Asymmetric Effects of Winning and Losing Experience in Multi-Unit Auctions

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Abstract

This study empirically links current behaviour with past performance in a competitive multi-unit auction setting to test extensions of the learning-by-doing hypothesis. A particular advantage of the data set is that it contains complete bidding histories from a multi-unit auction that recently underwent a design change from a uniform to a discriminatory auction format. Characteristics of this unique natural experimental setting ensures bidders were inexperienced in the discriminatory auction format and that experience at the individual bidder level can be accurately measured. Following the change in auction format, bidders are identified as adjusting their bid prices in a direction consistent with equilibrium predictions, confirming bidders' ability to learn from experience. Furthermore, while controlling for individual effects through bidder fixed effects, regression results suggest that winning and losing experiences have asymmetric effects on adjustments individual bidders make to their bidding strategy. In particular, losing experiences prompt bidders to increase bid prices whereas winning experiences explain reductions in bid prices. These learning effects are found to taper off shortly after a year following the implementation of the discriminatory auction format. Results of this study are important for policy makers and auctioneers of real-life auctions that may be contemplating a change in auction format. This study provides some insight into the time it takes for bidders to learn optimal bidding strategies which is important from a practical perspective as suboptimal behaviour negatively impacts the allocative efficiency and revenue earned by the auction mechanism.

Keywords: Uniform auction; discriminatory auction; learning; experience

1 Introduction

In recent years, there has been a substantial increase in the use of multi-unit auctions to allocate or re-allocate resources and assets. Examples include: personal communication services (Cramton 1997); wine (Ashenfelter 1989); C02 emissions permits (Cramton and Kerr 2002); sulphur dioxide permits (Joskow et al. 1998); treasury bills; (Nyborg et al 2002; Hortascu and McAdams 2010); and government procurement contracts (Krasnokutskaya and Seim 2011). This recent surge in the use of auctions is likely attributed to the growing consensus among economists that auctions are effective mechanisms to sell resources (Kastl 2011). For example, the Ontario government recently introduced legislation to reduce GHG emissions through a cap-and-trade system in which a multi-unit auction mechanism would facimilate the trading of carbon permits. However, the effectiveness of any auction mechanism critically hinges on the optimal choice of bidding strategies by individual bidders. A classic example of suboptimal bidding behaviour employed in an auction setting is the use of overbidding strategies (i.e., winner's curse) in first price oil lease auctions that has led to the bankruptcy of many oil firms (Capen et al 1971). Suboptimal bidding strategies are likely more numerous and nuanced in a multi-unit auction setting due to the increased size of the bidders' choice set (i.e., bid price, quantity of the number of bids to submit). Therefore, understanding if and how bidding strategies adapt as inexperienced bidders gain experience becomes an important empirical research question to ensure the effectiveness of real-life auction mechanisms.

The learning-by-doing concept was first developed by Selten and Stoecker (1986) to explain end behaviour in prisoner's dilemma supergames. This learning direction theory has since provided the foundational framework for a vast assortment of similar theories used to explain evolution of behaviour: impulse balance theory (Ockenfels and Selten 2005); adaptive learning models (Roth and Erev 1995). The cornerstone to this literature is the hypothesis that agents are capable of learning from experience and as a result will be more likely to select equilibrium strategies as they acquire experience. This hypothesis has been tested in many applications, particularly with experimental data (Roth and Erev 1995; Bereby-Meyer and Grosskopf 2008; Foreman and Murnughan 1996; Garvin and Kagel 1994; Casari et al 2007). Far fewer have tested the hypothesis using non-experimental data: with respect to single price auctions see Wang and Hu (2009) and Wilcox (2000); firm behaviour see Thorton and Thompson (2001); and for the service industry see Darr et al (1995).

This manuscript provides an empirical documentation into adjustment made to bidding strategies as bidder gain experience in the discriminatory auction and whether bidders respond asymmetrically to winning and losing experience. A unique data set of complete bidding histories collected from the Ontario dairy quota auction provides an interesting setting to test the learning-by-doing hypothesis as it recently underwent an auction format design change. In particular, the format of the Ontario dairy quota auction changed from a uniform to a discriminatory format in November 2006. As a result the data set covers six monthly uniform price auctions from May 2006 to October 2006 and 27 discriminatory auctions from December 2006 to February 2009. The unexpected nature of the auction format change ensures two key aspects of the empirical strategy. Firstly, the surprise nature of the auction format change ensures bidding behaviour prior to the November 2006 would be untainted Secondly, the setting ensures that all bidders participating in the auction following November 2006 were inexperienced in the discriminatory format. Therefore, if bidders have a capacity to learn in a multi-unit auction setting, this natural experiment would provide a perfect setting to document learning effects. This second point hinges on whether the the uniform and discriminatory auction formats are different enough in terms of pricing mechanism and optimal bidding strategies to illicit changes in individual bidding behaviour. The major difference between the discriminatory and uniform auction format arises in the price each successful bidder must pay: successful bidders pay their submitted bid for each unit awarded to them in the discriminatory auction, whereas in the uniform auction, all successful bidders pay the market clearing price; the bid that equate supply with demand. As a result, optimal bidding strategies in each auction are starkly different: bid true willingness to pay (WTP) in the uniform auction whereas bid below true WTP in the discriminatory auction (i.e., bid shade) (Ausubel et al 2014). It is argued that this difference in optimal strategy across these two auction format is sufficient to illicit learning effects.

