CDS Auctions and Informative Biases in CDS Recovery Rates[1]

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Abstract

Since 2005, recovery rates in the multi-trillion dollar credit default swap (CDS) market have been determined using a novel and complex auction format. This paper undertakes the first detailed empirical investigation of these auctions. We find that the auction price is significantly biased compared to pre- and post-auction market prices for the same instruments, with the average bias exceeding 20%. Nonetheless, econometric analysis shows that the auction is also significantly informative: information generated in the auction is critical for post-auction market price formation. Bidder behavior and auction outcomes are heavily influenced by "winner's curse" concerns, contributing to the observed bias; other factors, such as the exercise of monopsonistic market power also appear to matter. Finally, structural estimation of the auction under some simplifying assumptions suggests that alternative auction formats could reduce substantially the bias in the auction final price.

Keywords Credit default swaps, CDS credit-event auctions, price discovery, pricing bias, winner's curse, structural estimation of auctions.

1 Introduction

Since 2005, a novel and complex auction mechanism has governed settlement following a credit event in the credit default swap (CDS) market. This paper examines the performance of this auction over a multi-year horizon, including especially the efficacy of the auction's price-discovery process. It represents, to our knowledge, the first detailed empirical investigation of this subject.

Some background is useful. With a notional outstanding measured in the tens of trillions of dollars, credit default swaps (CDSs) are today among the most important of all financial instruments. Akin to insurance, a CDS is a financial security that offers protection against default[1] on a specified instrument: The buyer of protection in a CDS contract makes regular periodic "premium" payments to the seller until maturity of the contract or the occurrence of default, and receives, in exchange, a single contingent payment in the event of default.[2]

The size of this contingent payment and the manner in which it is determined are obviously central to gauging the value of CDS protection. For many years, CDS contracts were "physically settled," meaning that the protection buyer delivered the defaulted instrument—or any instrument from the same issuer that ranked *pari passu* with the defaulted instrument—and received "par" (i.e., the instrument's face value) in exchange. However, the extraordinary growth of the CDS market in the early 2000s led to a problem: for many names, the volume of CDSs outstanding far outstripped the volume of deliverable bonds, creating the potential for market-disrupting squeezes. Particularly dramatic was the case of Delphi Corporation which, at its bankruptcy in 2005, had an estimated $28 billion in CDSs outstanding against only $2 billion in deliverable bonds (Summe and Mengle, 2006).

In response to these developments, the CDS market underwent a radical change beginning in 2005, moving to a "cash settlement" system in which (i) a specially-designed auction mechanism was instituted to identify a price for the defaulted instrument, and (ii) protection sellers pay buyers par minus the auction-identified price.[3] A detailed description of the auction, including the considerations that went into its unusual design, is provided in Section 2, but briefly, CDS auctions are two-stage auctions. In Stage 1, participants make price and quantity submissions. The price submissions are used to identify an indicative price, called the *initial market mid-point*

[1] More precisely, a CDS offers protection against the occurrence of a *credit event*, a more inclusive notion than default. For example, in addition to traditional default events such as failure to pay or bankruptcy, the definition of a credit event in European and pre-2009 North American corporate CDS contracts includes *restructuring*, which is, loosely speaking, any postponement or reduction in principal or interest payable, or any change in seniority of the debt. For simplicity, we use the terms 'default' and 'credit event' interchangeably in this paper.

[2] We note that neither buyer nor seller of protection need have any exposure to the underlying instrument, i.e., the CDS can be "naked." This distinguishes CDS protection from traditional insurance which requires the presence of an insurable interest.

[3] The original auction format was modified in mid-2006; the modified system remains in place today. In April 2009, the auction was "hardwired" into all new CDS contracts as the default settlement mechanism. While participation in the auction was voluntary until April 2009, it is estimated that parties holding over 95% of the outstanding CDS instruments participated in each auction to that point.

or IMM, for the defaulted instrument. The quantity submissions are used to identify the *net open interest* or NOI, which is the amount auctioned in the second stage. Depending on the submissions, the NOI could be to sell or to buy; that is, the second stage auction could be for sale (a "standard" auction) or purchase (a "reverse" auction) of the specified quantity. This endogeneity of the form and size of the second-stage auction is one of the distinguishing features of CDS auctions. In the second stage, a uniform price auction is held for the NOI. Participants submit limit orders, and the auction's *final price*, the definitive price to be used for cash settling CDS contracts, is determined in the obvious way—but with a caveat: the auction rules limit how far the final price may deviate from the IMM.

This Paper

Our analysis opens in Section 4 with an examination of perhaps the most important intended contribution of the auction: price discovery. We find that auction prices, while substantially informative, are also on average severely biased. Two questions arise: (a) What are the possible sources of this bias?, and (b) Would the bias be reduced under alternative auction formats? These questions are examined in Sections 5 and 6, respectively. A summary of our findings follows.

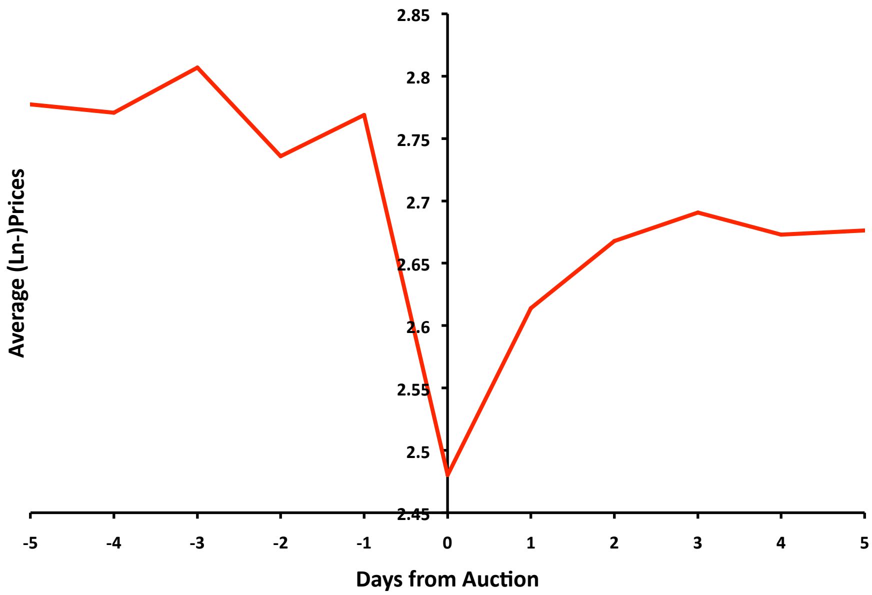
Price Discovery CDS auctions have the feature that the items being auctioned—the bonds deliverable into the auction—are traded in the market both before and after the auction. These market prices offer a natural comparison point for auction outcomes: How does the auction's final price relate to pre- and post-auction market prices? The preliminary evidence is discouraging: Market price data on the deliverable instruments indicates that, even after a careful elimination of outliers, auction prices appear to have a significant bias. For instance, in auctions with an NOI to sell (which are the vast majority of auctions in the data), both pre-auction and post-auction market prices are, on average, sharply higher than the auction-determined final prices (Figure 1).

Econometric analysis of market and auction data reveals, however, a more subtle and complex picture. Information generated in the auction—in particular, the auction's final price—is seen to be a *key* determinant of post-auction price behavior. Indeed, we find that in the presence of auction-related information, *no* pre-auction price or quantity information is significant in explaining post-auction price behavior. In short, auction outcomes may be (even severely) biased, but they are significantly informative; auction price discovery is important for the market.

These findings lead naturally to two questions: (a) What can explain the observed pricing bias?, and (b) Are there alternative auction formats that would lead to a smaller bias? We address these questions in Sections 5 and 6, respectively.

Bidder Behavior and the Auction's Price Bias An obvious suspect in inducing conservative bidding by participants and so leading to the auction's pricing bias is the presence of the *winner's curse*. Loosely put, the winner's curse in a common value auction is the observation that, by definition, the winning bid is the most optimistic of the submitted bids, so the expected valuation

Figure 1: Average Prices Pre- and Post-Auction



This figure describes the behavior of the average (log-)price of the deliverable instruments in the CDS credit-event auctions with a sell NOI 5 trading days before and after the auction date. Day-0 is the date of the auction and the day-0 price is the auction-determined final price. The data is described in Section 3 below and the calculation of average prices in Section 4.

of the item conditional on winner's information is less than the expected valuation conditional on the combined information of all bidders.[4]

In Section 5.1, we examine the impact of the winner's curse, both on individual bidder behavior and on auction outcomes. Concerning the former, we adopt the idea of *bid shading* from Nyborg, Rydqvist, and Sundaresan (2002), and estimate the extent to which an increase in the winner's curse causes bidders to behave more conservatively in the form of increased bid shading. Regarding the latter, we examine the degree to which an increase in the winner's curse is reflected in increased auction mispricing. We find very strong evidence that the winner's curse matters: even after controlling for other effects, our proxy measure for the winner's curse is highly significant, both statistically and economically, in explaining both bid shading and auction mispricing. For example, our estimates suggest that a one-standard deviation move in the value of the winner's curse measure increases the extent of bid shading by about 14.7% and increases the degree of auction underpricing in sell-auctions by around 13%.

In Section 5.2, we examine a range of other questions concerning auction behavior and auction

[4]For more details and a formal analysis, see, e.g., Milgrom and Webber (1982). Among the early papers in Treasury auctions looking at the winner's curse is Nyborg and Sundaresan (1996).

outcomes. We begin with *strategic* behavior—the exercise of monosonistic market power—by market participants that has been posited in the theoretical literature on auctions (Wilson (1979), Back and Zender (1993)) as a possible source of mispricing in divisible-good auctions. We find the data on CDS auctions is consistent with the kind of behavior that drives the constructed Wilson/Back-Zender equilibria and result in mispricing.

Section 5.2 also highlights several other aspects of interest concerning the auction including the behavior of market prices on the auction day; the impact of the winner's curse on liquidity provision in the auction; and the anomalous behavior of market price volatilities before and after the auction. Appendix B supplements this material with a study of learning dynamics within auctions.

