be significantly correlated to a series of vehicle characteristics such as mileage, whether the vehicle uses petrol as opposed to diesel, whether the keys are available and reported damage. Such vehicle characteristics have also been found to be correlated to bidder entry and winning amounts in other similar settings [Roberts 2009]. For these reasons, research designs that do not account for the endogeneity of reserve prices are unlikely to credibly identify causal reserve price effects.

More formally, in an RD design we are interested in identifying the causal impact of a binary treatment W_i on the observed outcome in auction i, Y_i. In our baseline regime Cat-C1 described in Column 1 of Table 1, the treatment variable W_i relates to whether the reserve price is set at a low value of $R_i = £40$ (so $W_i = 0$), or whether it is set at a high value of $R_i = .08 \times PAV_i$ (so $W_i = 1$). Hence the observed outcome can be written as,

$$Y_i = (1 - W_i)Y_i(0) + W_iY_i(1) = \left\{ \begin{array}{l} Y_i(0) \text{ if } W_i = 0 \\ Y_i(1) \text{ if } W_i = 1 \end{array} \right. . \tag{2}$$

Treatment assignment depends only on whether PAV_i, is above or below a fixed cut-off, $PAV_c = £1500$, so $W_i = 1(PAV_i \geq PAV_c)$ so we have a sharp regression discontinuity design (SRD) because W_i is a completely deterministic function of PAV_i [Hahn *et al.* 2001]. The identified parameter, denoted τ_{SRD}, is the average causal effect of the treatment at the discontinuity conditional on a vector Z_i of observed covariates other than PAV_i,

$$\begin{aligned} \tau_{SRD} &= E[Y_i(1) - Y_i(0)|PAV = PAV_c, Z] \\ &= \lim_{PAV \downarrow PAV_c} E[Y|PAV = PAV_c, Z] - \lim_{PAV \uparrow PAV_c} E[Y|PAV = PAV_c, Z]. \end{aligned} \tag{3}$$

We estimate this using non-parametric local linear regression methods as these have desirable properties with regards to speeds of convergence and bias [Fan and Gijbels 1996]. The kernel bandwidth is chosen to give positive weight to at least 30 observations on each side of the discontinuity when estimating (3), and we use triangular kernels. In the Appendix we show the robustness of our results to alternative choices of bandwidth and kernel.

3 Bidders' Behavior

It is worth briefly reiterating the robust predictions auction theory provides on how outcomes are affected by reserve prices in second-price auctions. The seminal works of Myerson [1981] and Riley and Samuelson [1981] consider exogenous entry and bidders having private values, and Milgrom and Weber [1982] first analyzed the common values case. A second wave of literature has considered endogenous entry in both private value [Levin and Smith 1994, Tan and Yilankaya 2006] and common value settings [Levin and Smith 1994]. From these papers and the related literature, we focus on predictions that are robust to assumptions on exogenous or endogenous entry, and whether bidders have private or common values. Theory provides robust reserve price predictions on *three* outcomes. These are that as reserve prices rise: (i) expected seller revenues rise conditional on sale; (ii) the number of bidders falls; (iii) the likelihood the object is sold falls.[16]

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[16]A third class of model emphasizes the role of reserve prices as *signals* to buyers of the object's value. In the exogenous entry case, the comparative statics remain unchanged as in the private and common values cases [Cai *et al.* 2007]. Assuming endogenous entry the sign of each comparative static is however ambiguous.

3.1 Descriptive Evidence on Outcomes Around the Discontinuity

To provide preliminary evidence of the impact of discontinuities in R_i on these auction outcomes we focus on Cat-C1 vehicle auctions. This is the most frequently observed RD regime in our sample. Given that treatment assignment is determined by whether PAV_i lies above or below the discontinuity at £1500, we define the assignment variable as $(PAV_i - 1500)$. We then plot estimates of the average value of the outcome Y_i in bins either side of zero for the assignment variable. We use bin widths of 50 and plot average outcomes, and the associated 95% confidence interval, over the range ±500 of the assignment variable, against the mid-point of each bin.[17]

In Figure 1B we see evidence of a jump in the average winning bid in the bins either side of the discontinuity. There is no evidence of comparable jumps in winning bids between any other pair of adjacent bins for the assignment variable. As described in Table 1, the magnitude of the jump in the reserve price is £80 as R_i jumps from £40 for $PAV_i < $ £1500, to £120 at the cut-off when $PAV_i = $ £1500. Figure 1B suggests the magnitude of the jump in winning bid at this cut-off is around £40. Hence the winning bid responds less than one-for-one to changes in R_i. This is to be expected given the evidence in Table 2 that winning bids tend to be far higher than the reserve price to begin with. Figure 1C provides descriptive evidence on how the number of bidders varies in bins either side of the assignment variable. We see a significant fall in the number of bidders at the reserve price discontinuity. Both pieces of descriptive evidence are in line with the robust predictions of auction theory.[18]

It is also interesting to note from Figure 1C on the number of entrants, that if we focus on assignment values away from the cut-off, then the descriptive evidence suggests there to be an implied *positive* correlation between R_i and the number of bidders. This is in sharp contrast to the implied negative *causal* impact of R_i on the number of bidders as evaluated precisely at the cut-off. In short, the descriptive evidence suggests that absent a credible research to uncover causal reserve price effects, there is the possibility of correlations between reserve price and outcomes such as the number of bidders being of the *opposite* sign to the true relationship.[19]

In the Appendix we describe a series of checks on the credibility of 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.

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[17]This bin width matches closely to the bandwidth used for the RD estimates.

[18]As further assurance that the relationship between the winning amount and reserve price is not purely mechanical, we note that there is also a jump in winning bids at the discontinuity for auctions with at least two bidders. Indeed the magnitude of the jump in winning bids is of slightly larger value than in Figure 1B, which hints at the possibility that reserve price effects on winning bids are larger in auctions in which more bidders choose to enter.

[19]This has implications for some psychological models of auctions. For example, models of auction fever suggest sellers set reserve prices below their true valuation to induce competition in ascending or open bid auctions. The most common prediction tested is that winning bids are increasing in the number of bidders, as surveyed in Ockenfels *et al.* [2007]. The descriptive evidence and our RD estimates do not support this as the causal impact of the reserve price on the number of bidders and winning bids is of opposite sign.

3.2   RD Estimates: Cat-C1 Auctions

Column 1 of Table 3 presents baseline RD estimates of the impact of reserve prices on winning bids and the number of entrants from Cat-C1 auctions. These estimates are shown in Panels A and B and imply that increasing the reserve price from £40 to £120 has the following impact for vehicles with $PAV_i = £1500$: (i) increases the winning bid by £33.6; (ii) decreases the number of bidders by 1.33. Both effects are significant at the 1% significance level and are in line with the descriptive evidence presented in Figures 1B and 1C. To more easily compare these estimates to those derived from the other RD regimes, Column 1 shows the implied marginal effect of a £1 increase in the reserve price on each outcome, and the associated 95% confidence interval for the implied marginal effect. The implied effect of a £1 increase in the reserve price is to increase the winning bid by £.42, and to decrease the number of bidders by .02.

Figure 2 shows the non-parametric RD estimates over a wide range of the assignment variable for both auction outcomes. These confirm the jump in each outcome variable at the reserve price discontinuity. Both figures confirm that when auctions with at least two entrants are considered and so the mechanical effect of reserve prices on winning bids is entirely eliminated, there remain large effects on winning amounts and the number of auction entrants.