Adjustments in bidding strategies are important from an auction performance perspective as suboptimal behaviour negatively impacts the effectiveness, the allocative efficiency as well as the revenue earned of the auction mechanism. Auctioneers need to consider the adjustment time for inexperienced bidders to understand the intricacies of the newly implemented auction mechanism and to identify and implement the optimal bidding strategy. Consequently it is important to document whether inexperienced bidders are able to adapt and how long the adaption process takes. The magnitude of these inefficiencies and lost of revenue during the learning period due to suboptimal behaviour must be considered when policymakers determine the cost associated with the implementation of an auction mechanism. Furthermore, gaining an understanding of how bidding behaviour adapts as bidders becomes more or less successful in past auctions is important from perspective of the Ontario dairy industry. The Ontario quota auction facilitates a large proportion of quota transfers across active producers in the industry on a regular, monthly basis. If bidders struggle to adapt bidding strategies following auction losses, it is likely that these bidders will miss important growth targets. Consequently, the dairy facilities of these bidders' who's growth is retarded will not achieve optimal economies of size which will negatively impact the efficiency of the industry in the long run if it persists.

The balance of the paper is divided into five sections. The next section provides a brief literature review of important studies to provide context and motivation for this study. Section three presents the equilibrium bidding predictions for both of the uniform and discriminatory auction formats derived by Ausubel et al (2014) and develop testable hypotheses. Section four provides a description of the data and variables followed by a discussion of the regression results in section five. Section six wraps up the paper with a summary and implications of the study.

2 Existing Learning-by-doing Literature

The existing literature applying learning-by-doing concepts to single unit auction settings are numerous in the laboratory setting (Bereby-Meyer and Grosskopf 2008; Garvin and Kagel 1994; Casari et al 2007). Far fewer applications exist in a real-life auction setting in which data is collected from actual bidders voluntarily participating in the auction under analysis. I focus on two important applications of the learning-by-doing concept on data collected from eBay relevant to this study

The first study by Wang and Hu (2009) analyze data from eBay auctions to examine the effect experience has on the evolution of bidding behaviour. Wang and Hu (2009) examine different products to construct experience measures that capture the amount of experience each bidder has from bidding for a product within a product class (in-category) as well as overall experience from bidding for any product in eBay (out-of-category). The authors hypothesize that in-category experience has a greater importance relative to out-of category experience, suggesting that experience is specific to a product class and may not extend to other product classes. In addition, the authors predict that winning and losing experiences have asymmetric effects on bidding behaviour and in particular winning should reinforce bidding strategy, making the bidder more complacent to remain with their existing strategy. Alternatively, a losing experience is likely to make a bidder adjust their strategy in future auctions.

Auction theory predicts the optimal bidding strategy for a bidder in an eBay style auction is to submit one bid equal to their true WTP near the end of the auction. The normative predictions of this optimal strategy as defined by Wang and Hu (2009) are measured in terms of: 1.) number of bids submitted in a given auction (i.e., the number of bid revisions); and 2.) late bidding strategies (i.e., bidding in the last few seconds of an auction). Regression results indicate bidding behaviour depends on total previous auction experience (out-of-category) rather than specific experience from bidding for a particular good in a product class (in-category). In particular, experience is shown to drive bidding behaviour closer to theoretical predictions (i.e., reduce the number of bids submitted and increase the likelihood of late bidding). Furthermore, Wang and Hu (2009) that found that following a losing experience, bidders were more likely to adjust strategies towards equilibrium bidding strategies. However, past winning experiences were found to have an insignificant effect on number of bids and a significant effect on hindering the use of optimal bidding strategies regarding the timing of the bid; confirming the hypothesis that winning and losing experiences have symmetric effects on adjustments to bidding behaviour.

A similar study by Wilcox (2000) also examines bidding behaviour of eBay users in which bidding histories from four different products (i.e., power drills, men's neckties, stapler and pottery) are collected spanning a one-month period. Wilcox (2000) uses the same normative predictions as Wang and Hu (2009) to evaluate adjustments made to bidding behaviour. In a regression analysis the author runs a logit regression in which the dependent variable takes a value of one if the bidder submitted a bid in the last minute and zero otherwise. Consistent with predictions, the author indicates that the regression results show that more experienced bidders are more likely to submit a bid in the last minute relative to inexperienced bidders. Furthermore, when experience is interacted with a dummy variable for whether the auctioned good had common value components (i.e., pottery, designer neckties), they find last minute bidding is even more likely, supporting the authors hypothesis that the effect for common value goods is stronger.

These two papers describe the extend to which the learning-by-doing concept has been applied to economic behaviour in auction settings in addition to highlighting the limitations of this field to single-unit auction settings. Overall, these two papers report consistent results confirming the learning hypothesis in a single-unit auction framework. However, it has yet to be tested whether these findings can be extended to a multi-unit auction setting. Unlike single-unit auctions, multi-unit auctions allow bidders to submit multiple bids at different price levels for varying levels of quantity, greatly increasing the complexity of a bidders' choice set. Due to this increased complexity, this multi-unit auction setting provides a more challenging environment for bidders to learn optimal strategies across multiple dimensions, making an application of the learning-by-doing hypothesis in this setting important.