Structural Estimation In Section 6, we carry out a structural estimation of the auction. The estimation is carried out under some simplifying assumptions that enable us to focus on the second stage of the auction. Utilizing the first-order conditions defining best responses, the estimation uncovers the distribution of signals that drive observed bids in each auction. Using the estimated signals, we then examine the counterfactual of what auction prices would have resulted under truthful bidding (i.e., under a Vickrey auction). We find that the extent of underpricing in equilibrium would be reduced sharply. Our estimates, in fact, provide a reduction in underpricing of about 20%, which mirrors almost exactly the average amount of underpricing we find in the data. Under (much) stronger assumptions, we examine the pricing impact of switching to a discriminatory auction format, and find that it would not be substantial.

The rest of this paper is organized as follows. Section 2 describes the auction mechanism in detail, highlights its unique characteristics, and provides a brief literature review, as well as a summary of comments from market participants concerning the auction. Section 3 describes the data sources we tap and the features of the data obtained. In Section 4, we test the efficiency of the auction's price discovery process, while Section 5 looks at bidder behavior in the auction. Section 6 carries out the structural estimation of the auction and counterfactual experiments. Section 7 concludes with a discussion of further avenues of research. The appendices carry material that supplements the presentation in the main body of the paper.

2 The Credit Event Auction

CDS credit-event auctions were designed by the International Swaps and Derivatives Association (ISDA) in collaboration with the auction administrators CreditEx and Markit. This section presents a detailed description of the auction.

The auction has two stages. All submissions to the auction in either stage must go through dealers; around 12-14 dealers, all of them large banks, participate in each auction. The first stage identifies (i) an indicative price for the defaulted instrument called the *initial market midpoint* or

IMM, and (ii) the *net open interest* or NOI, which is the quantity auctioned in the second stage. The second stage determines the *final price*, which is the price used to cash settle CDS contracts. Prior to the auction, a "cap amount" is specified which limits how much the auction's final price may differ from the IMM. The cap amount is typically set at 1% ($1 per face value of $100).

We describe the auction process below in detail, using data from the CIT auction conducted on November 20, 2009, as a running example.

Stage 1 of the Auction

In Stage 1, dealers make two sealed-bid submissions:

1. Two-way prices, called "inside-market prices," for the underlying deliverable obligations.

2. Physical settlement requests (PSRs) on behalf of themselves and their customers.

The submitted prices are for a specified quotation amount which is announced ahead of the auction. The quotation amount may vary by auction; for example, it was $10 million in the Washington Mutual auction in 2008, and $5 million in the CIT auction in 2009. The bid-offer spread in the submitted prices is also required to be less than a maximum amount which too is specified ahead of the auction. This maximum may vary by auction, but is typically 2%. That is, assuming a par value of $100, the ask price can be no more than $2 greater than the bid price.

The submitted PSRs represent quantities of the underlying deliverable bonds that dealers *commit* to buying or selling at the auction determined final price. The submissions must obey certain constraints. Only dealers with net non-zero CDS positions may submit PSRs. Sell-PSRs may only come from dealers who are net long protection; intuitively, a dealer with such a position would have been required to *deliver* bonds under physical settlement. Similarly, buy-PSRs can only be submitted by dealers who are net short protection. Lastly, the submitted PSR cannot exceed the dealer's total net exposure. For example, a dealer who is net long $10 million of protection can only submit PSRs to sell $$m$ million of bonds where $0 \leq m \leq 10$.

Customer PSRs are subject to the same two constraints and must be routed through a dealer. Customer PSRs are aggregated with the dealer's own PSR and the net order is submitted in the auction. We note that since only the dealer's net PSR is observed, it is impossible to tell what part of a submitted PSR represents customer orders and what part the dealer's own request. (Nor is this data collected by ISDA or the auction administrators.)

A major motivation behind the auction structure is to enable investors to replicate the outcomes of physically-settled CDS contracts. PSRs are the key enabling device here. Consider, e.g., an investor who is long protection and long the underlying bond. Under physical settlement, the investor would be left with cash worth par (say, 100) following a credit event. The same outcome can be achieved in the auction by submitting a PSR to sell the bond: if P is the auction final price, then the CDS is cash-settled for $100 - P$ while the bond is sold in the auction for P, leaving the investor with cash worth par. Absent PSRs, the investor has no guarantee of being able to sell the bond at the auction-determined price.

Once the first-round prices and PSRs have been submitted, three quantities are computed and made public by the auction administrators:

1. The *initial market mid-point* (IMM), determined from the submitted prices.
2. The *net open interest* (NOI), calculated from the submitted PSR quantities.
3. *Adjustment amounts*, computed using the submitted prices and the NOI.

The IMM To calculate the IMM, the submitted bid prices are arranged in descending order and the submitted offer prices in ascending order. All crossing or touching bids and offers are then eliminated. (A bid b is crossing or touching with an offer o if $b \geq o$.) Suppose n bids and offers remain. The best halves of these—the $n/2$ highest bids and $n/2$ lowest offers—are then averaged, and the result, rounded to the nearest eighth, is the IMM. (If n is odd, the best $(n+1)/2$ bids and offers are used.)

Figure 2 illustrates. using the CIT auction. The left-hand panel describes the bids and offers submitted by each of the 13 dealers in this auction. The right-hand panel arranges the submitted bids in descending order and the offers in ascending order. As the panel shows, three of the bids and offers cross or touch (i.e., bid $\geq$ offer). After eliminating these, 10 bids and offers remain. Taking the five highest bids and the five lowest offers, the arithmetic average of these ten numbers, rounded to the nearest eighth, is the IMM.

The NOI To calculate the NOI, the buy-PSRs are netted against the sell-PSRs to identify the remaining net position. Thus, for example, if a total of $100 million of "buy" and $140 million of "sell" orders were received as PSRs, then the NOI is to sell $40 million. Figure 3 describes the PSRs submitted in the CIT auction, and the resulting NOI.

The Adjustment Amounts The adjustment amounts are penalties levied for being on the "wrong" side of the market, that is, for bids that are higher than the IMM when the NOI is to sell, or for offers that are lower than the IMM when the NOI is to buy. This penalty is *not* levied if the bid or offer in question did not cross with another offer or bid. The CIT auction saw no adjustment amounts being levied since there were no bids greater than the IMM (see Figure 2).

The adjustment amount is computed by applying the difference (expressed as a percentage of the par value of 100) between the submitted price and the IMM to the quotation amount. For example, suppose an auction has an NOI to sell and the IMM is 50.00. Suppose the quotation amount is $2 million. Then, a dealer who submitted a bid of (say) 52.00 pays an adjustment amount of $\$(0.02 \times 2,000,000) = \$40,000$.

Figure 2: The CIT Auction: Price Submissions and the IMM

Dealer	Bid	Offer
Banc of America Securities LLC	69.25	71.25
Barclays Bank PLC	67	69
BNP Paribas	69	71
Citigroup Global Markets Inc.	68.75	70.75
Credit Suisse International	70	72
Deutsche Bank AG	70.25	72.25
Goldman Sachs & Co.	66.5	68.5
HSBC Bank USA, National Association	69	71
J.P. Morgan Securities, Inc.	69.75	71.75
Morgan Stanley & Co. Incorporated	68	70
Nomura International PLC	70	72
The Royal Bank of Scotland PLC	69	71
UBS Securities LLC	70	72

Inside Market Midpoint: 70.25

Bid	Offer	Crossing or Touching?
70.25	68.5	Y
70	69	Y
70	70	Y
70	70.75	N
69.75	71	N
69.25	71	N
69	71	N
69	71.25	N
69	71.75	N
68.75	72	N
68	72	N
67	72	N
66.5	72.25	N

Used to compute IMM

The left-hand panel of this figure describes the bids and offers made by participating dealers in the first round of the CIT auction. The right-hand panel presents the bids and offers in ordered form (decreasing bids, increasing offers). The IMM is calculated using these ordered bids and offers in the manner described in the text.

Figure 3: The CIT Auction: PSR Submissions and the NOI

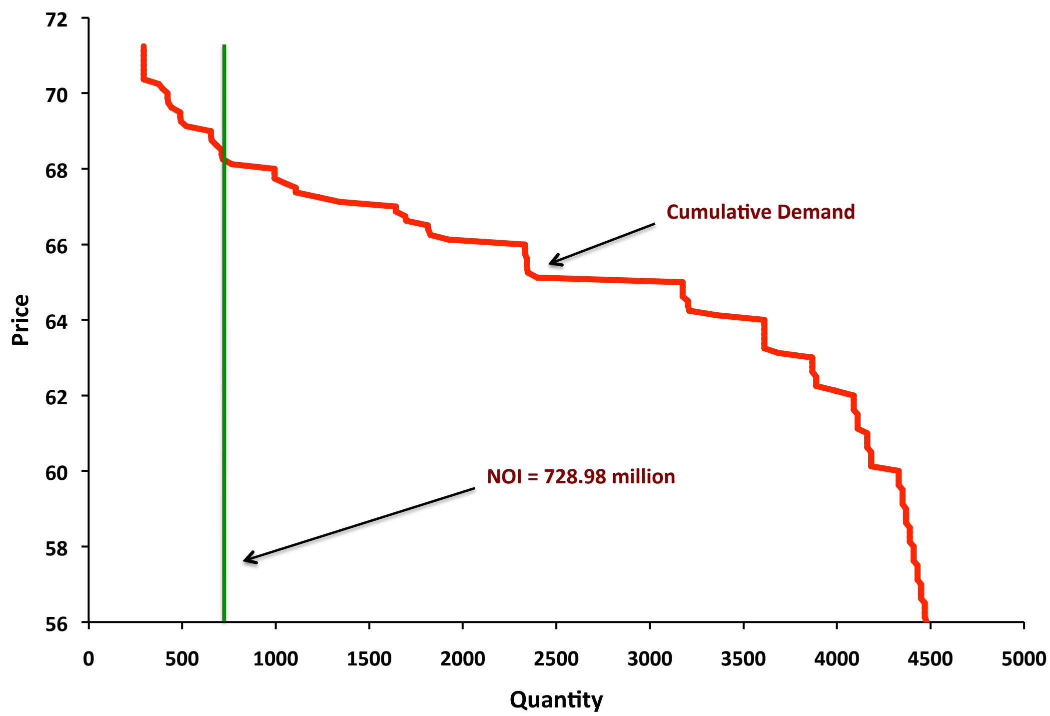
Dealer	Bid/Offer	Size
Banc of America Securities LLC	Offer	391.54
Barclays Bank PLC	Offer	74.618
Citigroup Global Markets Inc.	Offer	170
Credit Suisse International	Offer	152.352
Deutsche Bank AG	Offer	539
Goldman Sachs & Co.	Offer	80
HSBC Bank USA, National Association	Offer	3.018
Morgan Stanley & Co. Incorporated	Offer	0
The Royal Bank of Scotland PLC	Offer	104.195
BNP Paribas	Bid	107.096
J.P. Morgan Securities, Inc.	Bid	299
Nomura International PLC	Bid	141.603
UBS Securities LLC	Bid	238.044

Net Open Interest: $728.98 million to sell

Sum of Buy Physical Requests	$785.743m
Sum of Sell Physical Requests	$1,514.723m

This figure describes the physical settlement requests (PSRs) in the CIT auction and the resulting net open interest NOI. The NOI is obtained from the PSRs by aggregating the buy and sell orders separately and then netting them.