Following the discussion in Imbens and Lemieux [2008] on RD designs, Appendix Table A3 presents robustness checks on these baseline estimates relating to: (i) limiting the sample to auctions in which at least two bidders enter; (ii) narrowing the range of the assignment variable, $(PAV_i - 1500)$, to lie between the median above and below the actual cut-off value; (iii) placebo cutoffs; (iv) alternative bandwidths, kernels, and standard error calculations.

The third outcome auction theory provides robust predictions on is the effect of reserve prices on the likelihood the object remains unsold. These RD estimates are shown in Panel C of Column 1 in Table 3. In the baseline regime Cat-C1, higher reserve prices significantly increase the likelihood the item remains unsold and goes to second auction. The marginal effect is .003, relative to a baseline probability of the vehicle being unsold of 4.2%. Given the possibility that expected revenues are lower at second auction, this channel represents a first order cost of $\Delta R_i > 0$.

These baseline results are in line with the robust predictions of auction theory. To begin to be able to rule out some classes of model we note that the results imply the reserve price effects on the number of bidders and the winning bid are of *opposite* sign. This rules out a benchmark Vickrey [1961] style model of bidders holding IPV with exogenous entry and bidding their true valuation, because in that case the winning bid is independent of the reserve price if the reserve price is not binding. Of course, as noted by Bajari and Hortacsu [2003], the fact that the reserve price effects are of opposite sign for the number of bidders and winning bids remains consistent with richer private values models that allow for affiliated bidder values [Pinske and Tan 2005], as well as being consistent with common values models.[20]

---

[20]The results are also in line with the earlier evidence from experiments on reserve price effects in online auctions [Reiley 2006, Brown and Morgan 2009, Ostrovsky and Schwarz 2009], although only the first of these presents evidence on reserve price effects of the item being unsold. As shown in the next Section, in the absence of structural modelling, all three outcomes need to be estimated in order to make claims on the (local) optimality of

3.3 RD Estimates: Other Reserve Price Regimes

The remaining columns of Table 3 explore the consistency of these estimates across the full range of discontinuity regimes we observe. All jumps in reserve price occur at $PAV_i = £1500$, although the magnitude and direction of these jumps vary across the regimes.

To begin with, Columns 2 and 3 focus on the other Cat-C regimes. In regime Cat-C2 the jump in reserve prices is from £5 for $PAV_i < £1500$, to £120 at the cut-off when $PAV_i = £1500$. Despite the jump in R_i being of larger magnitude, we find the implied marginal effects of $\Delta R_i = £1$ to be very similar to those in the baseline regime Cat-C1. More precisely, the marginal effect on the winning bid is £.35 and this is not significantly different to the marginal effect of £.42 found in Cat-C1. Moreover, the implied marginal effect on the number of bidders of .02 is nearly identical to that found in regime Cat-C1. Finally, the reserve price impact on the likelihood the vehicle remains unsold is also of comparable magnitude across regimes Cat-C1 and Cat-C2.

Recall that in regime Cat-C2, to the left of the discontinuity the reserve price is set almost at its lowest possible level: $R_i = £5$ for $PAV_i < £1500$. Hence the results strongly suggest that in this environment we are not in a part of the parameter space where it is optimal for the auctioneer to set a zero reserve price [Levin and Smith 1994, Bulow and Klemperer 1996]. In the next Section we evaluate whether, conditional on a positive reserve price, the seller sets her reserve price at the locally optimal level.

Regime Cat-C3 provides a falsification check on these results because during that time period there is no discontinuity in reserve prices for Category-C vehicles at $PAV_i = £1500$ or at any other PAV_i. Reassuringly we observe there to be no significant change in any of the three outcomes in Cat-C3, suggesting there are no natural jumps in auction outcomes around $PAV_i = 1500$.

Column 4 repeats the analysis for regime Cat-B1 where the reserve price jumps *down* from £40 for $PAV_i < £1500$, to £5 at the $PAV_i = £1500$ cut-off. As the reserve price falls there is no significant effect on the winning bid, but the number of bidders significantly increases. The implied marginal effect is far smaller than in the Cat-C1 or Cat-C2 regimes. Column 5 uses the Cat-B2 regime in which there is no jump in the reserve price at $PAV_i = £1500$ as a falsification check. We find no evidence of there being a natural jump in auction outcomes at this PAV_i for the low value vehicles in Category-B. Finally, Column 6 repeats the analysis for Category-D vehicles for which there is never a jump in reserve prices over the entire study period. Reassuringly we also find that for high value vehicles there is no natural jump in auction outcomes at $PAV_i = 1500$.

Comparing our results to estimates of reserve price effects based on field experiments, we find that consistent with that body of evidence, we confirm the robust predictions of theory that: (i) expected seller revenues rise conditional on sale, as in Reiley [2006], Brown and Morgan [2009], and Ostrovsky and Schwarz [2009]; (ii) the number of bidders falls, as estimated in Reiley [2006] and Ostrovsky and Schwarz [2009]; (iii) the likelihood the object is sold falls, as also reported in Reiley [2006].

Despite this reassuring similarity of findings, there are some more subtle differences in findings

reserve prices that are set by the auctioneer.

that are worth highlighting. For example, comparing the RD estimates from Cat-C1 and Cat-C2 regimes, to those in the Cat-B1 regime, the evidence implies outcomes are more sensitive to reserve prices in: (i) auctions with more actual entrants; (ii) auctions for objects that have higher *ex ante* valuations. This first result is counter to the evidence from field experiments presented in Reiley [2006] from online auctions for collectible trading cards, and those in Ostrovsky and Schwarz [2009] from online auctions for advertisements. Both those papers find reserve price effects to be larger in auctions in which a smaller number of bidders enter.

Of course there are potentially many differences across these auction environments that might drive these differences – the auction format in Reiley [2006] is a first price auction, and the setting in Ostrovsky and Schwarz [2009] is best modelled as a generalized second price auction environment in which multi-unit auctions take place. Also, the nature of bidders valuations – be they private, affiliated, common, or some combination, might also differ across these objects.

Finally, we note that 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 2009]. Unlike in some RD applications where there is just one natural discontinuity to exploit, for example based on 50-50 legislative vote shares [Lee *et al.* 2004], in our setting there is no particular economic significance to basing our RD estimates around the $PAV_i = £1500$ cut-off. In the Appendix we address this concern and therefore bolster the external validity of our results, 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 $PAV_i = £2000$.

4 Seller's Behavior

4.1 Optimality of Reserve Prices

We now study the auctioneer's revenue maximization problem. To see how the documented RD estimates map to the auctioneer's expected revenue we introduce some notation: π denotes the auctioneer's revenue from a vehicle's auction, and we define a dummy variable S, set equal to one if the vehicle is sold in its first auction, and zero otherwise. As above, we use Z to denote all vehicle characteristics except PAV. $\Pr[S = 1|PAV, Z]$ denotes the probability the vehicle is sold at first auction, $E[\pi|PAV, Z, S = 1]$ denotes the expected revenue conditional on the object being sold at first auction and $E[\pi|PAV, Z, S = 0]$ denotes the expected revenue from re-auctioning in

second or potentially higher auctions. Hence the auctioneer's *ex ante* expected revenue is,

$$
\begin{aligned}
E\left[\pi|PAV,Z\right] &= E\left[\pi|PAV,Z,S=1\right]\Pr\left[S=1|PAV,Z\right] \quad\quad\quad (4)\\
&\quad +E\left[\pi|PAV,Z,S=0\right]\Pr\left[S=0|PAV,Z\right]\\
&= E\left[\pi|PAV,Z,S=1\right]\\
&\quad +\left\{E\left[\pi|PAV,Z,S=0\right]-E\left[\pi|PAV,Z,S=1\right]\right\}\Pr\left[S=0|PAV,Z\right].
\end{aligned}
$$