3 Multi-Unit Auction Theory

This section describes the existing theoretical frameworks for multi-unit auctions and discusses equilibrium bidding behaviour in both the uniform and discriminatory auctions. A thorough understanding of both formats is necessary to distinguish differences in the optimal bidding behaviour across these two auction formats and establish the fact that bidders had to learn new optimal bidding strategies following the change in auction format.

In both the uniform and discriminatory auction formats, bidders submit a bid function consisting of multiple price-quantity bid pairs. The auctioneer ranks these bids in descending order beginning with the highest bid price. The market clearing price is determined by the price that equates supply of the auctioned good with demand. The major difference between the uniform and discriminatory auction formats is the price each successful bidder must pay: successful bidders pay their submitted bid for each unit awarded to them in the discriminatory auction, whereas in the uniform auction, all successful bidders pay the market clearing price.

Ausubel et al (2014) provides a theoretical model to derive optimal bidding behaviour for the uniform and discriminatory auction under the following assumptions: independent private valuations, constant marginal valuation and absence of market power.[1] Under these assumptions, the theoretical model predicts that in the discriminatory auctions, it is optimal for bidders to submit a flat bid function that is shaded below their true WTP. The intuition is similar to that of the first price auction: If bidders submit a truthful bid and win, their payoff will be zero; therefore, bidders have an incentive to submit a bid below their WTP to ensure a positive payoff. As the amount of bid shading increases, bidders are decreasing the probability of winning the unit(s) in addition to increasing their expected payoff if they happen to win. Therefore, the optimal amount of bid shading will strike a balance between these two factors. However, there exists no close form solution as to the optimal amount of bid shading.

Alternatively, Ausubel et al (2014) predicts that in the uniform auction it is optimal for bidders to submit a flat bid function that is equal to their true WTP. The intuition is as follows: Due to the large number of bidders in any given auction, the probability of any one bidders' bid sets the clearing price is essentially zero, therefore bidders have no incentive to shade their bids. Asa result, the only incentive a bidder has to submit a bid below WTP is to reduce a bidder's probability of winning the bid (i.e., probability the bid is higher than the market clearing price) and has no influence on setting the market clearing price. It follows that truthful bidding is the optimal bidding strategy in the uniform auction as it maximizes a bidder's probability of winning.

Comparing these two auction formats, it is clear that bidding strategies are different. As bidders move from the uniform pricing to the discriminatory pricing auction, the optimal bidding strategy changes from truth-telling to bid shading. However, it is not obvious if and how quickly bidders will learn that a truth-telling strategy that was optimal in the uniform auction will no longer be optimal in the discriminatory auction.

Interestingly, if we examine the difference in bidding behaviour from the choice set of the bidder more closely, it is clear that differences in optimal bidding behaviour across these two auction formats only occurs in one of the choice dimensions of the bidder. In particular, truth-telling and bid shading only differ in the price dimension; all other choice dimensions of the bidder remain unchanged across different auction formats. Examples of choice dimensions that are identical across auction formats are: the optimal number of bids to submit and the proportion of quantity demanded placed on maximum bid price. In the case of these two dimensions, Ausubel et al (2014) predicts they are identical across both formats: submit one price-quantity bid pair with the total quantity demanded specified at the maximum bid price. Therefore, the multi-dimensionality of the bidders' choice set in both the uniform and discriminatory auction formats provides a setting to test whether the effect of experience is different across these different dimensions for a given bidder. The next section defines our hypotheses more formally based on these theoretical predictions of optimal bidding behaviour in the uniform and discriminatory auction in the context of the learning-by-doing framework.

[1] See Elskamp (2016) for a thorough description of the appropriateness of these assumptions in the context of the Ontario dairy industry.

3.1 Learning-by-doing Hypotheses in Multi-unit Auction

The first hypothesis examines whether bidders were experienced in the uniform auction. Recall, the uniform auction format had been implemented since 1980, giving bidders sufficient time to become "experienced" in the sense that they had figured out their optimal bidding strategy. If there is evidence that bidders were still learning in the uniform auction, then it is very unlikely that learning can be detected in the two year time frame of our data set containing bidding observations from the discriminatory auction format.

H1: Auction experience has no effect on adjustments in bidding behaviour in the uniform auction due to the fact that bidders are "experienced" in the uniform auction format.

Hypotheses 2 through 4 pertain to adjustments in bidding behaviour in the discriminatory auction. By focusing on "inexperienced" bidders in the sense that all bidders participating in the Ontario dairy quota auction had never participated in a discriminatory auction format, it is straightforward to analyze whether adjustments made to bidding strategies resulted from experienced acquired, or if adjustments in bidding behaviour are just random.