Figure 4: The CIT Auction: PSR Submissions and the NOI



This figure describes the cumulative demand curve in Stage 2 of the CIT auction. The cumulative demand curve is obtained by summing over the limit orders submitted in this stage of the auction. The NOI is also shown in the figure.

With this, Stage 1 of the auction is complete. If the calculated NOI at the end of Stage 1 is zero, then the IMM acts as the final price for cash settlement of all CDS trades, and the auction is concluded. If the NOI is non-zero, the auction moves to Stage 2.

Stage 2 of the Auction

In Stage 2, a uniform-price auction is held to fill the NOI. Since the NOI could be to buy or to sell, the auction has the unusual characteristic that the quantity auctioned in the second stage as well as whether that quantity is for sale or purchase (i.e., whether the second-stage auction is a "standard" or "reverse" auction) are endogenous consequences of Stage 1 behavior.

In Stage 2, dealers submit limit orders on behalf of themselves or their customers; there is no limitation on participation in this stage. In addition, the relevant side of the price submissions from Stage 1 are also carried forward into the second part of the auction as limit orders for the specified quotation amounts.

If sufficient limit order quantities are not received to fill the NOI, then the final price is set to zero if the NOI is to "sell," and to par if the NOI is to "buy." Otherwise, the auction's final price is determined from the limit orders as the price that fills the NOI, but with one additional constraint: If the NOI is to sell, then the final price cannot exceed the IMM plus the cap amount, while if the NOI is to buy, the final price cannot be less than the IMM minus the cap amount.

Figure 4 shows the cumulative demand curve in the second stage of the CIT auction that obtains in the obvious way by summing the submitted limit orders. Limit orders were submitted for prices ranging from 56 to 71.25, and the cumulative quantity demanded, summed over all prices, was a little under $4.50 billion, over 6 times the NOI of $728.98 million. The final price in the auction was 68.125.

Relation to Other Auction Forms

The credit-event auction format shares features in common with some other auction forms but is distinct from all of these, and is more complex than most. In contrast to the endogeneity of the CDS credit-event auction that was highlighted above, most auctions in practice (and in the academic literature) deal with a fixed quantity that is specified in advance as being for sale or purchase. The challenge is to design an auction format that optimizes the auctioneer's expected cash flows;[5] what makes this a non-trivial problem is asymmetric information, i.e., that the auctioneer does not know the bidders' private information concerning the value of the object being auctioned. There is no analog of this cash flow optimization objective in credit event auctions; rather, price-discovery and smooth CDS market settlement are the key goals.

Broadly speaking, there are two kinds of auctions to which CDS auctions bear some similarity: two-stage auctions and Treasury auctions. Two-stage auctions, studied in Ye (2007), are employed to sell complex and high-valued assets. Like CDS auctions, they have a first stage used to identify an indicative price, and a second round that identifies the definitive final price. However, the similarities end here. Two-stage auctions are commonly single-unit auctions with a single winning bidder; there are no first-stage quantity submission decisions to be made by the participants. More importantly, in two-stage auctions as currently used in practice, the only role of the first-stage bids is to restrict participation in the second round to those submitting the highest first-stage bids; the bid has no other payoff consequence.

Auctions of Treasury securities worldwide resemble the second stage of credit-event auctions with a sell-NOI: in both cases, there is a given quantity being auctioned, bidders submit limit orders, and the final price is determined by matching the aggregate demand curve to the available supply. Treasury auctions worldwide have been widely studied in the literature; see, e.g., Nyborg and Sundaresan (1996) on US auctions; Nyborg, Rydqvist, and Sundaresan (2002) on Swedish auctions; Keloharju, Nyborg, and Rydqvist (2005) on Finnish auctions; and Hortacsu or

[5]That is, maximizes the expected revenues for a "sell" or standard auction, and minimizes expected cash outflow for a "buy" or reverse auction.

MacAdams (2010) on Turkish auctions.

The Literature on Credit-Event Auctions

There are, as far as we know, only four other papers on credit-event auctions. Two of them, Helwege, et al (2009) and Coudert and Gex (2010) are empirical studies. Helwege, et al, looks at empirical features of credit-event auctions up to March 2009, including a comparison of the auction final price to the market prices on the day of and the day after the auction. A portion of our analysis in Section 4 is based on similar questions, but our analysis has the benefit of more data and is carried out in greater detail. Coudert and Gex examine the performance of the auction process in individual cases including Lehman Brothers, Fannie Mae and Freddie Mac. Their focus is on the functioning of the market in stressful times; they also provide some documentation of the bounce in prices after the auction date compared to the auction's final price.

The other two papers, Du and Zhu (2011) and Chernov, Gorbenko, and Makarov (2011) are primarily theoretical models of CDS auctions. The models are developed in the spirit of Wilson (1979): there is no asymmetric information, and the post-auction bond value is taken to be common knowledge. Thus, the typical concerns of the auction literature—price discovery, information generation in the auction, the winner's curse—are not the focus. Rather, the question is how strategic behavior could cause the auction-determined price to deviate from this exogenously-specified "true" price solely on account of monopsonistic behavior.

Taking first stage outcomes as given, Du-Zhu describe a model of the second stage of the auction. They show that the model has equilibria in which prices are systematically biased, with sell-auctions resulting in prices that are too high (relative to fair value) and buy-auctions in prices that are too low. (Taking sell-auctions as the reference point, we will refer to these as "overpricing" equilibria. As we shall see in Section 4, empirical data exhibits exactly the opposite pattern to this prediction, namely that of *under*pricing.) Chernov, Gorbenko and Makarov derive subgame-perfect equilibria of a full two-stage game. They show that both overpricing and underpricing equilibria are possible, with the conditions under which the latter obtain depending on the size of dealers' net CDS positions entering the second stage relative to the NOI.

3 The Data and Descriptive Statistics

Our auction data comes from `http://www.creditfixings.com`, a website run by Creditex, one of the two co-adminstrators of the credit-event auctions. The site provides considerable detail on each auction including (a) whether auction is an LCDS (Loan CDS) or CDS auction, and in the latter case, whether the underlying deliverable instruments are senior or subordinated; (b) the list of deliverable instruments in each auction identified by their ISINs, (c) the list of participating dealers, (d) the prices and PSRs submitted by each dealer (identified by name) in Stage 1 of the auction, (e) each limit order (price and quantity) submitted by each dealer in Stage 2 of the auction, (f) whether and what penalties were levied on the dealers, and (g) information on the auction's IMM, NOI, and final price.

Table 1 describes the auction types and the names involved in the auctions. There were a total of 76 auctions over the period 2008-10,[6] the bulk of them (51) in 2009. Of these, 54 were CDS auctions and 22 were LCDS auctions. Our analysis in this paper focuses only on the CDS auctions. Table 1 provides a list of the underlying firms in these auctions. (Six firm names appear twice because there were separate auctions for their senior and subordinated bonds.)

Descriptive statistics on deliverable bonds and participation in CDS auctions are presented in Table 2. Panel A provides summary statistics on the deliverable bonds. On average, there were 30+ deliverable bonds per auction, but with huge variation, ranging from a single deliverable bond (in 5 different auctions) to a high of 298 deliverables (the CIT auction). The median number was 5.5, with 6 auctions (all financial firms) having more than 100 deliverable bonds.

Panels B-D of Table 2 deal with dealer participation in the auction. 12-13 dealers participated in each auction, with the numbers remaining stable over time. Around 75% of all auctions had an NOI to "sell" at the end of Stage 1, and 25% had an NOI to "buy," with the split again remaining roughly stable over time. Dealer participation was roughly the same regardless of whether the auction turned out to have a buy NOI or a sell NOI, but, as as Panel D shows, the number of limit orders submitted in the second round was significantly higher for sell-NOI auctions compared to buy-NOI auctions. The aggregate quantity demanded in Stage 2 (summed over all prices) vastly exceeded NOI in every auction, although there were often huge bids submitted at very low prices; Figure 5 illustrates with the Lehman auction: the NOI was $4.92 billion.

Panel C of Table 2 describes the penalties (adjustment amounts) for off-market first-round price submissions. On average, 1.2 firms got penalized in each auction, with a minimum of zero and a maximum of 5. Several dealers suffered multiple penalties, with HSBC leading the list with 8 penalties over the three-year span.

Where our analysis only concerns behavior within the auction, we use data from all 48 auctions involving non-subordinated bonds. Where we also use market prices of the deliverable bonds (e.g., in the analysis of price discovery in Section 4), we use market price data from TRACE. We look mainly at a horizon of 5 trading days before the auction to 5 trading days after the auction. Market price data is available (i.e., at least one deliverable bond is traded over this horizon) for 27 of the auctions; the names appear in boldface in Panel B of Table 1. The remaining auctions have deliverables such as trust-issued securities or euro-denominated covered bonds on which TRACE had no information. Twenty-two of the 27 auctions meet the stronger criterion that there is at least one trade in a deliverable bond (possibly a different deliverable bond on each day) on each of the 10 trading days in our horizon; four of these are "buy" auctions (i.e., have a

[6]There were only three auctions in 2006 and a single one in 2007. Since the format of the auction was changed in late-2006, we focus our analysis on the period 2008-10.