Two points are of note. First, as shown in Table 2, the vast majority of vehicles are sold at first auction and those that are not are usually sold at the second auction. For expositional ease, we therefore refer to outcomes when $S=0$ as what occurs if the vehicle comes up for second auction. Second, the marginal cost of holding onto an unsold vehicle is approximately zero for the auctioneer. This cost is borne by the salvage yard where the vehicle is physically located. Hence in this setting, most costs are fixed and so changes in revenue translate almost one-for-one into changes in profit. The marginal impact of R_i on expected revenue (or profit), as evaluated at the discontinuity where $PAV_i = PAV_c = £1500$, can be decomposed into three terms,

$$
\begin{aligned}
&\frac{\Delta E\left[\pi|PAV=PAV_c,Z\right]}{\Delta R_i} \quad\quad\quad\quad (5)\\
&= \frac{\Delta E\left[\pi|PAV=PAV_c,Z,S=1\right]}{\Delta R_i}\\
&\quad +\left\{\begin{array}{c}E\left[\pi|PAV=PAV_c,Z,S=0\right]\\-E\left[\pi|PAV=PAV_c,Z,S=1\right]\end{array}\right\}\frac{\Delta\Pr\left[S=0|PAV=PAV_c,Z\right]}{\Delta R_i}\\
&\quad +\left\{\begin{array}{c}\frac{\Delta E[\pi|PAV=PAV_c,Z,S=0]}{\Delta R_i}\\-\frac{\Delta E[\pi|PAV=PAV_c,Z,S=1]}{\Delta R_i}\end{array}\right\}\Pr\left[S=0|PAV=PAV_c,Z\right]
\end{aligned}
$$

The first term is the impact of the reserve price on the winning amounts in the auction conditional on the item being sold. This is identified from the previously documented RD estimate.

The second term comprises two components: the first is just the average difference in winning amounts between the first time auction, and expected revenue conditional on the item remaining unsold at first auction. This average value can be simply observed in the data. The second component is the impact of the reserve price on the likelihood the item remains unsold at first auction, which is again identified from the RD estimate in Table 3.

The final term comprises two components. The component outside the parentheses is the probability the item is unsold at first auction and can be observed from the data. The component in parentheses corresponds to the differential impact the reserve in the first auction, R_i, has on winning amounts in first and *second* auctions. The effect on the first time auction $\frac{\Delta E[\pi|PAV=PAV_c,Z,S=1]}{\Delta R_i}$ is the RD estimate described above. The effect on the expected revenue in the second time auction $\frac{\Delta E[\pi|PAV=PAV_c,Z,S=0]}{\Delta R_i}$ is the one component of (5) that we need to estimate using non-experimental methods. To do so requires using data from second time auctions. These auctions are identified in our data. In the Appendix we describe how we use OLS to estimate the correlation between

the reserve price in the first-time auction and the winning bid in the second time auction.[21]

4.2 Results

Table 4 shows each component of (5) for Cat-C1 vehicles. The components in Columns 1 to 3 are descriptives from the data. The components in Columns 4 and 6 are derived from the previously documented RD estimates in this regime. The component in Column 5 is based on the non-experimental estimates from second time auctions described above and in the Appendix. As the RD estimates exploit auctions in which $PAV_i = PAV_c = £1500$, all the descriptives are constructed for such auctions.

The last column then substitutes all of these components into (5) to evaluate the marginal effect of reserve prices on the auctioneer's expected revenue. We find this marginal effect to be $-.030$ so that if the auctioneer were to raise her reserve price by £1, then for vehicles with $PAV_i = £1500$ her expected revenue (and profit) would decrease by £.03. To reiterate, this estimate takes account of reserve price effects on winning bids in the first time auction, as well as the reserve price effect on the possibility the vehicle remains unsold and outcomes in second auctions.

The next two rows provide upper and lower bounds on this estimate using the extremes of the 95% confidence interval for each estimate and descriptive. These show that the marginal reserve price effect lies between $-.162$ and $.105$. As this contains zero we conclude that the auctioneer, in this setting, is setting her reserve prices to be locally optimal.

This is in contrast to evidence from laboratory settings. For example, Barrymore and Raviv [2009] find that reserve prices decrease the number of bids and bidders, increase revenue conditional on sale, but seller's profits are maximized by setting no reserve because of the negative effect of reserve prices on the likelihood of sale. In terms of evidence from real world field experiments, only Reiley [2006] presents evidence on all the margins required to estimate the equivalent of (5). He reports mixed evidence on auctioneer's behaving optimally. He finds that revenues are locally declining in the reserve price, although this negative effect is not estimated precisely. Clearly, a potential avenue for future work is to use structural estimation methods to derive the auctioneer's globally optimal reserve price [Paarsch 1997].

5   New Evidence on Bidder Composition

We now exploit the full richness of the data to present novel evidence on how reserve prices affect auction outcomes. This evidence relates to reserve price effects along margins that have not been much studied but that are informative for the development of future theory. Table 5 presents the results for each RD regime.

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[21]Theory does not offer much guidance on the expected sign of this marginal effect. Indeed such dynamic effects within re-auctions are not much studied [McAfee and Vincent 1997]. Although not the focus on the analysis in this paper, our data is amenable to further probe these dynamic effects across auctions for the same object, in future research.

5.1 Potential Bidders

To first build on the previously estimated reserve price effect on the actual number of entrants, we use web views data to explore how reserve prices impact the number of *potential* bidders. For the most recent auctions in the Cat-C1 and Cat-D1 regimes, web views data is available. We define the potential number of bidders as those that view the auction website at least five times. The presented results are robust to small changes to this definition. Panel A shows that in Cat-C1 auctions, potential bidders significantly fall with reserve prices. This might indicate that those bidding for such vehicles are not so specialized and there are some bidders on the margin of considering to endogenously enter such auctions.

The implied marginal effects show that the number of potential bidders is however significantly less sensitive to the reserve price than is the number of actual bidders – the marginal effects of reserve prices on potential and actual bidders are $-.003$ and $-.017$ respectively.[22] This suggests that search behavior, as measured by web browsing histories, is far less sensitive to reserve prices than are actual entry decisions.

We provide two falsification checks on this result. The first exploits the Cat-D1 regime where there is no jump in R_i. As shown in the final column of Panel A, there is no significant change in the number of potential bidders at $PAV_i = £1500$. The second check estimates how jumps in the reserve price affect the number of bidders that view the web page *once*, reported in Panel B. Recall that when potential bidders first view the auction web page, no information is revealed about the reserve price. Hence there ought to be no effect of the reserve price on the number of bidders that view the web page once. Reassuringly, the results in Panel B confirm this is the case.[23]

5.2 Bidder Characteristics

We next explore how the average characteristics of entrants in general, and winners in particular, are impacted by reserve prices. We focus on two characteristics: bidder win rates as defined in (1), and the months the bidder has been registered with the auctioneer as a proxy of their bidding experience. Panels C and D in Table 5 present the RD estimates on these margins, where we first average each characteristic over *all* bidders that enter. Column 1 shows that as reserve prices rise in Cat-C1 auctions, the average win rate and bidding experience of bidders that remain in such auctions, significantly rises. Put another way, less experienced bidders and less successful bidders are those that choose not to enter auctions with exogenously higher reserve prices, all else equal.[24]

---

[22]Bajari and Hortacsu [2003] present structural estimates that also find a significantly negative effect of public reserves on the number of potential bidders. Although not directly reported, their estimates also seem to imply the number of potential bidders is less sensitive to reserve prices than the actual number of bidders.