An interesting extension from the traditional learning-by-doing hypothesis is that different rates of convergence are expected across different dimensions of the bidding strategy. Differential learning may reflect similarities in optimal bidding strategies between the uniform and discriminatory. Recall, the optimal bidding strategy of truth-telling (bid shading) in the uniform (discriminatory) auction format are identical across some dimensions of the bidder's choice set and are different across others. For the dimensions that are identical across the uniform and discriminatory auction formats (i.e., number of bids submitted; proportion of total quantity placed at maximum bid price), experience is predicted to have no effect on adjustments in bidding behaviour. Rather, adjustments made in these two dimensions are likely purely random.

H2: Auction experience has no effect on adjustments made to bidding behaviour in the number of price-quantity bid pairs or the proportion of total quantity placed at the maximum bid price.

Alternatively, in the dimension that is different across auction format, experience is hypothesized to have a significant effect on convergence of individual bidding behaviour towards equilibrium predictions. More specifically, H3 predicts that adjustments in bid prices submitted in the discriminatory auction should be observed. This reflects the fact that bidders have to learn that a truth-telling strategy is no longer optimal in the discriminatory auction. Rather bidders have to discover that submitting bids shaded below their WTP is optimal. H2 predicts that auction experienced acquire by individual bidders will facilitate this learning process.

H3: Auction experience leads inexperienced bidders to select equilibrium bidding strategies in the price dimension.

The fourth hypothesis builds on the results of Wang and Hu (2009) that wining and losing experiences has asymmetric effects on adjustments in bidding behaviour and extends it to a multi-unit auction setting. In particular, H4 predicts that following an auction loss, bidders will be more likely to converge towards equilibrium predictions in the price dimension. Alternatively, following an auction win, bidders will make very minor adjustments to bid prices in the next auction that are random and will not vary with experienced. The latter portion of H4 reflects the fact that once bidders find a successful strategy, they will likely become complacent.

H4: Losing experiences induces bidders to select optimal bidding strategies in the price dimension, submit higher bids, whereas winning experiences prompt bidders to become complacent.

4 Empirical Approach

4.1 Data

The data used in this study comes from the Ontario Milk Marketing Board (i.e., the Dairy Farmers of Ontario (DFO)). Complete bid histories are made available from all bidders participating in the monthly auction between May 2006 and July 2009. See Table 1 for summary statistics of the 32 auctions contained in the data set. As previously mentioned, an interesting characteristic of the Ontario quota auction making it an unique setting to test multi-unit auction theory is that it has recently undergone an auction design experiment. In particular, the format of the Ontario dairy quota auction changed from a uniform to a discriminatory price format in November 2006. As a result the data set covers 27 discriminatory auctions from December 2006 to February 2009. It should be noted that producers were given *no* notification of this change in auction format occurring in November 2006.[2]

[2]Under the Canadian system of supply management, dairy production quota is measured by a kilograms of butterfat per day (roughly equivalent to the milk one dairy cow will produce in one year) in addition to determining the producer's share of the national MSQ allotment. Quota is the property of the Dairy Farmers of Ontario (DFO) (i.e., the provincial milk marketing board) and it is allotted to producers for the production of milk indefinitely. The DFO has the right to adjust quota holdings based upon reduction in demand for milk (both provincially and nationally). Furthermore, producers must meet quality standards outlined under the Milk Act as enforced by the DFO. The DFO maintains the right to cancel or remove quota from producers that do not comply with their standards. In terms of the impact of holding quota on producer's balance sheet, quota is a type of property called Eligible Capital Property (ECP).

Table 1: Summary Statistics of the Ontario Dairy Quota Auctions Between May 2006 and February 2009

	Format	Num.Bidders	Num. Bids	Clearing Price	Total Q.Demanded	Avg Num.Bids/Bidder	Avg Q. Demanded/Bidder
May 06	UA	371	432	29700	1988.2	1.16	5.36
Jun 06	UA	340	389	30500	1850	1.15	5.44
Jul 06	UA	217	248	30001	1100	1.17	5.07
Aug 06	UA	189	218	30010	1106.7	1.18	5.86
Sep 06	UA	205	246	30800	1253.8	1.2	6.12
Oct 06	UA	184	214	30995	1100.5	1.19	5.98
Dec 06	DA	354	619	29000	2286.2	1.72	6.46
Jan 07	DA	267	419	29600	1605.9	1.63	6.01
Feb 07	DA	346	478	30015	1945.1	1.39	5.62
Mar 07	DA	271	364	30501	1993.3	1.37	7.36
Apr 07	DA	151	207	29995	1032.2	1.4	6.84
May 07	DA	109	167	27502	400.5	1.45	3.67
Jun 07	DA	240	435	26837	1488.4	1.68	6.2
Jul 07	DA	249	455	27120	1797.1	1.69	7.22
Aug 07	DA	233	387	28102	1685.4	1.58	7.23
Sep 07	DA	188	317	29200	1446.5	1.62	7.69
Oct 07	DA	140	193	29210	952.9	1.5	6.81
Nov 07	DA	76	110	28101	373.4	1.53	4.91
Dec 07	DA	138	228	27670	787.2	1.61	5.7
Jan 08	DA	237	383	28213	1325.9	1.56	5.59
Feb 08	DA	341	527	29501	1864.5	1.54	5.47
Mar 08	DA	341	482	30666	1944.9	1.42	5.7
Apr 08	DA	291	426	31505	1732.7	1.47	5.95
May 08	DA	238	339	32405	1527.2	1.47	6.42
Jun 08	DA	201	285	33235	1241.2	1.47	6.18
Jul 08	DA	119	158	33805	682	1.44	5.73
Aug 08	DA	75	109	33115	495	1.46	6.6
Sep 08	DA	72	118	30651	426.2	1.5	5.92
Oct 08	DA	191	339	30205	1465.9	1.64	7.67
Nov 08	DA	143	233	30310	860.7	1.6	6.02
Dec 08	DA	147	224	30610	865.2	1.56	5.89
Jan 09	DA	125	191	30610	710	1.6	5.68
Feb 09	DA	140	208	30601	645.4	1.56	4.61