Table 1: CDS Auctions 2008-10: List of Firms

Panel A of this table lists the auction types (CDS and LCDS) that were conducted over the period 2008-10. Panel B lists the underlying firms for the CDS auctions. The data was collected from the Creditex website, http://www.creditfixings.com. The bold-faced names in the list represent those firms on whose deliverable bonds trading data is available on TRACE, as explained in the text.

Panel A: Types of Auctions

Year	Number of Auctions	CDS Auctions	Of which Subordinated	LoanCDS Auctions
2007	1			1
2008	16	14	5	2
2009	51	32	1	19
2010	9	8		1
Total	77	54	6	23

Panel B: Underlying Names in the CDS Auctions

Abitibi	Freddie Mac Subordinated	**Millenium**
Aiful	**General Motors CDS**	NJSC Naftogaz of Ukraine
Ambac Assurance	Glitnir Banki hf. Senior	**Nortel Corp**
Ambac Financial	Glitnir Banki hf. Subordinated	**Nortel Ltd.**
Bowater	**Great Lakes**	**Quebecor**
Bradford & Bingley Senior	Hellas	**R. H. Donnelley**
Bradford & Bingley Subordinated	**Idearc CDS**	**Rouse**
CIT	JSC Alliance Bank	**Six Flags CDS**
Capmark	JSC BTA	**Smurfit-Stone CDS**
Cemex	Japan Airlines Corporation	**Station Casinos**
Charter Communications CDS	Kaupthing banki hf. Senior	Syncora
Chemtura	Kaupthing banki hf. Subordinated	TakeFuji Corp
Ecuador	Landsbanki Íslands hf Senior	Tembec
Equistar	Landsbanki Íslands hf Subordinated	Thomson 2.5-year maturity bucket
FGIC	**Lear Corp CDS**	**Tribune CDS**
Fannie Mae Senior	**Lehman Brothers**	Truvo
Fannie Mae Subordinated	**Lyondell CDS**	**Visteon CDS**
Freddie Mac Senior	LyondellBasell	**Washington Mutual**

Table 2: CDS Auctions 2008-10: Descriptive Statistics

This table describes summary statistics on CDS auctions between 2008 and 2010, such as the number of bidders per auction, the number of bids per auction in each round, etc. The data was collected from Creditex via the auction-by-auction details posted on their website http://www.creditfixings.com. "Number of Firms" refers to the number of underlying firms on whom CDS contracts had been written that were settled by the auctions. The "Number of Auctions" exceeds the "Number of Firms" because some firms had more than one auction (one to settle CDS on their senior debt and one to settle CDS on their subordinated debt). The information pertains only to CDS auctions, not LCDS auctions.

Panel A: Deliverable Bonds in CDS Auctions 2008-10

Deliverable Bonds		No. of Auctions with	
Average per Auction	30.5	1 Deliverable Bond	5
Median	5.5	≤ 5 Deliverables	27
Highest	298	> 10 Deliverables	17
Lowest	1	> 30 Deliverables	12
		> 100 Deliverables	6

Panel B: Participation in Stage 1 of the Auctions

Year	Number of Firms	Number of Auctions	Average No. of Dealers	No. of Auctions with "Sell" NOI	% of Auctions with "Sell" NOI	Average No. of Dealers in Auctions with "Sell" NOI	Average No. of Dealers in Auctions with "Buy" NOI
2008	9	14	13	10	71.4%	13	13
2009	31	32	12	25	78.1%	12	12
2010	8	8	14	6	75.0%	14	13
Overall	48	54	13	41	75.9%	13	12

Panel C: Penalties after Stage 1

Year	Firms Penalized Per Auction: Average	Maximum	Minimum	Total No. of Penalties	Dealers Penalized Most Often	No. of Penalties
2008	1.43	4	0	20	HSBC & Morgan Stanley	5 each
2009	1.22	5	0	39	Citi, JPMorgan & UBS	6 each
2010	1.13	2	0	9	Barclays & Credit Suisse	2 each
Overall	1.26	5	0	68	HSBC	8

Panel D: Participation in Stage 2 of the Auctions

Year	Number of Firms	Number of Auctions	Avg No. of Round 2 Bids	No. of Auctions with "Sell" NOI	Average No. of Bids in Auctions with "Sell" NOI	Average No. of Bids in Auctions with "Buy" NOI
2008	9	14	68	10	87	21
2009	31	32	57	25	60	47
2010	8	8	73	6	84	43
Overall	48	54	62	41	70	38

Table 3: CDS Auctions 2008-10: Trading in Deliverable Bonds

This table describes summary statistics on trading in the deliverable bonds of the CDS auctions described in Table 1. The numbers pertain to only the 27 auctions for which data on trading in the deliverable bonds is available, as explained in the text. The data comes from TRACE. In Panel B, "Large Trades" refers to $1 million+ trades. In Panel C, Day A-1 refers to the day before the auction; "Normalized NOI" refers to the ratio of the NOI to the Day A-1 Trading Volume; and three outliers are excluded from the computations as noted below the table.

Panel A: Frequency of Trades in the Deliverable Bonds

	No. of Trades in the Deliverable Bonds in the			
	5 Days Before the Auction	1 Day Before the Auction	1 Day After the Auction	5 Days After the Auction
Average	73	87	157	94
Median	8	11	37	20
Maximum	1,393	1,393	3,103	3,103

Panel B: Frequency of Large Trades in the Deliverable Bonds

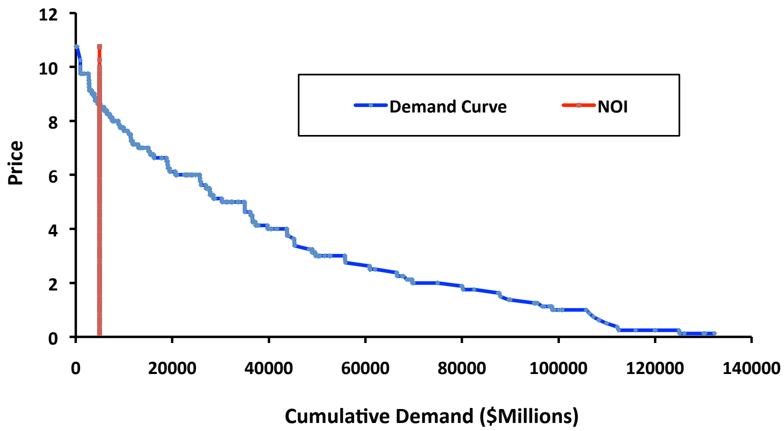
	No. of $1 million+ Trades in the Deliverable Bonds in the			
	5 Days Before the Auction	1 Day Before the Auction	1 Day After the Auction	5 Days After the Auction
Average	9	11	27	18
Median	2	2	20	8
Maximum	111	93	174	226

Panel C: NOI and Bond Trading Volumes

	Volume Figures in $ Millions		
	Trading Vol: Day A-1	**Net Open Interest**	**Normalized NOI**
Mean	71.7	505.7	11.7
Median	25.3	151.6	7.8
Quartile 1	9.4	84.3	2.6
Quartile 3	70.3	438.2	17.9
Maximum	487.3	4,920.0	38.7
Minimum	5.0	8.6	0.7

Note: Three outliers (Bowater, RH Donnelley, and Tribune with Normalized NOIs of 2934, 187, and 67, respectively) are excluded in the computations.

Figure 5: The Lehman Second-Stage Demand Curve



This figure describes the aggregate demand curve submitted in Stage 2 of the Lehman credit-event auction. The aggregate demand curve is obtained by summing over all submitted limit orders. The red vertical line represents the NOI, which was $4,920 million.

NOI to buy) and the remaining are "sell" auctions.

Summary statistics on the frequency and size of trades are presented in Table 3. Panels A and B deal respectively with the total number of trades and the number of "large" trades (i.e., trades over $1 million. TRACE provides the dollar-size of all trades under $1 million, but trades over that amount are simply reported as $1 million+ trades). Panel A shows that trading volume creeps up before the auction, and then increases sharply on the day after the auction. While trade moderates somewhat after that, the number of trades remains far higher than in the days before the auction. Panel B shows a similar trend for large trades. Finally, Panel C relates the size of the auction (the NOI) to the trading volume one day before the auction. As the numbers show, the former is typically an order of magnitude larger with the mean (resp. median) of the NOI-to-trading-volume ratio being 11.7 (resp. 7.8).

4 Price Discovery in the Auction

In this section, we examine the importance of auction-generated information to post-auction trading. The principal question that concerns us here is: How good is the auction at price discovery? For example, is there information in the auction's final price for subsequent trading of the deliverable bonds? Is there any more information than was already present in the pre-auction prices? How does the other auction-generated information—PSRs, NOI, second-stage limit orders—affect post-auction behavior? We use data on market prices and traded quantities for the deliverable bonds in the 27 boldfaced auctions of Table 1 to study these questions.

Identifying a Representative Market Price

As a first step, we need to identify from the market prices a candidate price for the deliverable instrument on each day in the horizon using the traded market prices of the deliverable instruments. We begin by eliminating the data points in TRACE that are clearly erroneous (e.g., some Lehman trades report a trade price of $100 even while most trades took place in a neighborhood of $10-$20, and the auction final price was $8.625). A second, more subtle concern shows up in the cleansed data set: For some companies, certain issues of deliverable bonds have trade prices that are systematically and sharply different from other issues. An example is Charter Communications, whose auction-determined final price was $2.375. Of the 19 deliverable obligations for Charter, two (both of which were issued by Charter's parent company but were deliverable into the auction) traded at pre-auction market prices of $9-$10, while all the other deliverables traded at prices around $2-$3. This suggests the existence of issue-specific influences on the prices.