[23]As discussed earlier in relation to Table 2, it is harder to define the number of potential bidders in Cat-B auctions. Indeed the descriptive evidence suggests that for such low valued vehicles that are predominantly bought for scrap, bidders need to view the auction web page only once before deciding whether to enter or not. Therefore defining a potential bidder in Cat-B auctions as an individual that views the web page once, Panel B in Table 5 shows that in regime Cat-B1 there are insignificant reserve price effects on potential bidders.

[24]Similar results are also obtained if we refine these bidder characteristics, as relating to experience and win rates within Category-C auctions for example.

While the implied marginal effects on bidders' characteristics of $\Delta R_i = \pounds 1$ are small as is to be expected, the magnitude of the effect at the jump actually observed, $\Delta R_i = \pounds 80$ in Cat-C1 auctions, is large and economically significant. To see this, note that from Column 1 of Table 2 the standard deviation of win rates among bidders is .082. Hence the RD estimate suggests a considerable effect size on this dimension of bidder characteristics of .011/.082 = .13. In other words, moving incrementally from one side of the cut-off to the other, all else equal, increases the win rates of those bidder that still chose to enter by 13%.

Two implications follow immediately from this result. First, it helps ameliorate the econometric concern that more experienced bidders are informed about the discontinuous relationship between PAV_i and R_i. If that were the case we would expect to see a significant bunching of more experienced bidders to the left of the cut-off. The RD estimates suggest the opposite. Second, if bidder characteristics correlate to bidder valuations, this result strongly suggests that bidder entry decisions are endogenous in the sense that the valuations of bidders that enter the auction differ markedly from those that could have potentially entered the auction.[25]

The remaining Columns in Panels C and D show that: (i) as with the reserve price estimates on all other margins, the marginal effects are of similar magnitude and significance in Cat-C1 and Cat-C2 regimes; (i) in lower value Cat-B1 auctions, where recall the RD estimate is identified from a jump *down* in the reserve price at the $PAV_i = \pounds 1500$ cut-off, the implied marginal effect on the win rate of bidders is of the same sign and magnitude as in Cat-C1 auctions, but only borderline significant, while there are no significant reserve price effects on bidders' experience; (iii) the falsification checks based on the Cat-C3, Cat-B2 and Cat-D1 regimes suggest that there is no natural jump in bidder characteristics at the $PAV_i = \pounds 1500$ cut-off in any vehicle category.

Panels E and F repeat the analysis focusing on the characteristics of the auction *winner*. We see that there is a somewhat similar pattern of reserve price effects. In particular: (i) winning bidders have significantly higher win rates in Cat-C1 and Cat-C2; (ii) in Cat-B1 auctions the stronger effect appears to be on the win rate of winners rather than their experience; (iii) the falsification checks in Cat-B2 and Cat-D1 regimes are passed, although there is a significant effect in Cat-C3. However this finding is somewhat inconclusive as the effect is actually of the opposite sign to that in Cat-C1 and Cat-C2.

Finally, comparing the reserve price effects on winners to those on the average entrant in regime Cat-C1, we see that the implied marginal effects on both winning bidder characteristics are significantly smaller than for the average bidder. This suggests, as is intuitive, that winning bidders are not the *marginal* entrant into the auction as reserve prices rise, all else equal. This is again suggestive of their being endogenous entry into these auctions.

Taken together, the results on margins of behavior studied in the Section are informative for the development of future theory. Existing auction models typically remain silent on how bidder

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[25]As shown in Figure A1D and discussed further in the Appendix, the raw correlation between the assignment variable ($PAV_i - 1500$) and the average win rate of entrants is of opposite sign to the RD estimates – we generally observe auctions with higher reserves being correlated to lower win rates among bidders. This again highlights another margin in which in the absence of a credible research design that accounts for the endogeneity of reserve prices, can lead to estimates of reserve price effects that are of the wrong sign.

characteristics might be affected by aspects of auction design and how such characteristics relate to bidder valuations. These results also provide a basis from which, in future work, to construct and estimate a structural model of bidder's behavior in this setting.

6   Discussion

Online auctions are one of the most significant form of online commerce. This paper contributes to the empirical literature on online auctions by presenting evidence from 260,000 online auctions of second-hand cars to identify the impact of public reserve prices on auction outcomes. To establish causality, we present evidence from multiple regression discontinuity (RD) research designs. To the best of our knowledge, we present among the first applications of an RD design in industrial organization in general, and empirical auctions more specifically.

In line with theoretical predictions that are robust to assumptions on bidder valuations and endogenous entry, we find an increase in reserve price: (i) decreases the number of actual bidders; (ii) decreases the likelihood the object is sold; (iii) increases expected revenue conditional on the object being sold. Bringing together these estimates to calibrate the overall impact of reserve prices on the auctioneer's expected revenue, we find that the reserve price policy followed by the auctioneer is locally optimal in that a small change in reserve price would not significantly change the seller's expected revenue or profit.

In this paper, we have focused on testing the positive theoretical predictions of reserve price effects on auction outcomes. In ongoing research we provide normative predictions on the *globally* optimal reserve price based on structural modelling [Paarsch 1997]. As a precursor to that structural analysis, we briefly discuss two important features of the auction environment that have to be determined: whether bidder entry into auctions is endogenous, and the nature of bidder valuations.

On endogenous entry, the final set of results we have presented in Section 5 provide novel evidence on how the number of potential bidders and bidder characteristics are causally impacted by reserve prices. These results suggest bidder entry is endogenous in our setting: the number of potential bidders is impacted by reserve prices, and the characteristics of bidders that do enter – in terms of their experience and historic win rates – significantly differ from those bidders that do not enter with higher reserves. Any structural model would need to be able to explain such patterns of search behavior and selective entry as reserve prices vary.

On bidder valuations, it might be reasonable to assume these differ depending on the type of vehicle category considered. Cat-C vehicles are bought for the value of their spare parts and so it seems likely that bidders' valuations contain a significant private value component. For those auctions the RD estimates provide clear evidence consistent with the robust predictions of theory: higher reserve prices cause expected seller revenues to rise conditional on sale, the number of actual bidders falls, and the likelihood the object is sold falls. In contrast, Cat-B vehicles are predominantly purchased for their scrap metal value. There is a common market price for scrap

but information about the overall market quality might be dispersed amongst bidders. Hence the argument for bidders having pure common values is perhaps more compelling than for Cat-C vehicles.[26]

Finally, we note that the richness of our data opens up a broad research agenda for future work. First, the data can be used to better understand dynamic effects across auctions in first and second time auctions for the same vehicle. This has entered as one component of the calibration of the auctioneer's first order condition for expected revenue maximization shown in Table 4. One dynamic feature that is revealed in this calibration exercise is that *if* the auctioneer could somehow reduce the marginal impact of the reserve price on the likelihood the object remains unsold (namely set the component in Column 3 to zero), then the main channel through which the auctioneer incurs costs from setting higher reserves, would be shut down. With no adverse effect on the likelihood the object remains unsold, the auctioneer might then find it optimal to raise reserve prices all else equal. It is of interest to study such dynamic effects because: (i) such effects potentially exist whenever positive reserve prices are set; (ii) re-auction reserve prices are found to be a qualitatively important determinant of objects being sold in first term auctions and hence on the auctioneer's expected revenue.[27]

A second direction to explore in future research is to better account for bidders' behavior when searching over auctions. By exploiting data on web browsing histories, we will be able to contribute to the nascent literature on search and transactions in online environments [Hortacsu *et al.* 2010]. Again, preliminary data analysis suggests that the prominence with which auctions are displayed to potential bidders when they first log onto the website has significant effects on the likelihood they enter and subsequent bidding behavior. This opens up the possibility of jointly structurally estimating a model of online search and behavior conditional on entry. This helps open up new avenues in research related to how much studied auction features such as reserve prices, interact more broadly with the design of online environments.