Participation in the Ontario dairy quota auction is voluntary and restricted to registered Ontario dairy producers. Each month, bidders wishing to participate in the auction must submit their bids between the 20th of a month to the first of the following month (for example: between March 20th to April 1st to participate in the April exchange). Bidders have access to two avenues to submit their bids during this time period: an automated telephone service or on-line. Each bid (also referred to a price-quantity pair) contains: 1.) the amount of quota to be sold or purchased listed in kilograms of quota; and 2.) the units price they are willing to pay for one kilogram of quota. Bidders are permitted to submit an unlimited number of these price-quantity bid pairs in a given auction. The auction results are released on the first business day of the month and provide a summary of successful and unsuccessful bids.[3] Following the intuition from previous studies (i.e., Goertz 2000), I expect that the revelation of past auction information revealing distribution of bids that were successful and successful will likely expedite learning effects. Finally, bidders in the Ontario dairy quota auction are considered skilled due to the important role acquiring quota has in the production process: without the purchase of new quota, growth in production is restricted. This contrasts the majority of the existing learning-by-doing literature confined to laboratory settings (i.e., Garvin and Kagel 1994; Bereby-Meyer and Grosskopf 2008) in which individual learning effects have been shown to be biased upwards (Casari et al 2007).

The data contains complete bidding histories in which a multi-dimensional strategy space is made available to bidders. As previously highlighted, the substantial size of the choice set including bid prices, quantities, number of bid pairs, broadens the scope to observe convergence of individual bidding behaviour. The majority of bidders demand more than one of quota (i.e., multi-unit demand). This is an important distinction that separates the empirical analysis from existing literature often considering a simplified setting in which bidders have demand for a single unit (i.e., Garvin and Kagel 1994), limiting the complexity of observable bidding strategies. The presence of bidders with multi-unit demand in the data set provides a setting to observe and analyze more complex bidding strategy that include: the number of price-quantity bid pairs submitted; proportion of total quantity placed at each bid price, etc.

4.2 Dependent Variables

Three dependent variables are defined from the observed bids to capture individual bidding strategies. Let q_k and p_k represent the quantity and price specified for the kth bid pair in which k can take on any positive integer. The first-difference of these three dependent variables is calculates as part of the estimation strategy.

The first variable defined to capture bidding behaviour is the proportion of total quantity submitted at the maximum bid price. The rational for focusing on the quantity demanded at the maximum bid price is that it is likely one of the components of the bidding strategy receiving considerable thought by each bidder as it has the highest probability of being successful. As the ratio tends to zero (one), it indicates less (more) quantity is placed on the maximum bid price. An increase in the proportion of total quantity placed on the maximum bid is characterized as a movement towards equilibrium bidding behaviour in which all units are specified at the maximum bid price.

[3] Quota purchases and sales are effective on the first day of the month following the exchange month. For example, a producer submits a bid on March 31st will observe on April 1st if the bid was successful but will not be granted the quota bid for until May 1st. In terms of payment, successful bidders are required to submit payment to the DFO by the last business day of the month prior to the effective date of the quota purchases (in the example: the last business day of April). If payment is not made to the DFO by the 8th day of the effective month (in the example: May 8th), then the DFO will withhold the proceeds of all subsequent milk proceeds until the balance is fully paid. Seller of quota will receive payment from the DFO by the 20th of the month following the exchange month (in the example: May 20th).

$$Weight = \frac{q_k^{max}}{\sum_{k=1}^{K} q_k} \qquad where: q_k^{max} = q_k[which.max(p_k)] \forall k = 1, 2, , K$$

The first difference of this variable for an individual bidder (i) is specified as:

$$\Delta Weight_i = Weight_{ti} - Weight_{(t-1)i}$$

The second component of bidding strategies defined captures the number of price-quantity bid pairs submitted. During the time frame of this study, there was no institutional restriction on the number of price-quantity bid pairs a bidder can submit in a given auction, other than a \$15 cost per additional bid pair. This lack of restriction is uncommon in the existing discriminatory auction literature in which bidders in treasury auctions are often restricted to a finite number of price-quantity bid pairs. For example, Kastl 2011 reports that bidders in the Czech treasury auction are restricted to submit 10 price-quantity bid pairs. A decrease in the number of price -quantity bid pairs submitted is defined to be consistent with bidders adapting equilibrium bidding strategies in which only one price-quantity bid pair is submitted for all units a bidder demands. The first difference of this variable for an individual bidder (i) is specified as:

$$\Delta Num\ of\ Bids_i = Num\ of\ Bids_{ti} - Num\ of\ Bids_{(t-1)i}$$

The final dependent variable captures the magnitude of the maximum bid price. As mentioned in the previous section, it is optimal for bidders to place a bid equal to their true WTP in the uniform auction and a bid shaded below their true WTP in the discriminatory auction. Unfortunately, as previously mentioned there exists no theoretical predictions on the optimal size of bid shading in the discriminatory auction. However, theory does predict a positive amount of bid shading, therefore it may still be informative to examine adjustments in bid prices as bidders gain experience. To overcome the latent nature of individual bidders' true WTP, a first-difference approach is employed.[4] Underlying this approach is the assumption that bidders' valuations of quota will remain constant across sequential. Therefore, to capture adjustment made to bid prices, the first difference of bidders' maximum bids are constructed as follows:

$$\Delta Max\ Bid\ Price_i = Max\ Bid_{ti} - Max\ Bid_{(t-1)i}$$

4.3 Control Variables

Explanatory variables used in the regression model are described below. Summary statistics for both dependent and explanatory variables are provided in Table 2.

Cumulative auction experience combines all auction experience that an individual bidder acquired from having participated as a bidder in the Ontario dairy quota auction (i.e., submitted bids to purchase quota).

[4]There exists a growing field of econometric papers attempting to recover latent WTP from observed bid data. See Kastl (2011) and Hortascu and McAdams (2010) for examples of these approaches using treasury auction data.

The variable is dynamic in the sense that it tallies up bidders' experience across monthly auctions. This variable is also auction format specify such that two separate cumulative auction experience variables are constructed, one for each auction format (i.e., *Cumulative UA Experience* and *Cumulative DA Experience*) In contrast to other studies that begin calculating experience at an arbitrary point determined by availability of data, the discriminatory auction experience variable is an accurate measure as the natural experimental setting clearly defines the start date of the discriminatory auction format.

Cumulative auction experience is differentiated into two separate experience variables to capture bidder's past auction performance in the discriminatory auction format. *Cumulative DA wins* and *Cumulative DA losses* are two separate variables that tally up auctions in which a bidder won or lost, respectively. However, due to the nature of the quota auction and bidders' multi-unit demands, bidders can observe complete and incomplete losses (wins). A complete loss (complete win) describes a bidder losing (winning) all bids submitted in an auction. Whereas an incomplete loss (incomplete win) describes a bidder losing (winning) only a portion of bids submitted. For the purpose of the analysis, complete auction wins and complete auction losses are analyzed to provide a well defined variable that accurately captures past auction performance.

A time trend is included to control for variations in bidding behaviour occurring across monthly auctions. Time trend is interacted with these four explanatory variables: cumulative UA experience, cumulative DA experience; cumulative DA winning experience; and cumulative DA losing experience to examine whether the effect of each type of experience changes across time. In the case of the discriminatory analysis, the time trend captures the number of months since the implementation of the new auction format. Therefore we expect that the further in the past this implementation is, the effect of experience on adjustments to bidding behaviour will be diminished. Auction clearing price is lagged one month and likely captures market fundamentals from the previously monthly auction. For example, a higher past clearing price may indicate that it is likely bidders lost a larger proportion of their bids relative to when the clearing price is lower. Therefore, past clearing price may explain some variations in adjustments in bidding behaviour due to previous market conditions that are invariant across individual bidders. Finally, individual fixed effects are included in the model to capture unobservable heterogeneity among bidders that is likely to impact bidding behaviour such as risk aversion, discount factor, etc.

Table 2: Summary Statistics Of Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
[-1.8ex]	Uniform Auction Format				
[-1.8ex] Δ Max Bid Price$_{UA}$	523.149	1226.127	-14770	14840	631
Δ Num. Bids$_{UA}$	-0.07	0.553	-3	2	631
Δ Weight$_{UA}$	0.027	0.226	-0.833	0.857	631
Cumulative UA Experience	1.704	0.996	1	5	631
Past Clearing Price$_{A}$	30270.381	462.045	29700	30995	631
[-1.8ex]	Discriminatory Auction Format				
[-1.8ex] Δ Max Bid Price$_{DA}$	226.641	1961.026	-10552	20001	1925
Δ Num. Bids$_{DA}$	-0.105	1.041	-9	6	1925
Δ Weight$_{DA}$	0.03	0.312	-0.926	0.962	1925
Cumulative DA Experience	2.643	1.947	1	13	1925
Cumulative DA Loses	1.613	1.356	0	9	1925
Cumulative DA Wins	0.539	0.783	0	5	1925
Past Clearing Price$_{DA}$	28560.992	1160.907	26837	30501	1925

5 Results

Table 3 reports the results from three separate regression models that are used to document adjustments made to bidding behaviour in the uniform auction. Regression results for variation in bid prices, proportion of total quantity placed on maximum bid and number of bids are reported in Model 1, Model 2 and Model 3, respectively. Focusing first on Model 1 to examine H1, the coefficient on cumulative UA experience is statistically insignificant, confirming H1. More specifically, controlling for individual bidder characteristics with fixed effect, Model 1 indicates adjustments in the price dimension are not explained by experience acquired in the uniform auction. This finding is consistent with bidder using the same bidding strategy in terms of the price across sequential uniform auctions. This behaviour is explained by bidders being sufficiently experienced in the uniform auction format to have found and continued to have utilized their optimal bidding strategy. Focusing on Model 2 and Model 3 in Table 3, cumulative UA experience has statistically insignificant effects on adjustments made to the proportion of total quantity demanded at maximum bid and number of bids, respectively. In summary, Model 1 through 3 in Table 3 provide evidence to confirm H1 in three bidding dimensions that changes in bidding behaviour cannot be explained by auction experience. Rather, these results are consistent with bidders' having the capacity to learn in a multi-unit auction setting.