There are two approaches we use to extract a "representative" market price from the data given this problem. The first is manual: we eyeball the data, and remove all those deliverable issues whose prices exhibit egregious and systematic differences (e.g., the Charter tickers mentioned above) from other deliverables on the same name. This eliminates 6 of the 512 deliverables over all the auctions combined.[7] Using the remaining data, we calculate on each given day the average of the traded prices over all the deliverable bonds on that day, and treat this as the representative price for the bond on that day. (We weight the average by trade size, but our results are unchanged if we use an equally-weighted average.)[8]

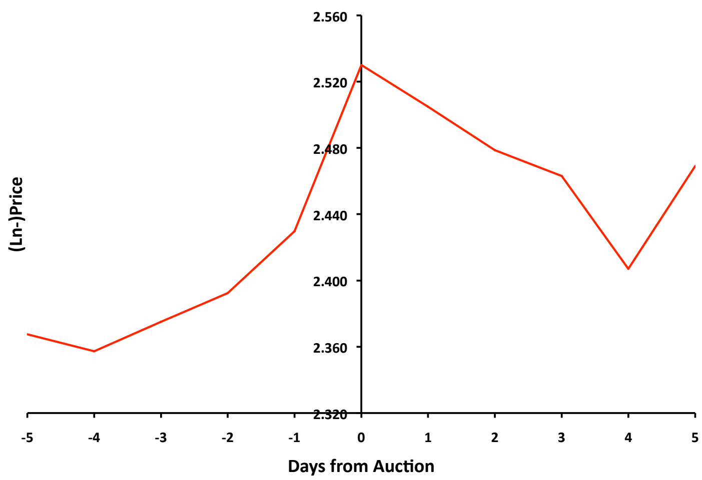
Although only a small handful of bonds are eliminated by the first approach, some of these trade quite heavily on some days. Our second approach looks to use all the data and acts as a check on the first approach. It accommodates the possibility of systematic or persistent differences in the prices of different deliverable bonds on a given name, and distinguishes between the fundamental or "pure" price and the issue-specific effect. To identify the pure bond price in the presence of these effects, we run the following set of regressions on each day: letting i index the CDS underlying name, and j the deliverable bonds on that name, we estimate

$$p_{ijk} \;=\; \bar{p}_i + u_{ij} + \epsilon_{ijk}, \tag{1}$$

[7]That is, over all the 27 auctions on which we have traded bond prices. Note that the average number of deliverables in these auctions is $512/27 \approx 19$, less than the average of 30.5 in all auctions (Table 2).

[8]Since there are several deliverable bonds in a given auction, there is an implicit "cheapest-to-deliver" option that should perhaps be taken into account in computing the comparison market price. In general, using an average price over all deliverables may overstate the comparison market price. Our eyeballing of data and throwing out the bonds with systematically and egregiously higher prices is meant to address this issue too. Our second approach implicitly achieves the same objective by removing "issue-specific" price effects. As noted below, the two approaches yield very similar prices and analytical results.

Figure 6: General Motors: Prices Pre- and Post-Auction



This figure presents the average (log-)price of the deliverable instruments in General Motors auction for 5 trading days before and after the auction date. Day-0 is date of the auction and the day-0 price is the auction's final price.

where p_{ijk} is the log of the observed price for the k-th trade in the j-th deliverable bond in auction i (or "name" i).[9] In words, (1) the bond price is the sum of three components: a "pure" price $\bar{p}_i$, an obligation-specific term u_{ij} which is meant to capture systemic or persistent pricing biases, and a "trading noise" term ϵ_{ijk}. The quantity $\bar{p}_i$ is then taken to be the (log of the) market price of name i on that particular day; we refer to it as the "estimated price."

Importantly, the levels of the prices estimated under the two methods are very close, and, in many cases, almost identical. The results are independent of the approach used.

Preliminary Evidence: The Price Patterns

Using either approach to estimate a representative price, the raw data suggests that, on average, market prices both before and after the auction differ significantly from the auction's final price. As shown in Figure 1 in the Introduction, in sell-auctions (those with a sell-NOI), the average price is sharply higher on either side of the auction date than the auction price. The average (log-)price in the figure is calculated by taking the average of the estimated prices $\bar{p}_i$ obtained in the second approach above; exactly the same shape obtains if we use the weighted-average price instead. Nor is the pattern caused by a few outliers—most individual sell-auctions exhibit this V-shaped pattern around the auction day. While we have only four buy-auctions in this sample (Cemex, General Motors, Six Flags and Station Casino), three of them display broadly

[9] We are grateful to Joel Hasbrouck for suggesting this approach.

the opposite pattern; Figure 6 describes the behavior of General Motors' prices.

Econometric Analysis

Figures 1 and 6 suggest that the auction may not be doing an efficient job at price discovery. To delve deeper into this question, we ask: Is there information in the auction prices that is important for post-auction market prices of the bonds, more information than there was in the pre-auction market prices? Tables 4 and 5 provide an answer using regression analysis. The first table uses the (weighted-)average price calculated from the data, while the second table uses the estimated prices obtained using (1).

Table 4 takes as the dependent variable the "return"

$$\frac{P_i^{\text{Post}}}{P_i^{\text{Pre}}} \tag{2}$$

where the numerator and denominator represent, respectively, the average price of name i on the first trading day after the auction and the last trading day before the auction. The independent variables considered in the regressions include (a) pre-auction market information such as volume of trading and the variability of prices on the day before the auction; and (b) auction-generated public information such as the auction final price (normalized by P_i^{Pre}), the total PSRs, the variability in PSR requests, the NOI normalized by the daily trading volume, etc. (For full definitions of all the right-hand side variables in this and succeeding regressions, see Appendix A.)

The table reports the results of five regressions. Column 1 uses solely the pre-auction market variables as independent variables. Column 2 adds to this the final price as an independent variable. Column 3 uses all the variables—pre-auction market and auction-generated. Column 4 uses only the auction-generated information. Column 5 uses only the auction-generated information but leaves out the final price.

The results are striking. The pre-auction market variables have no explanatory power; they are never significant in any specification, and by themselves produce an adjusted R^2 of effectively zero. The single most important explanatory variable—and the only one that is significant across the board—is the auction final price. Adding it alone to the pre-auction market information raises the adjusted R^2 to 74%; while excluding it, and including all other auction-generated information again produces an adjusted R^2 of effectively zero.

Table 5 presents the results of a similar analysis carried out using the estimates $\bar{p}_i$ derived from the regressions (1). The dependent variable in this case is the analog of (2), namely

$$\bar{p}_i^{\text{Post}} - \bar{p}_i^{\text{Pre}}, \tag{3}$$

Table 4: Price Discovery: Regression Analysis I

This table presents the results of regression analysis for several specifications of the dependent variables. In all cases, the independent variable is the "return" defined by $P_i^{\text{Post}}/P_i^{\text{Pre}}$, where the numerator is the average price on the day after Auction i and the denominator is the average price on the day before. The independent variables include subsets of pre-auction market information (the level of the average price, the variance of price trades, the one-day "return" in average prices, the dollar quantity traded, and the number of trades) and information revealed in the auction (the normalized final price, the volume of PSRs and variance in PSR requests, the NOI and the NOI normalized by daily trading volume, etc). Standard errors appear in parenthesis. As usual, we use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	Spec 1	**Spec 2**	**Spec 3**	**Spec 4**	**Spec 5**
Intercept	0.077	-0.389	0.047	0.22	0.92 ***
	(0.81)	(0.40)	(0.47)	(0.14)	(0.10)
AvgPrice_Pre	0.0024	0.00087	0.00078		
	(0.002)	'(0.0010)	(0.0012)		
Var_1Day_Pre	2.2	6.72	7.31 *		
	(3.66)	(1.9)	(3.73)		
Ret_1day_Pre	0.69	0.62	0.062		
	(0.75)	(0.36)	(0.49)		
AvgQty_Pre	3.45E-08	-4.26E-09	-1.84E-08		
	(2.69e-08)	(1.45e-08)	(1.76e-08)		
Trades_Pre	0.000054	-0.000016	0.000063		
	(0.00014)	(0.000069	(0.000092)		
FinalPriceNorm		0.74 ***	0.87 ***	0.79 ***	
		(0.12)	(0.20)	(0.14)	
Total_PhySett			-0.00015	-0.000087	-0.00011
			(0.00011)	(0.000088)	(0.00016)
Var_PhySett			4.43E-06	4.35E-06	3.94E-06
			(3.76e-06)	(2.94e-06)	5.39e-06)
OpenIntAmtNorm			0.0038	0.005 **	-0.0029
			(0.0025)	(0.0021)	(0.003)
OIDummy			-0.0075	0.003	0.13
			(0.069)	(0.061)	(0.10)
RecessionDummy			0.086	0.031	0.065
			(0.083)	(0.049)	(0.09)
FracFilledCarryOver			0.14	0.068	0.03
			(0.15)	(0.13)	(0.24)
No of obs	18	18	18	20	20
R-sq	0.21	0.83	0.93	0.81	0.3
Adj R-sq	-0.12	0.74	0.75	0.69	-0.0137

Table 5: Price Discovery: Regression Analysis II

This table presents the results of regression analysis for several specifications of the dependent variables. In all cases, the independent variable is the "return" defined by $\bar{p}_i^{\text{Post}}/\bar{p}_i^{\text{Pre}}$, where the numerator is the quantity identified by running the regression (1) on the deliverable bonds of Auction i the day after the auction, and the denominator is the quantity identified by running the same regression on the day before the auction. The independent variables include subsets of pre-auction market information (the level of the average price, the variance of price trades, the one-day "return" in average prices, the dollar quantity traded, and the number of trades) and information revealed in the auction (the normalized final price, the volume of PSRs and variance in PSR requests, the NOI and the NOI normalized by daily trading volume, etc). Standard errors appear in parenthesis. As usual, we use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
Intercept	-0.3522 **	-0.01848	-0.1644	-0.02911	-0.10197
	(0.1254)	(0.08757)	(0.1798)	(0.09462)	(0.14005)
EstPrices_Pre	0.00317	-0.000056	0.00059		
	(0.00228)	(0.0014)	(0.0019)		
Var_1day_Pre_EstP	3.403	3.26819 ***	3.2566 **		
	(2.0347)	(1.1284)	(1.4035)		
Trades_Pre	0.000126	0.000026	0.0001		
	(0.00018)	(0.00001)	(0.00015)		
AvgQty_Pre	4.456E-08	3.31E-09	-1.982E-10		
	3.169E-08	1.876E-08	2.557E-08		
LogFinalPriceNorm		0.5186 ***	0.4577 ***	0.47069 ***	
		(0.0827)	(0.1143)	(0.1025)	
Total_PhySett			-0.000034	-0.00003	-0.000055
			(0.00017)	(0.00014)	(0.00022)
Var_PhySett			0.000001	0.000002	0.000003
			(0.000005)	(0.000005)	(0.000007)
OpenIntAmtNorm			0.00099	-0.00043	-0.0094
			(0.0083)	(0.0078)	(0.01136)
RecessionDummy			0.12404	0.0508	0.00924
			(0.1339)	(0.0828)	(0.1235)
OIDummy			0.1042	0.057	0.2459 *
			(0.1008)	(0.09476)	(0.1282)
FracFilledCarryOver			-0.01787	-0.04809	-0.2099
			(0.1452)	(0.1403)	(0.2040)
No of obs	22	22	22	23	23
R-sq	0.24	0.78	0.81	0.69	0.26
Adj R-sq	0.06	0.71	0.61	0.55	0

where $\bar{p}_i^{\text{Post}}$ and $\bar{p}_i^{\text{Pre}}$ are the estimates of $\bar{p}_i$ derived one day after and one day before the auction, respectively. The right-hand side variables again include several pre-auction market price and quantity variables, and auction-generated information. The key component of the latter, the analog of the normalized final price in the first regression, is the quantity

$$\ln(P_i^{\text{Auc}}) - \bar{p}_i^{\text{Pre}}, \tag{4}$$

where P_i^{Auc} is just the final price determined in auction i.