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[26]A large literature exists on empirical tests to distinguish private and common values, as summarized in Hendricks and Porter [2007]. We have explored some of these tests, although no single test is necessarily conclusive because inevitably each tests a joint hypothesis on both the nature of bidder valuations and some other aspect of the auction environment, such as exogenous bidder entry. With this caveat in hand we note that, following the discussion of the test based on the winners' curse in Milgrom and Weber [1982] and Bajari and Hortacsu [2003], we find that the average bid of a given bidder is increasing in the number of bidders in line with both an affiliated private values and common environment [Pinske and Tan 2005]. As we have previously discussed, the data does rule out a benchmark Vickrey [1961] style model of bidders holding IPV with exogenous entry and bidding their true valuation, because in that case the winning bid should be independent of the reserve price if the reserve price is not binding.

[27]To begin exploring such effects, we have designed and implemented a field experiment in conjunction with the auctioneer in which we engineered exogenous variation in the reserve price set in *second* time auctions. Preliminary analysis indeed suggests that raising reserve prices in second time auctions significantly reduces the likelihood the item remains unsold at first auction.

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 [2009] 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. Finally, 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,

$$\log w_{jmt} = \alpha_m + \beta_t + \Pi\mathbf{Z} + u_{jmt}, \tag{6}$$

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 (6).[28]

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,

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[28]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.

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.[29]

For winning bids we then construct the residuals after estimating (6) and 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 (6) 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 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 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.

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.[30]

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

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[29]We also estimated a specification analogous to (6) 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.

[30]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.

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 however ameliorated by the fact that the 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 more direct evidence on this, 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. We see that 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).

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.[31] 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.

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[31]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.

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 2009]. Unlike in some RD applications where there is just one natural discontinuity to exploit, for example based on 50-50 legislative vote shares [Lee *et al.* 2004], 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 switch from regime Cat-C3 to Cat-C2 has the properties that: (i) for vehicles with $PAV_i < £1500$, over time $\Delta R_i = (.08 \times PAV_i) - 5$; (ii) for vehicles with $PAV_i \geq £1500$, $\Delta R_i = 0$. 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_i 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.

We proceed as follows. 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 (6). 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 set equal to one if regime Cat-C1 is in place on date t, and zero if regime Cat-C2 is in place. Finally, we note that 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,

$$\log y_{jmt} = \alpha_m + \beta_0 C_t^j + \beta_1 DPAV_{jmt} + \beta_2 \left[C_t^j \times DPAV_{jmt} \right] + \Gamma_j \mathbf{Z}_j + \Gamma_t Z_t + u_{jmt}, \qquad (7)$$

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.[32]

For outcomes on winning amounts and the probability the vehicle remains unsold we estimate (7) using OLS. On the number of bidders, a specification analogous to (7) 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 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 3, 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

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[32]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}.

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 3, 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

A second strategy by which we provide external validity to our findings is to exploit the most recent data. In particular, 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 results from 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 then shows that when the discontinuity occurs at the relatively high 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 time auctions. In our auction database 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.

Clearly, given the short time frame between first and second-time auctions, and the lower reserve price in the second auction, bidders might have an incentive to delay their participation in the original auctions [McAfee and Vincent 1997]. A dynamic analysis of bidding behavior across auctions lies outside the scope of this paper. However, Table A6 shows that: (i) only slightly fewer bidders enter second auctions compared to first time auctions; (ii) there are significantly fewer second time auctions in which only one bidder enters; (iii) the win rate among bidders does not significantly differ across first or second time auctions.

To estimate $\frac{\Delta E[\pi|PAV=PAV_c,Z,S=0]}{\Delta R_i}$ we proceed as follows. 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 for auction has observable characteristics Z_j, including its model m. We then estimate how the winning bid in the re-auction is correlated to the original reserve price for the same vehicle in its first time auction, R_{1jmt}, using the following panel data model,

$$\log w_{2jmt} = \alpha_m + \beta_t + \Pi\mathbf{Z} + \gamma R_{1jmt} + u_{jmt}, \tag{8}$$

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.[33]

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 imply that the marginal effect of a £1 increase corresponds to an increased winning bid in the re-auction that is higher by £.24. This is the estimate of $\frac{\Delta E[\pi|PAV=PAV_c,Z,S=0]}{\Delta R_i}$ we then use to calibrate (5).

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Table 1: Reserve Price Regimes

	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**
Reserve Price for Vehicles with PAV<£1500	40	5	**Reserve Price=8% of PAV**	40	5	**Reserve Price=10% of PAV**
Form of Discontinuity in Reserve Price at PAV=£1500:	**Jumps up from 40 to 120**	**Jumps up from 5 to 120**	**No jump at PAV=1500**	**Jumps down from 40 to 5**	**No jump at PAV=1500**	**No jump at PAV=1500**
Reserve Price for Vehicles with PAV>£1500	**Reserve Price=8% of PAV**	**Reserve Price=8% of PAV**	**Reserve Price=8% of PAV**	5	5	**Reserve Price=10% of PAV**
Percentage of Auctions with PAV<1500	**.437**	**.470**	**.459**	**.532**	**.499**	**.153**
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

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 include proxy bids. The pre-accident value refers to an engineer's valuation of the vehicle prior to it being involved in any accident.

Table 2: Auction Outcomes, by Discontinuity 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
A. Auction Outcomes						
Winning Bid (£)	501	419	510	229	183	1562
	(1088)	(950)	(1040)	(399)	(342)	(2706)
Winning Amount / Reserve Price	2.85	12.2	2.67	36.7	36.6	2.73
	(3.21)	(37.8)	(17.6)	(81.5)	(68.9)	(9.70)
Number of Bidders	4.49	4.06	2.88	3.39	3.28	6.88
	(3.14)	(2.98)	(2.92)	(2.00)	(1.91)	(4.90)
Percentage of Auctions With One Bidder	.069	.085	.203	.094	.079	.053
	(.254)	(.279)	(.402)	(.291)	(.270)	(.224)
Vehicle Unsold [Yes =1]	.042	.073	.248	.020	.039	.054
	(.201)	(.260)	(.432)	(.142)	(.193)	(.225)
B. Bidder and Bid Characteristics						
Number of Unique Winners	3156	1791	1429	374	374	3890
Number of Unique Bidders	4862	2335	1739	492	423	5801
Win Rate of Winning Bidders	.281	.297	.313	.315	.343	.273
	(.147)	(.149)	(.165)	(.134)	(.145)	(.158)
Win Rate Among All Bidders	.222	.238	.264	.267	.291	.193
	(.082)	(.087)	(.114)	(.067)	(.086)	(.079)
Percentage of Winners that Report Being Private Buyers	23.2	0	Not available	1	0	23.1
Number of Bids Placed	13.8	10.6	7.76	8.27	7.45	22.0
	(17.0)	(12.2)	(11.2)	(8.96)	(7.27)	(21.7)
C. Web Views						
Number of bidders that view the webpage at least once	73.9	-	-	11.4	-	182
	(71.8)			(13.2)		(160)
Number of bidders that view the webpage at least 5 times	6.64	-	-	1.73	-	10.2
	(3.33)			(1.35)		(9.85)
Number of bidders that view the webpage at least 10 times	1.78	-	-	1.19	-	3.26
	(1.13)			(.584)		(2.54)

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. Data on the type of bidder is not available for the entire period of the Cat-C3 regime and so no statistic is reported for the percentage of winners that report being private buyers.