Table 4 examines the empirical evidence to accept or reject H2 and H3 predicting that bidding behaviour adjusts as bidders gain experience in the discriminatory auction. Regression results for variation in bid prices, proportion of total quantity placed on maximum bid and number of bids are reported in Model 1, Model 2 and Model 3, respectively. Focusing on Model 1 in Table 4 the coefficient for cumulative DA experience is negative and statistically significant. This negative relationship suggests that as bidders gain more experience in the discriminatory auction they are likely to submit lower bid prices. In other words, for each additional discriminatory auction a bidder participated in, bidders will adjust their bids lower by \$231.50. This adjustment is consistent with bidders realizing that bidding below their WTP will increase their expected payoffs, as bidders now have to pay their bids if their bid is successful.[5] Interestingly, the interaction between cumulative DA experience and time trend is positive and statistically significant suggesting that this downward adjustment in bid prices is somewhat halted in later months. Take for example the first discriminatory auction (Time = 1 in December 2006) to a year later (Time = 12 in December 2007). The total effect of cumulative experience when Time = 1 is -\$214.20 and -\$23.90 when Time = 12. Interestingly, by the 14th month the effect of experience on changes in bid prices approaches zero, suggesting that bidders likely found their optimal bid price in the discriminatory auction at this point.

Models 2 and 3 in Table 4 reports regression results of how changes in the weight placed on the maximum bid price and number of bids submitted changes as bidders gain experience in the discriminatory auction, respectively. In both Model 2 and 3, the coefficient on cumulative DA experience is statistically insignificant, suggesting that adjustments in bidding behaviour in these two dimensions was not affected by experience gained. Furthermore, the coefficient on the interaction term between cumulative DA experience and time trend had no effect on either bidding dimensions. These results are consistent with H2 indicating that the effect of experience would be negligible for dimensions of the bidders' choice set that were not predicted to change with the change in auction format from uniform to discriminatory. These findings suggest that bidders carried over their knowledge of the optimal strategy from the uniform auction in the context of these two dimensions and quickly found out that it was also optimal in the discriminatory auction.

Finally, Table 5 reports regression results to examine whether different types of auction experience in

[5] This is in stark contrast to a decrease in bid price in the uniform auction format that would only decrease the probability of winning.

Table 3: Examine the Learning-by-doing Hypotheses in Uniform Auction

	(Model 1) Δ Max. Bid Price	(Model 2) Δ Weight	(Model 3) Δ Num. Bids
Cumulative UA Experience	-1038.9	-0.122	0.434
	(702.2)	(0.123)	(0.295)
Cumulative UA Experience × Time Trend	182.5	0.0146	-0.0563
	(119.5)	(0.0189)	(0.0460)
Clearing Price (t-1)	-0.136	-0.0000469	0.000136
	(0.373)	(0.0000754)	(0.000180)
Constant	4489.6	1.525	-4.472
	(11740.8)	(2.354)	(5.635)
N	631	631	631
R^2	0.293	0.395	0.467

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

terms of performance have asymmetrical effects on bid prices in the discriminatory auction. The coefficient on cumulative DA losses is positive and statistically significant suggesting that bidders with more past auction losses are likely to submit higher bid prices. In particular, for each additional auction that the bidder lost all units demanded, he/she submits bid prices that are $596.90 higher on average. In other words, as bidders experience more losses, they appear to adjust bidding strategies in such a way that will increase their likelihood of winning; consistent with H4 predicting bidders will be motivated to adjust bidding behaviour. Interestingly, the coefficient on past auction wins is negative and statistically significant, indicating that previous auction wins have the opposite effect of past auction losses on bid prices. In fact, for each additional past auction win, on average, an individual bidder is likely to decrease her bid price $ 2367.60. This effect does not support H4 predicting that winning experiences would have no effect on bid prices as bidders were expected to become complacent and make only minor/random changes to bidding strategies. Alternatively, it appears that successful bidders may be willing to trade off the probability of winning with the expected payoff they could get by submitting bids substantially lower following a complete auction win. These results are consistent with existing single-unit literature examining the asymmetric effects of wining and losing experiences on adjustments made to bidding behavior.