Once again, the results are striking, and strongly back the findings in Table 4 on the relevance especially of the auction-generated final price. When no auction-generated information is included in the regression (Column 1), the regression has no explanatory power; none of the pre-auction variables are significant and the adjusted R^2 is a bit under 6%. Adding the normalized final price (4) alone to the right-hand side variables increases the adjusted R^2 to 71%, with the newly added variable being highly significant. The normalized final price is, indeed, the only variable to be significant across the board, and in the presence of both market and auction-generated variables.

In summary, the evidence is strong that auction prices are biased but informative. What then could be the source of the observed biases? We turn to an examination of this question.

5 Behavior in the Auction

An immediate suspect for the observed underpricing is, as noted in the Introduction, the presence of a "winner's curse" effect, which should cause participants to bid more conservatively. In Section 5.1, we gauge the impact of the winner's curse on bidding behavior and auction outcomes.

Section 5.2 then turns to an examination of other aspects of bidding behavior. We begin with the effect of a second factor that the theoretical literature has suggested could potentially lead to underpricing: *strategic* behavior by participants, i.e., the exercise of market power. Then, we highlight a number of other interesting aspects of the auction including including the impact of the winner's curse on liquidity provision in the auction; the behavior of market price volatilities pre- and post-auction; and the behavior of market prices on the day of auction. Appendix B supplements this presentation with a study of the learning dynamics *within* auctions.

5.1 The Winner's Curse, Bid Shading, and Auction Underpricing

The winner's curse is a function of how dispersed is the information entering the auction. We proxy its intensity using the variance of the first-round price submissions made by dealers. The justification is obvious: to the extent that these submissions are based on a dealer's information concerning the fair price of the good being auctioned, a more disperse set of first-round submissions implies a more dispersed information set, and so a more severe winner's curse.

Table 6: Bid-Shading and the Winner's Curse

This table presents the results of regressing the degree of bid-shading on the variance of Round 1 bids (a proxy for the winner's curse) and a measure of illiquidity.

	Spec 1		**Spec 2**		**Spec 3**	
Intercept	0.0821		-0.0024		0.0399	
	(0.0718)		(0.0787)		(0.0700)	
Var_Rnd1Bid_Norm			3.0197	***	1.2933	***
			(0.2731)		(0.3616)	
Dealer_PSR_Norm	0.0673		0.0955		0.0774	
	(0.1780)		(0.1933)		(0.1713)	
Recession_Dummy	0.2029	***	0.1299		0.1505	**
	(0.0773)		(0.0855)		(0.0759)	
OpenInterest_Norm	0.0246	***			0.0174	***
	(0.0019)				(0.0027)	
Nobs	151		151		151	
R-Square	0.57		0.49		0.6	
Adj R-Square	0.55		0.47		0.59	

We first examine if an increase in this proxy causes bidders to behave more conservatively, specifically, if it increases *bid-shading* by participants. Bid-shading is an idea introduced in Nyborg, Rydqvist, and Sundaresan (2002). The degree of bid-shading by a participant is given by

$$1 - \frac{\text{average submitted price}}{\text{post-auction market price}}$$

where the numerator refers to the quantity-weighted average price submitted by that participant in Round 2 of the auction, and the denominator is the market price one day after the auction.

Table 6 describes the results from regressing the degree of bid-shading on the winner's curse proxy (normalized by the final price). Importantly, since auction volumes are sometimes substantially larger than daily traded volumes, we include the NOI normalized by the average daily-traded volume as a control. In the presence of secondary market illiquidity, we would expect an increase in the normalized NOI to increase bid shading and auction mispricing.[10]

The table shows that the winner's curse has a large impact on bidder behavior in the expected direction. The proxy is strongly statistically significant. Importantly, it is also strongly

[10]The use of additional volume-related control variables did not substantially alter the statistical or economic significance of these key variables, nor did including an explicit measure of secondary-market illiquidity computed via the Amihud (2002) approach.

Table 7: The Drivers of Underpricing

This table presents the results of regressing the degree of underpricing in sell-auctions on the variance of Round 1 bids (a winner's curse proxy) and a measure of illiquidity. The dependent variable in all cases is the ratio of the auction final price to the market price one day after the auction.

	Spec 1		Spec 2		Spec 3	
Intercept	0.9534	***	0.9896	***	0.9937	***
	(0.1135)		(0.0958)		(0.0982)	
Var_Rnd1Bid_Norm			-1.1296	***	-1.3378	***
			(0.3712)		(0.5223)	
Recession_Dummy	-0.0110		0.0482		0.0503	
	(0.1259)		(0.1076)		(0.1101)	
OpenInterest_Norm	-0.0047				-0.0022995	
	(0.0034)				(0.0040)	
Nobs	18		18		18	
R-Square	0.11		0.39		0.4	
Adj R-Square	0.0009		0.3		0.27	

economically significant: The standard deviation of the normalized variance of Round 1 bids in the data is 0.114, so, using the coefficient in Specification 3, a one standard-deviation increase in the winner's curse proxy increases the degree of bid-shading by roughly 1.2933×0.114 or about 14.7%.

The normalized NOI too has a positive coefficient and is strongly statistically significant with a positive coefficient. This is as expected. It is also economically significant—the standard deviation of the normalized NOI is about 6.6, so a one standard deviation move in the variable causes bid-shading of an additional $6.6 \times 0.0174 = 11.4\%$.

If fear of the winner's curse causes participants to bid more conservatively, is this also reflected in the auction underpricing? Table 7 shows this is indeed the case. The regressions in the table take as the dependent variable the degree of underpricing (the ratio of the auction final price to the post-auction market price). The winner's curse proxy is strongly statistically significant across across the board in explaining underpricing. It is also strongly economically significant: Using the coefficient in Specification 2 for illustration, a one-standard deviation move in the normalized variance of Round 1 bids causes underpricing to increase by 1.1296×0.114 or about 13%. However, while normalized NOI has the right sign in this case, it is, unlike Table 6, statistically insignificant here, perhaps because of the low number of observations.

Table 8: The Impact of Strategic Considerations

This table presents the results of a two-stage estimation of the effect of the slope of the aggregate demand curve facing a dealer (i.e., the slope of the sum of all the other dealers' demand curves) on the slope of responding dealer's submitted demand curve. In the first stage of the estimation process, we instrument the slope of the aggregate demand curve, and in the second stage estimate the desired impact. Further details may be found in the text.

First Stage		
Dependent Variable: Avg_CompSlope		
Intercept	-2.2417	**
	(1.0232)	
Var_CompPhysSett	8.95E-06	***
	(2.97E-06)	
Var_Rnd1Bid	0.9997	
	(0.727)	
OpenInt_Norm	-0.0500	
	(0.0862)	
Var_1DayPre	-1.0382	***
	(0.3965)	
No of Obs	92	
R-sq	26.25	
Adj R-sq	22.85	
F	4.04	
Prob > F	0.005	

Second State		
Dependent Variable: DealerSlope		
Intercept	7.2844	***
	(2.2608)	
Avg_CompSlope	1.8586	**
	(0.8580)	
Var_Rnd1Bid	-16.6123	***
	(4.6125)	
OpenInt_Norm	0.0645	
	(0.2401)	
No of Obs	92	
R-sq	10.27	
Test of Endogeneity		
Ho: variables are exogenous		
GMM C Statistic chi^2(1): 3.0354		
(p = 0.0815)		

5.2 Other Aspects of Auction Behavior

This section examines several other aspects of auction outcomes. We begin with a look at the impact of strategic behavior on auction outcomes. Then, we move on to an examination of liquidity provision in the auction and the role played by the winner's curse here. Thirdly, we look at the behavior of market *volatilities* pre- and post-auction, and highlight an apparent puzzle. Finally, we examine the behavior of market prices *on* the auction day. Appendix B supplements this material by pointing to some interesting aspects of *within*-auction learning dynamics.

Liquidity and Strategic Considerations

Wilson (1979) and Back and Zender (1993) suggest that "strategic" behavior by bidders (the exercise of monopsonistic market power) may result in underpricing in divisible-good auctions. A fundamental insight in their approach is that the marginal cost curve facing a bidder in a uniform-price auction is *endogenous*; it is determined by the residual supply curve after subtracting the total demand curve of the other bidders. Using this insight, Wilson and Back-Zender construct equilibria in their respective models in which the submission of steep demand curves by the remaining bidders leads the last bidder to respond also with a steep demand curve. The consequence is underpricing in equilibrium.[11]

Motivated by the Wilson/Back-Zender arguments, we examine how the slope of the submitted demand curve for one dealer reacts to an increase in the slopes of the others' aggregate curve. Since the slopes are jointly determined in equilibrium, there is an endogeneity problem that must be addressed. We apply a two-stage estimation process where in the first stage we estimate the average of the competitors' slopes as a function of the variance of Round 1 price submissions and the variance of the competitors' physical settlement requests. The first of these variables is included to control for asymmetric information. The second variable, the variance of competitors' PSRs, is an instrument for the average competitors' slope. The choice of instrument need meet two conditions: that it affect the competitor's slope and that it not affect the dealer's own slope. PSRs, which represent customer orders, provide dealers with information, so affect their aggressiveness and the slope of the submitted demand curve. The variance of the competitors' PSRs is based on each competitor's PSR and hence should affect the competitor's slopes. However it should not affect the dealer's own slope.