Table 3: Bidders' Behavior - RD Estimates of Reserve Price Effects

Non Parametric Regression Discontinuity Results

Bootstrapped standard errors in parentheses, based on 50 replications

	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
Auction Outcome						
A.Winning Bid	33.6***	40.4***	-3.34	2.60	-2.31	-2.28
	(3.80)	(5.50)	(4.49)	(4.13)	(2.78)	(4.88)
Implied ΔOutcome/ΔR	.420***	.351***		-.074		
	[.336, .504]	[.267 , .435]		[-.328, .179]		
B. Number of Bidders	-1.33***	-2.13***	.001	.127**	-.064	-.046
	(.081)	(.070)	(.079)	(.050)	(.054)	(.066)
Implied ΔOutcome/ΔR	-.017***	-.018***		-.003**		
	[-.018, -.016]	[-.020, -.017]		[-.006, -.001]		
C. Vehicle Unsold [Yes =1]	.104***	.244***	-.002	-.003	-.009	.007
	(.006)	(.008)	(.005)	(.005)	(.008)	(.008)
Implied ΔOutcome/ΔR	.003***	.002***		.000		
	[.003, .003]	[.002, .002]		[.000, .000]		
Number of Auctions	56959	41124	33500	20646	21569	60202

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 4: Seller's Behavior - First Order Conditions With Respect to Auction Reserve Price

	(1) Winning Amount, Re-auction	(2) Winning Amount, First Auction	(3) Probability Unsold	(4) Marginal effect on probability unsold	(5) Marginal Effect on Winning Amount in Re-auction	(6) Marginal Effect on Winning Amount	(7) Marginal Effect on Expected Profit
RD Estimates (ΔR_1=80)	$E[\Pi \mid PAV = 1500, S = 0]$	$E[\Pi \mid PAV = 1500, S = 1]$	$\Pr[S = 0 \mid PAV = 1500]$	$\dfrac{\partial \Pr[S = 0 \mid PAV = 1500]}{\partial R_1}$	$\dfrac{\partial E[\Pi \mid PAV = 1500, S = 0]}{\partial R_1}$	$\dfrac{\partial E[\Pi \mid PAV = 1500, S = 1]}{\partial R_1}$	$\dfrac{\partial E[\Pi \mid PAV = 1500]}{\partial R_1}$
1. Cat-C1, Regime 1|PAV=1500	103	242	.107	.003	.113	.420	-0.030
2. Lower bound	92	248	.094	.003	.016	.336	-0.162
3. Upper bound	114	235	.121	.003	.210	.504	0.105

Notes: The components in Columns 1 to 3 are descriptives from the data. The components in Columns 4 and 6 are derived from the documented RD estimates in this Cat-C1 regime. The component in Column 5 is based on the non-experimental estimates from second time auctions. In Row 2 (3) we calculate the lower (upper) bound on the marginal effect on profits using the appropriate values at the edge of the relevant 95% confidence interval for estimated values.

Table 5: Reserve Price Effects on Novel Margins of Bidder's Behavior

Non Parametric Regression Discontinuity Results
Bootstrapped standard errors in parentheses, based on 50 replications

	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
Auction Outcome						
A. Number of Potential Bidders	-.273***					.046
	(.077)					(.154)
Implied ∆Outcome/∆R	-.003***					
	[-.005, -.001]					
B. Number of Bidders That View the Webpage Once	1.70			.409		1.44
	(1.53)			(.316)		(2.74)
Implied ∆Outcome/∆R	.021			-.012		
	[-.016, .059]			[-.029, .006]		
C. All Bidders: Win Rate	.011***	.012***	.001	-.005*	.002	-.000
	(.002)	(.003)	(.003)	(.003)	(.003)	(.002)
Implied ∆Outcome/∆R	.000***	.000***		.000*		
	[.000, .000]	[.000, .000]		[.000, .000]		
D. All Bidders: Months Since Registered	2.90***	1.76***	-.093	-.367	-.024	-.899
	(.625)	(.447)	(.364)	(.734)	(.414)	(.565)
Implied ∆Outcome/∆R	.083***	.015***		.010		
	[.048, .118]	[.008, .023]		[-.031, .052]		
E. Auction Winner: Win Rate	.008*	-.002	-.013*	-.012*	.002	.001
	(.005)	(.005)	(.007)	(.007)	(.008)	(.005)
Implied ∆Outcome/∆R	.0001*	-.000		.0003*		
	[-.00001, .0002]	[-.000, .000]		[-.000, .001]		
F. Auction Winner: Months Since Registered	2.50**	1.68*	.308	-1.08	.310	-1.51*
	(1.10)	(.909)	(.585)	(.954)	(.627)	(.869)
Implied ∆Outcome/∆R	.031**	.015*		.031		
	[.004, .058]	[-.001, .030]		[-.023, .084]		
Number of Auctions	56959	41124	33500	20646	21569	60202
Number of Auctions (Webviews data)	43855	-	-	7323	-	22101

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Observations in all rows, except those for whether the vehicle is unsold, relate to auctions where there is at least one bidder. Each coefficient is estimated from a separate non parametric regression using a rectangular 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. The win rate for a given bidder is the fraction of past auctions she has entered, that she has won. This is then averaged across all bidders in an auction to obtain the auction win rate.

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

Dependent Variable:	Category C, Regime 1			Category B, Regime 1	Category D
	(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

Outcome Variable	A. Samples and Placebos				B. Bandwidth, Kernels and Standard Errors			
	(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

Outcome Variable	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
A. Winning Amount	33.6***	138.8*	3.46
	(3.80)	(82.6)	(9.96)
Implied ΔOutcome/ΔR	.420***	.888*	
	[.336, .504]	[-.156, 1.93]	
B. Number of Bidders	-1.33***	-.805	-.013
	(.081)	(.804)	(.152)
Implied ΔOutcome/ΔR	-.017***		
	[-.018, -.016]		
C. Vehicle Unsold [Yes =1]	.104***	.039	.0001
	(.006)	(.013)	(.0001)
Implied ΔOutcome/ΔR	.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).