Moving now to the coefficient on the interaction term between cumulative losing experience and time trend, a negative effect on bid price is identified. This negative coefficient works to temper the increase in bid prices found on cumulative losing experience. A positive coefficient on the interaction term between cumulative winning experience and time trend is reported in Table 5. This positive effect also works to temper the effect of winning experiences on bid prices, but in the opposite direction as above. In particular, for each month that passes, the effect of each additional winning experience will be smaller by $143.10. In other words, after an entire year has passed since the discriminatory auction was introduced (T=12), the effect of a winning experience will be -$651.6 in December 2007 compared to an effect of -$2224.50 in December 2006. These tapering out effect that time appears to have on both wining and losing experiences provides evidence to suggest that bidders eventually finding their optimal bidding strategy and stick with it, regardless of past auction performance.

Table 4: Examine the Learning-by-doing Hypotheses in Discriminatory Auction

	(Model 1) Δ Max. Bid Price	(Model 2) Δ Weight	(Model 3) Δ Num. Bids
Cumulative DA Experience	-231.5*	0.00596	0.0316
	(122.1)	(0.0223)	(0.0724)
Cumulative DA Experience $\times$ Time Trend	17.30**	-0.000501	-0.00179
	(8.176)	(0.00154)	(0.00534)
Clearing Price (t-1)	0.612***	0.0000254**	-0.0000986**
	(0.0596)	(0.0000103)	(0.0000361)
Bidder Fixed Effects	yes	yes	yes
Constant	-18993.8***	-0.779**	2.985**
	(1808.8)	(0.316)	(1.103)
N	1925	1925	1925
R^2	0.380	0.222	0.196

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table 5: Examine the Asymmetric Effects of Winning and Losing in the Discriminatory Auction

	(Model 1) Δ Max. Bid Price
Cumulative DA Losing Experience	596.9***
	(158.0)
Cumulative DA Winning Experience	-2367.6***
	(289.9)
Cumulative DA Losing Experience $\times$ Time Trend	-30.41**
	(11.25)
Cumulative DA Winning Experience $\times$ Time Trend	143.1***
	(21.65)
Clearing Price (t-1)	0.350***
	(0.0634)
Bidder Fixed Effects	yes
Constant	-13260.0***
	(1684.5)
N	1925
R^2	0.425

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

6 Discussion

This manuscript provides an empirical documentation into adjustment made to bidding strategies as bidder gain experience in the discriminatory auction and whether bidders respond asymmetrically to winning and losing experience. A unique data set is used containing information on individual bidding strategies used by bidders over two widely used multi-unit auction formats: uniform and discriminatory auction. Characteristics of this unique natural experimental setting ensures bidders were inexperienced in the discriminatory auction format and that experience at the individual bidder level can be accurately measured.

Overall the results of the analysis confirm bidders' ability to learn from auction experience and adjust bidding behaviour in a direction consistent with equilibrium bidding strategies. In particular, bidders are identified as adjusting bid prices downward after the implementation of the discriminatory auction, consistent with bid shading strategies as predicted by Ausubel et al (2014). These learning effects are found to taper off shortly after a year following the implementation of the discriminatory auction format. Interestingly, in the two dimensions of the bidding strategy predicted to be the same across auction formats, there is not a significant change in behaviour following the format change. This suggests that bidders may have carried over knowledge of optimal strategies from the uniform to use in the discriminatory auction format. This result highlights the potential benefit of selecting auction formats that have some similarities in bidding strategies such that bidders can carry over some "knowledge" and "experience" from the previous auction format to the newly implemented one. In addition, the results of the empirical analysis identifies asymmetric effects of winning and losing experience on bid prices. As bidders experience more past loses, they are more likely to increase bid prices. This adjustment is consistent with bidders selecting bidding strategies that will increase their probability of success, and confirms with the learning-by-doing hypothesis. In contrast, as bidders experience more complete wins they are more likely to decrease their bid price, forgoing the likelihood of winning for a higher expected payoff.

Auctioneers may find the results of this study information for multiple reasons. Mainly, the results indicate that inexperienced bidders have the ability to learn optimal bidding strategies in the complex, multi-unit auction format. Secondly, the methodology of this study provides information for auctioneers in regards to the observable factors (i.e., number of bids, quantity specified at different prices) to assess whether bidders are using optimal strategies in the discriminatory auction. Moreover, these results suggest that learning effects taper off by the 14th auction (i.e., 14 months following the implementation of the discriminatory auction format). Although this time line likely cannot be extrapolated to other auctions outside of the Ontario dairy industry, it does provide an insight into the sort of time line policymakers should consider for the possible duration of the adjustment period inexperienced bidders need to understand the intricacies of the newly implemented auction mechanism and to identify and implement optimal bidding strategies. The fact that bidding behaviour in the discriminatory auction settled down shortly after one year following its implementation is encouraging for policymakers of real-life multi-unit auctions contemplating the introduction of a new auction mechanism and are concerned about efficiency and revenue losses due to suboptimal bidding behaviour from inexperienced bidders. In addition, although this study did not measure these effect, it is likely that auction design parameters such as: the frequency of the auctions (i.e., bi-weekly, monthly, annually, etc) and degree of information provided to bidders following the auction (i.e., summary of all successful and unsuccessful bids) greatly influences the rate of learning. Further research is needed to fully measure the magnitude of the allocative inefficiencies and revenue lost during the adjustment period as well as the effect auction design parameters may have on the rate of learning in multi-unit auctions.

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