Table 8 presents the findings. In line with the Wilson/Back-Zender hypothesis, the coefficients of the second-stage regression show that an increase in the competitor's average slope leads to a sharp increase in the dealer's own submitted slope. The choice of instrument is also backed (albeit, with a p-value of 0.08, somewhat weakly).

[11] The Wilson/Back-Zender models have no asymmetric information, so the "true" price of the good being auctioned is common knowledge. "Underpricing" means that the equilibrium price is lower than this true price.

Table 9: Liquidity Provision and the Winner's Curse

This table presents the results of regressing the slope of the submitted demand curves on a proxy for the winner's curse (the variance of Round 1 bids), a measure of illiquidity, and other control variables.

	Spec 1		**Spec 2**		**Spec 3**	
Intercept	-21.0913	***	-4.9514		-6.2938	
	(8.1791)		(7.9132)		(7.9653)	
Var_Rnd1Bid			-15.9468	***	-15.0488	***
			(2.6802)		(2.7648)	
Recession_Dummy	-6.00E+00		0.0386		-1.7891	
	(8.98E+00)		(8.1506)		(8.2573)	
OpenInterest_Norm	5.50E-01	**			0.2649	
	(2.19E-01)				(0.2068)	
Nobs	151		151		151	
R-Square	0.04		0.19		0.2	
Adj R-Square	0.02		0.18		0.18	

Liquidity Provision and the Winner's Curse

We measure the liquidity provision of a dealer in the auction by the average slope of the dealer's submitted demand curve. (To calculate the average slope, we compute the slope between successive price-quantity pairs in the submitted demand curve, and take the arithmetic average of these slopes.) A steeper demand curve implies a greater price change for a given quantity change, so implies a lower degree of liquidity provision.

Table 9 looks at the impact of several variables, including notably, secondary market illiquidity and the winner's curse proxy, on the slope of the demand curve submitted by a participant. Intuitively, as the anticipated winner's curse or market illiquidity increase, a steeper demand curve should result. The numbers show strong support for this behavior. The winner's curse proxy is strongly statistically significant. It is also strongly economically significant: a one standard-deviation increase in the value of the proxy (about 1.12) changes the slope by $(-15.05 \times 1.12) = -16.8$, which is over 70% of the average demand curve slope in our entire sample of about -23.

A Puzzle: The Behavior of Volatilities

As an indirect test of the auction's price discovery, we can examine how price *volatility* behaves before and after the auction. For this purpose, we use the residuals from (1) to estimate the variance. Table 10 presents this data. If auctions contribute significantly to lowering uncertainty about the true price of the bond, then one would expect post-auction volatility to be significantly lower than pre-auction volatility. The table shows, puzzlingly, that this is not the case: volatility actually goes *up* on average after the auction. For example, the variances one day after the auction are higher than the variances one day before the auction, both on average (by 0.0419) and for well over 60% of the individual names. Similarly, the variance 2, 3, and 4 days after the auction is higher than the variance 2, 3, and 4 days before the auction. It's only on day 5 that the pattern shifts to a negative number, albeit barely so.

How does one reconcile these findings on volatility with the findings on auction informativeness? A partial clue may lie in the behavior of trading volumes: Table 3 showed that trading volumes increase significantly after the auction. One possible explanation for this is that new informed traders (e.g., vulture funds and investors in distressed securities) who were not auction participants enter the market only post-auction, perhaps because they are waiting for trading related to the auction to die out. Their entry raises trading volumes, but in addition, as auction-generated information is incorporated into post-auction market prices, the new information coming in also raises price volatilities. We believe this is a plausible explanation of the price-volume-volatility patterns we have documented here.

Auction Day Market Data and the Auction Final Price

Trading in the underlying deliverable bonds also occurs on the auction day, and exhibits patterns of considerable interest. Volumes go up hugely, running, on average, at 15 times the volume on the trading day preceding the auction ("day A-1"), or roughly the same order of magnitude as the auction NOIs. (As Table 3 showed, auction NOIs are, on average, around 12 times the size of the trading volume on day A-1.)

Intra-day price behavior is also intriguing. We break the trading day into three sub-periods: pre-IMM, an "interim" period stretching from the IMM to the determination of the auction final price, and a post-auction period. For 15 of the sell-NOI auctions, we have data on trading during each of the three sub-periods. The behavior of average (log-)prices over these three sub-periods is described in Figure 7. Pre-IMM prices are, on average, a little higher than the IMM and well above the final price. Prices fall sharply in the interim sub-period, to a level between the IMM and the auction final price. The fall is likely driven by perceived arbitrage opportunities between the anticipated auction final price and the higher market price; consistent with this view, we find that large (i.e., $1 million+) seller-initiated customer trades outnumber larger buyer-initiated ones by better than a 3-to-2 margin.[12] Post-auction, prices increase slightly from the levels of the interim sub-period, perhaps reflecting anticipation of the market price increase post-auction.

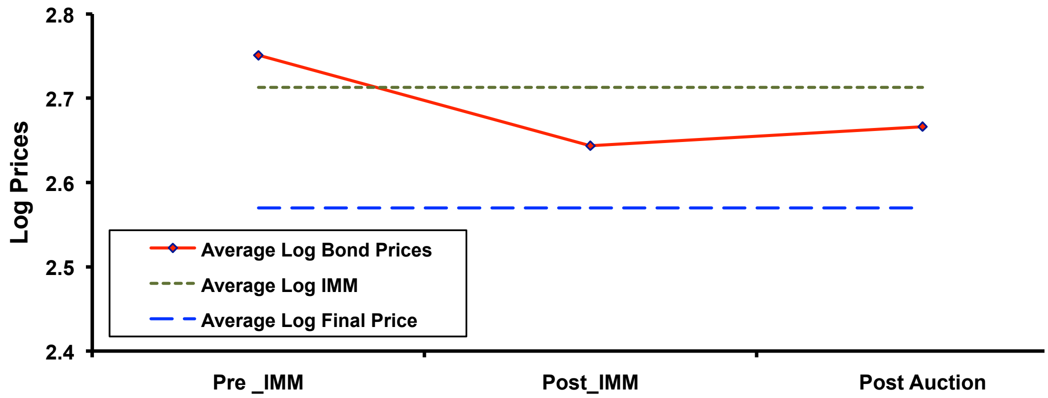
[12] This is also true for smaller trades if CIT is omitted. Data on who initiates the trade is not available for some firms including Lehman and Washington Mutual. The numbers are over the 11 for which the data is available.

Table 10: Price Discovery: The Behavior of Volatility

This table presents market price variances of the auctions' deliverable bonds. The variances are estimated using the residuals of the price estimation equation, as described in the text. The numbers in the table should be interpreted as follows: the "1day" column is the variance one day after the auction minus the variance one day before the auction; the "2day" column is the variance two days after the auction minus the variance two days before the auction; and so on. Blank entries indicate that there was no data or there was insufficient data to compute the variances on at least one of the two days.

	Difference in Variances				
	1day	2day	3day	4day	5day
Abitibi	0.1253	0.0578	-0.3843	0.0085	-0.0072
AmbacFin	0.0094	0.0034	0.0058	0.0155	0.0060
Bowater	0.0017		0.0055	-0.0059	-0.0003
CIT	-0.0003	0.0003	0.0005	-0.0004	-0.0012
Capmark	0.0042	-0.0025	-0.0092	-0.0025	-0.0062
Cemex	0.0001	0.0000	0.0000	-0.0001	0.0000
Charter	0.6286		0.6263	0.5458	
Chemtura	0.0019		0.0713	0.0486	-0.0716
GM	0.0023	0.0023	-0.0022	0.0002	0.0014
GreatLakes	0.0022		0.0023	0.0122	
Idearc	0.0057		-0.0057	0.0375	0.0036
LearCorp	0.0000	0.0037	0.0016	0.0001	0.0078
Lehman	-0.0464	-0.0447	-0.0366	-0.0246	-0.0035
Lyondell		0.0117		0.0093	0.0464
Millenium					
NortelCorp	-0.0016	0.0029		0.0024	0.0013
NortelLtd	0.0397	0.0889		0.0004	0.0013
Quebecor		-0.0005	0.0000	0.0001	0.0000
RHDonnelley		-0.0392	0.0137		-0.0004
Rouse	0.0012	0.0043	0.0156	0.0038	0.0001
SixFlags	0.0013	0.0089	-0.0090	0.0036	-0.0022
SmurfitStone	-0.0229	0.0027		-0.0382	-0.0163
StationCasinos	0.0011	0.0033			
Tribune	0.1584	0.2713	-0.0711	-0.1181	0.0038
Visteon	0.0094		-0.0008	0.0000	
Wamu	-0.0002	0.0000	0.0001	0.0000	-0.0003
Average	0.0419	0.0197	0.0112	0.0217	-0.0018
Positive	16	14	11	15	9
Negative	6	5	9	7	12

Figure 7: Auction-Day Price Behavior



This figure shows the behavior of average log-prices in each of three sub-periods on the auction day. The three sub-periods are: pre-IMM, the interim period between the announcement of the IMM and the revelation of the auction final price, and post-auction. For each sub-period, we calculate the value-weighted average price of each bond, then take the average over all the auctions of the logs of these prices. There are 13 auctions in our sample for which we have price data in each of the three sub-periods.