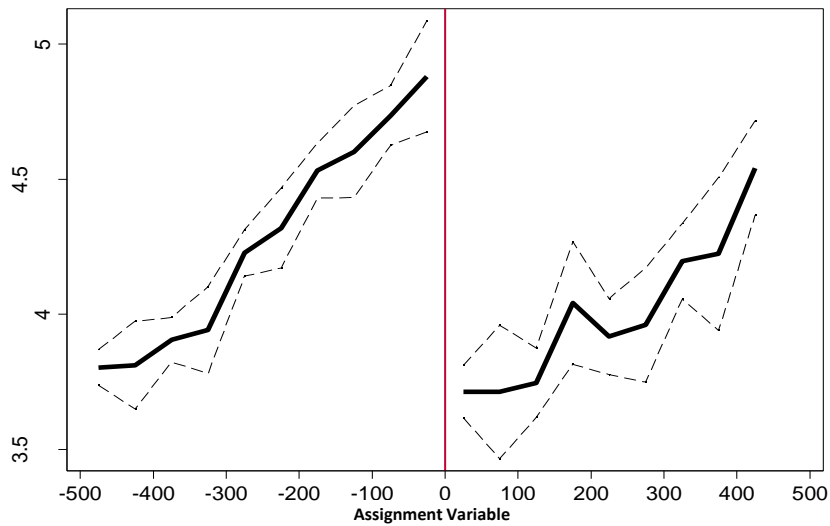# Figure 1: Regression Discontinuity Design and Outcomes

1A. Category C Vehicle Reserve Prices: Regime 1
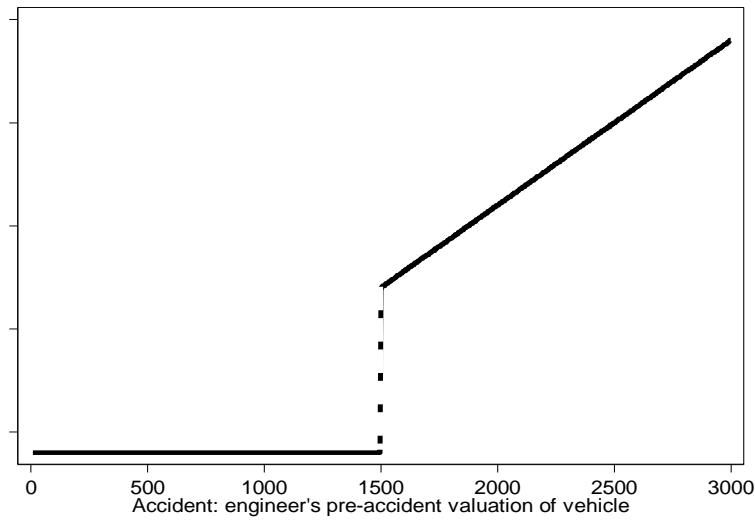
Accident: engineer's pre-accident valuation of vehicle

1B. Winning Amount by Assignment Variable for Category C Regime 1 Vehicles

Assignment Variable
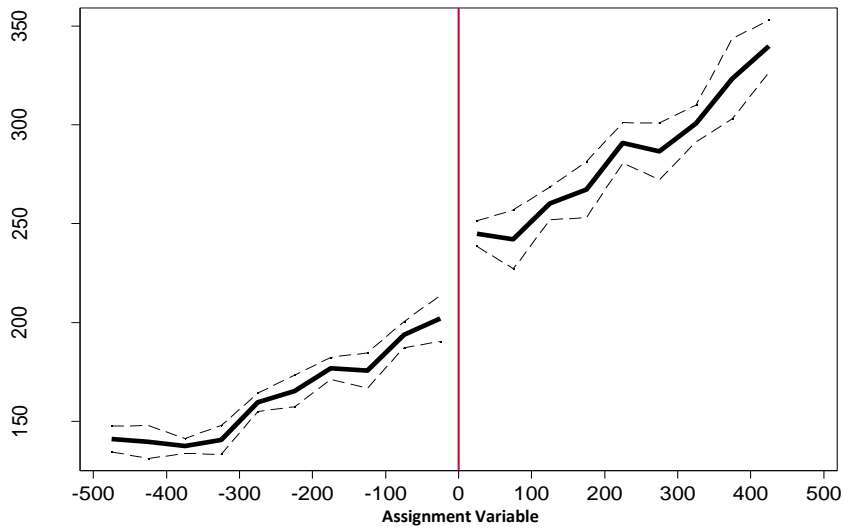
1C. Number of Bidders by Assignment Variable for Category C Regime 1 Vehicles
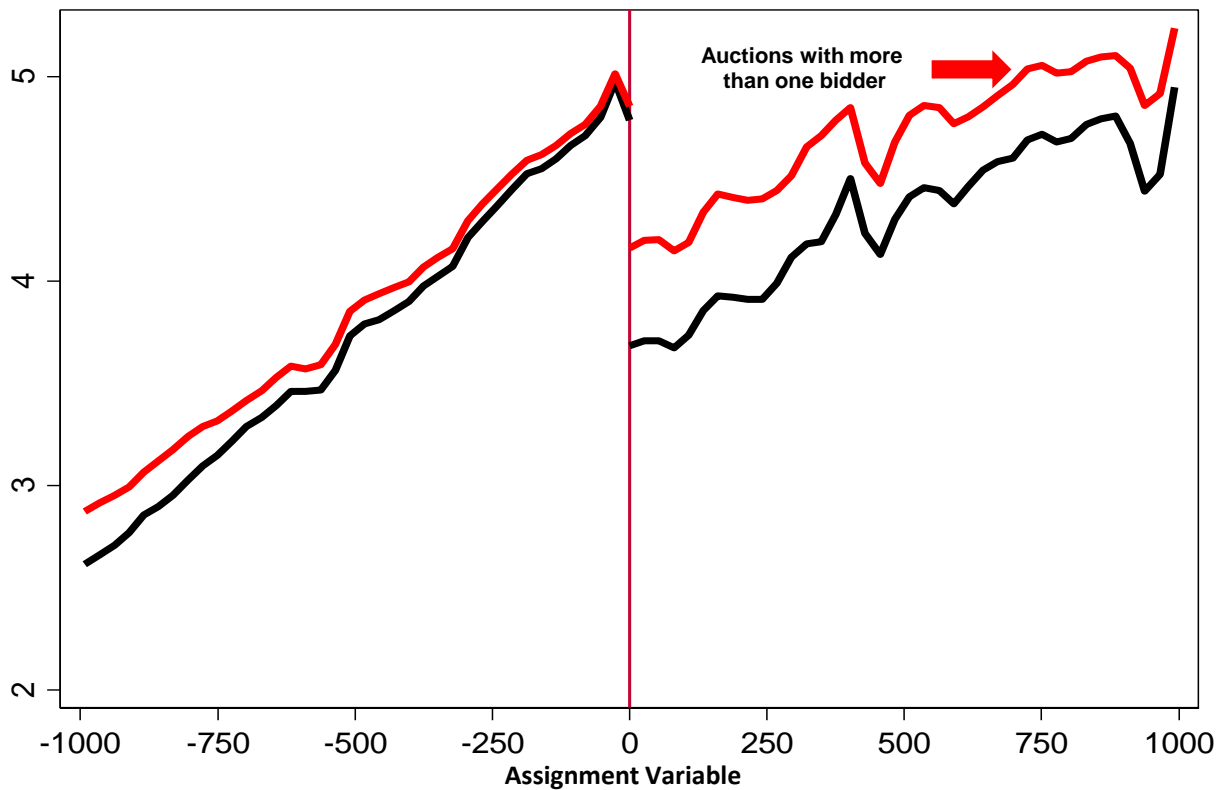

Assignment Variable

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 the relationship between the engineers pre accident valuation of the vehicle and its auction reserve price. Figures 1B and 1C plot over bins of width 50 over the assignment variable, the average winning bid and the average number of bidders, respectively. These averages are graphed at the mid point of each bin. In each Figure the average and its associated 95% confidence interval is shown in dashed lines.

Figure 2: Non Parametric Regression Discontinuity Estimates

2A. Winning Amount by Assignment Variable for Category C Vehicles
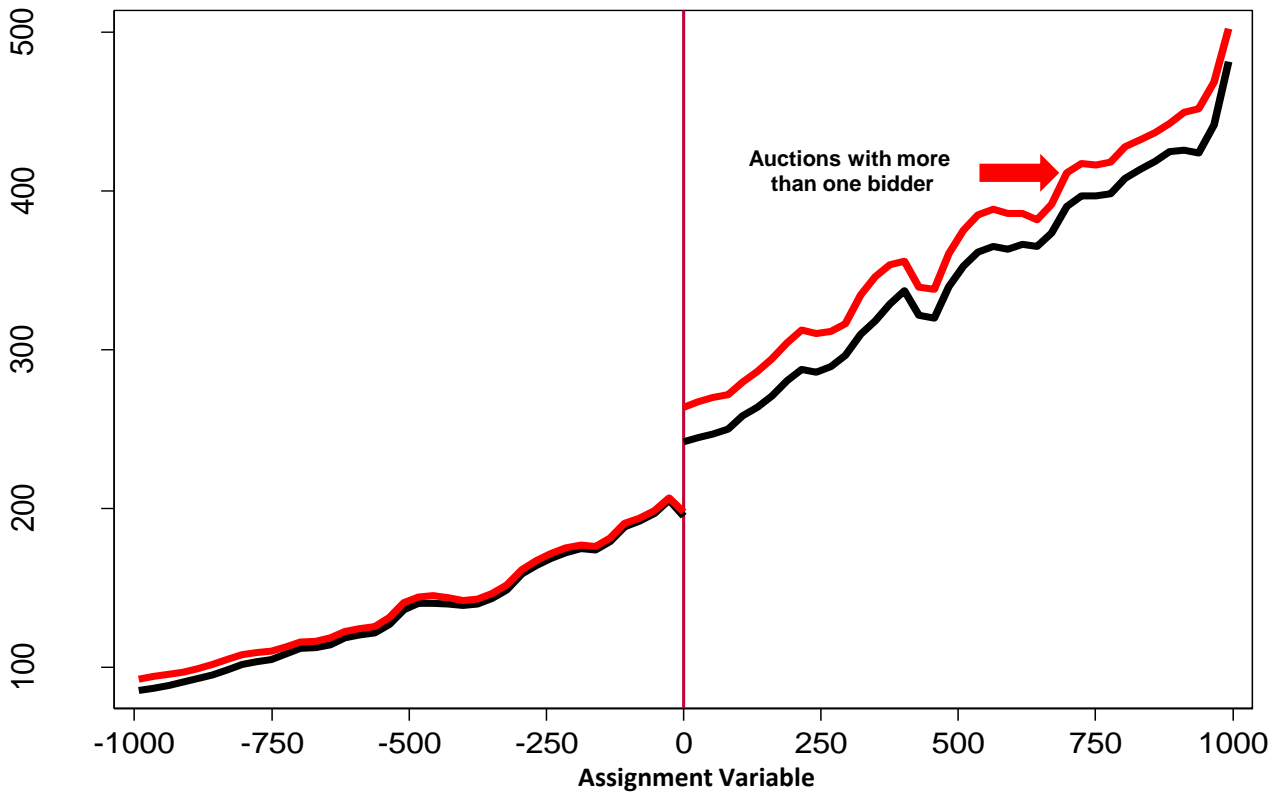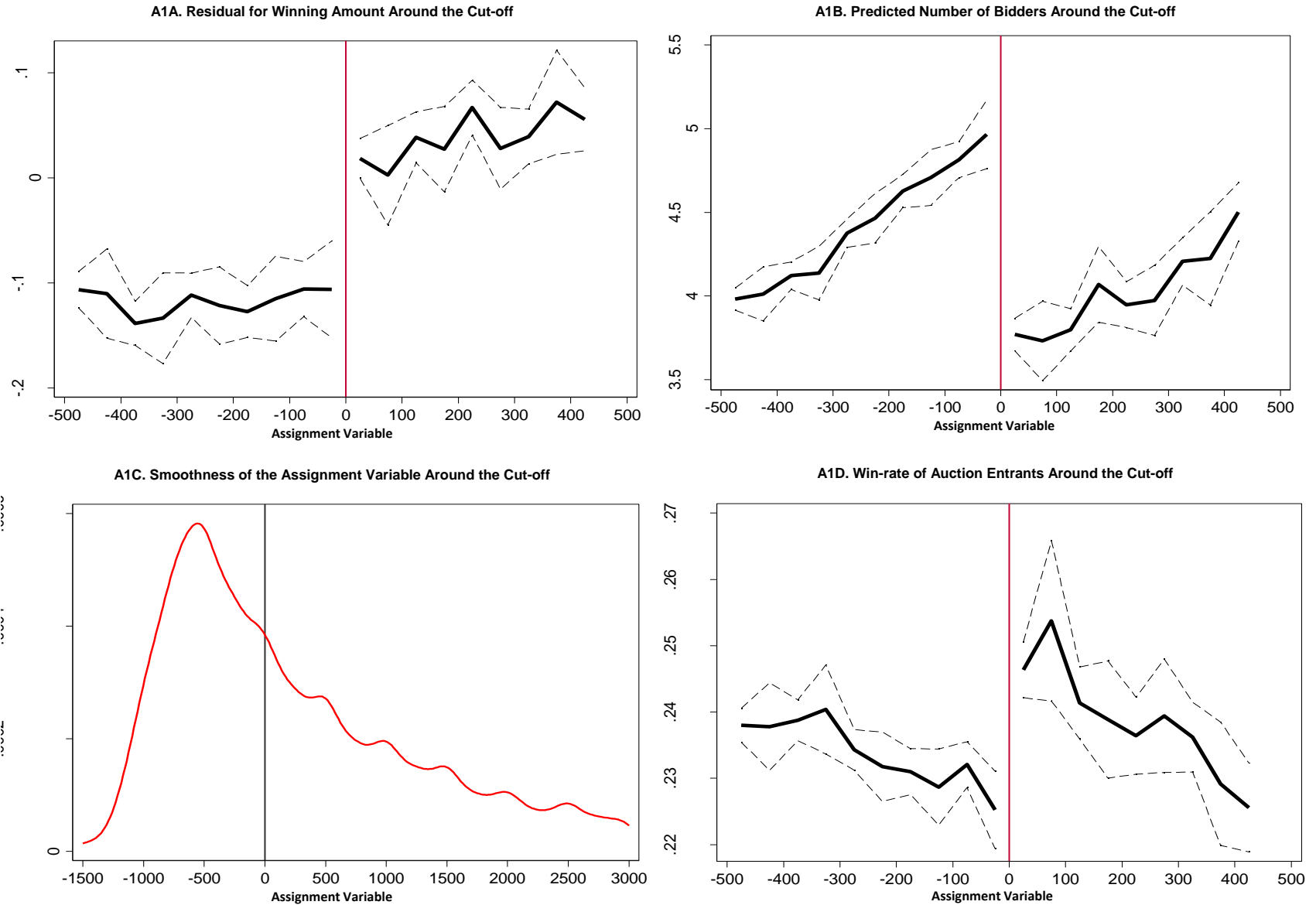

2B. Number of Bidders by Assignment Variable for Category C Vehicles

Notes: Both figures use auction data from Category C vehicle auctions during regime 1, which is in place from July 10th 2006 until November 17th 2008. The figures show the non-parametric estimates of how winning bids and the number of bidders vary with the reserve price effect at all values of the assignment variable from -1000 to +1000.

Figure A1: Regression Discontinuity Specification Checks

A1A. Residual for Winning Amount Around the Cut-off

A1B. Predicted Number of Bidders Around the Cut-off

A1C. Smoothness of the Assignment Variable Around the Cut-off

A1D. Win-rate of Auction Entrants Around the Cut-off

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, (PAV_{i}-1500). 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.