6 Structural Estimation and Counterfactual Experiments

In this final section, we attempt a structural estimation of the auction to recover the distribution of privately-observed signals. We then use the estimates to look at a counterfactual experiment of what equilibrium outcomes would have been under alternative auction formats. The results here are meant to be indicative rather than definitive, because we make some simplifying assumptions on the auction to facilitate estimation (the assumptions are described below). As usual in the auction setting, bids are presumed to be based on privately-observed signals. Our estimation extracts non-parametrically the underlying distribution of the signals from the distribution of submitted bids. Then, using the estimated distribution, we compare outcomes under the current auction format with those under a uniform-price auction with truthful bidding. Under stronger assumptions, we also identify the equilibrium price under a discriminatory auction format. Our approach adapts theoretical results and structural estimation techniques for Treasury auctions developed by Hortascu and MacAdams (2010), Kastl (2008) and others.

We begin by making explicit the assumptions underlying the estimation procedure. Then, we describe the resulting structure of equilibrium, and the identification and estimation procedures. Finally, we describe our estimation results and the results of the counterfactual experiments. Since the estimation uses only the sell-NOI auctions data, we focus on presenting only that case.

Assumptions

The key assumptions underlying our estimation are the following:

1. Dealers are net flat in terms of their CDS exposure entering the auction, and do not submit physical settlement requests (PSRs) in Round 1. Round 1 PSRs come only from customers.

2. Bond values to dealers have both common value and private value components. The Initial Market Midpoint (IMM) and the Net Open Interest (NOI) announced prior to Round 2 bidding are sufficient statistics for the common value component of the underlying bonds. *Conditional on the IMM and NOI*, dealers have symmetric independent private values drawn from an identical distribution F before submitting their bids in Round 2.

3. The demand curves submitted in Round 2 are strictly decreasing and continuously differentiable.

4. The observed data comes from a symmetric Bayes Nash equilibrium.

Assumption 1 is based on our discussions with market participants (see Section 2). It implies that of the quantity and price submissions made in Round 1, only the latter is reflective of the dealer's information concerning the bond values. This helps simplify the analysis significantly, as we can disaggregate the impact of the information component of the dealer with the non-strategic component (customer orders) of the flow of orders. Assumption 2 is mostly self-explanatory; the existence of a private value component in bond values may be justified by appealing to dealers' own risk-management and portfolio considerations that drive their demands for net positions after the auction. The last part of the assumption helps segregate the influence of others' signals on the value function of the dealer. Assumption 3 is important for the identification and estimation and argument given later in the section. It is only meant to be an approximation, since in reality dealers submit discrete bids as a step function. Given the symmetry in the assumed structure of the game, Assumption 4 is a natural condition to impose on equilibrium.

Bidding and Equilibrium

There are n bidders ("players") in the auction. After the first stage of the auction (in particular, after observing the IMM), dealer i receives a signal s_i concerning his private valuation V_i of the bond. Signals are independent and drawn from identical distributions. Let $F(\cdot|\text{IMM})$ be the common distribution from which each dealer's signal is drawn. Given the signal s_i, dealer i's valuation V_i of the bond is a (possibly degenerate) random variable with $E[V_i \,|\, s_i, \text{IMM}] = s_i \times \text{IMM}$. Let $L(\cdot|s_i, \text{IMM})$ be the distribution of V_i given s_i and the IMM; note that if L is degenerate, then we simply have $V_i = s_i \times \text{IMM}$.

After observing the signal s_i, player i submits a demand schedule $x_i(\cdot; s_i)$, where $x_i(p; s_i)$ is the quantity demanded by i at the price p. Let $X = (x_1, \ldots, x_n)$ denote a vector of strategies and $S = (s_1, \ldots, s_n)$ a vector of signals. As usual, let X_{-i} and S_{-i} denote the vectors corresponding to "everyone-but-i," and let (X_{-i}, y_i) denote the vector X but with x_i replaced by y_i. We restrict attention to strategies x_j that are strictly decreasing and continuously differentiable in p.

For notational ease, we normalize the NOI quantity to 1. Given a vector of strategies X and a vector of signals S, the price $p(X, S)$ that results in the auction is the value of p that satisfies

$$\sum_{i=1}^{n} x_i(p, s_i) \;=\; 1.$$

Player i does not know the values of s_j for $j \neq i$, but given (X, s_i), player i can compute the auction price $p(X, (S_{-i}, s_i))$ that would result for each possible S_{-i}. So from knowledge of the distribution of signals, i can compute the probability distribution of auction prices that will result given (X, s_i). Let H denote the resulting distribution:

$$H(p \mid X, s_i) \;=\; \text{Prob}\; (p(X, S) \leq p \mid X, s_i)\,.$$

Then, i's expected profit from the strategy vector X given s_i is

$$\Pi_i(X, s_i) \;=\; \int \left[\int (V_i - p) x_i(p; s_i) dH(p \mid X, s_i) \right] dL(V_i | s_i). \tag{5}$$

Player i chooses $x_i(\cdot; s_i)$ to maximize this expected profit for each s_i. A Nash equilibrium is a strategy vector $X^* = (x_1^*, \ldots, x_n^*)$ such that for each i and each s_i, x_i^* maximizes $\Pi((X_{-i}, y_i), s_i)$ over i's strategy choices y_i. Given the symmetric structure of the game, we focus on symmetric equilibria $X^* = (x^*, \ldots, x^*)$.

Appealing to calculus of variations arguments, Wilson (1979) describes the first-order conditions for the problem of maximizing $\Pi(X, s_i)$ over i's strategy choices x_i:

$$E\left[(V_i - p) H_p(p | X, s_i) + x_i(p; s_i) H_x(p | X, s_i)\right] \;=\; 0,$$

where the expectation is taken over the distribution L of V_i given s_i. The only term inside the expectation that depends on V_i is the first term V_i itself. So we can write this equivalently as

$$(E[V_i | S_i] - p) H_p(p | X, s_i) + x_i(p; s_i) H_x(p | X, s_i) \;= 0,$$

or, using $E(V_i \mid s_i) = s_i \times$ IMM and rearranging,

$$\text{IMM} \times s_i = p - x_i(p, .) \frac{H_x}{H_p} \tag{6}$$

In equilibrium, each player's strategy must meet the necessary condition (**??**). We exploit this requirement in our estimation procedure below.

Identification and Estimation

If the data we observe is generated by the equilibrium of the second stage as described above, then Condition (6) helps us non-parametrically identify the signals s of the bidders using the observed bids and the IMM, as we describe here. Define the observed distribution of the residual supply curve facing a bidder as

$$G(p, y) = Pr\{y \leq NOI - \sum_{j \neq i}^{N} x(p, s_j)\}$$

G measures the probability that the quantity demanded x will be less than the (stochastic) residual supply faced by bidder i. If the joint distribution of $\{(x(p, s_j), j \neq i\}$ can be estimated from the data, then this probability can be estimated for all (p, x) pairs, and then we have

$$H[p, x(p, s_i)] \; = \; G(p, y)|_{y=x(p,s_i)}$$

$$H_p \; = \; \frac{\partial}{\partial p} G(p, y)|_{y=x(p,s_i)}$$

$$H_x \; = \; \frac{\partial}{\partial y} G(p, y)|_{y=x(p,s_i)}$$

Hence, the signals will be identified from the distribution of observed bids.[13]

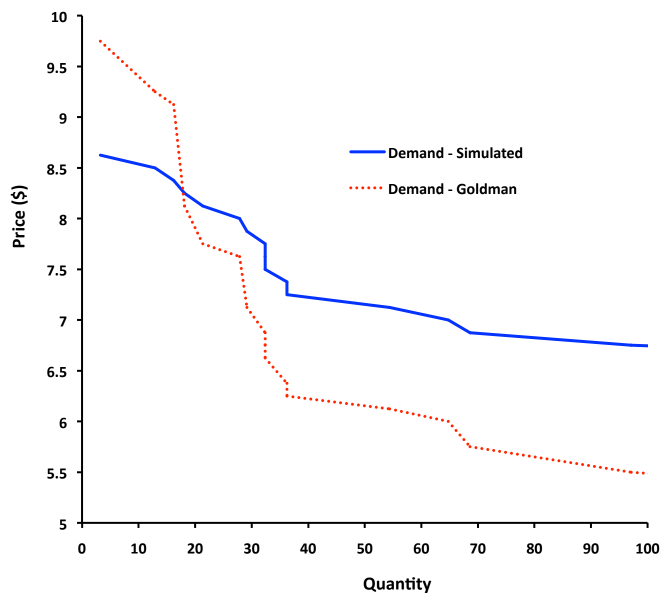
Resampling procedure

Hortacsu and Mcadams (2010) describe an approach for consistently estimating the residual supply curve for a bidder. We describe their resampling procedure here. Note that due to private value assumption, each bidder i would care about other's bidding strategies only through their impact on the residual supply. Let their be T auctions and N total no of bidders. The following procedure will consistently estimate the residual supply function for each bidder hence his winning probability:

- Fix bidder i and a bid x_{it} made by this bidder in an auction t.
- Draw a random subsample of $N - 1$ bid vectors with replacement from the sample of N bids in the data set for each auction.
- Construct bidder i's realized residual supply were others to submit these bids, to determine the realized market-clearing price given i's bid $x_{it}(.)$, as well as whether bidder would have won quantity $x_{it}(.)$ at price $p_{it}(.)$ for all i.

[13] To be sure, bidders in reality do not submit a strictly downward sloping demand function; rather they submit a step function. In such a case, what we identify and estimate here are like bounds of the distribution of signals (Hortacsu and Mcadams, 2010). We abstract away from these considerations.

Figure 8: A Simulated Demand Curve



This figure shows an example of a simulated demand curve used in calculating the probabilities of getting orders filled. The dotted red line is the actual demand curve submitted by Goldman Sachs in the second stage of the Lehman auction. The solid blue line is an example of a demand curve for the remaining dealers obtained by sampling with replacement from the actual demand curves submitted by the other dealers at the auction. The NOI quantity is normalized in the figure to 100.

- Repeating this process many times allows one to consistently estimate each of bidder i's winning probabilities $H(p, x_i())$, simply as the fraction of all subsamples given which bidder i would have won a xth unit at price p.

- The derivatives $H_p(.)$ and $H_x(.)$ are computed as numerical derivatives.

We use these estimated distributions of $H_p(.)$ and $H_x(.)$ and plug these in the right hand side of the first order condition along with the observed demand curve and equilibrium price to estimate the values of s. A kernel is fitted on these values to get the nonparametric distribution of signals.

Estimation Results

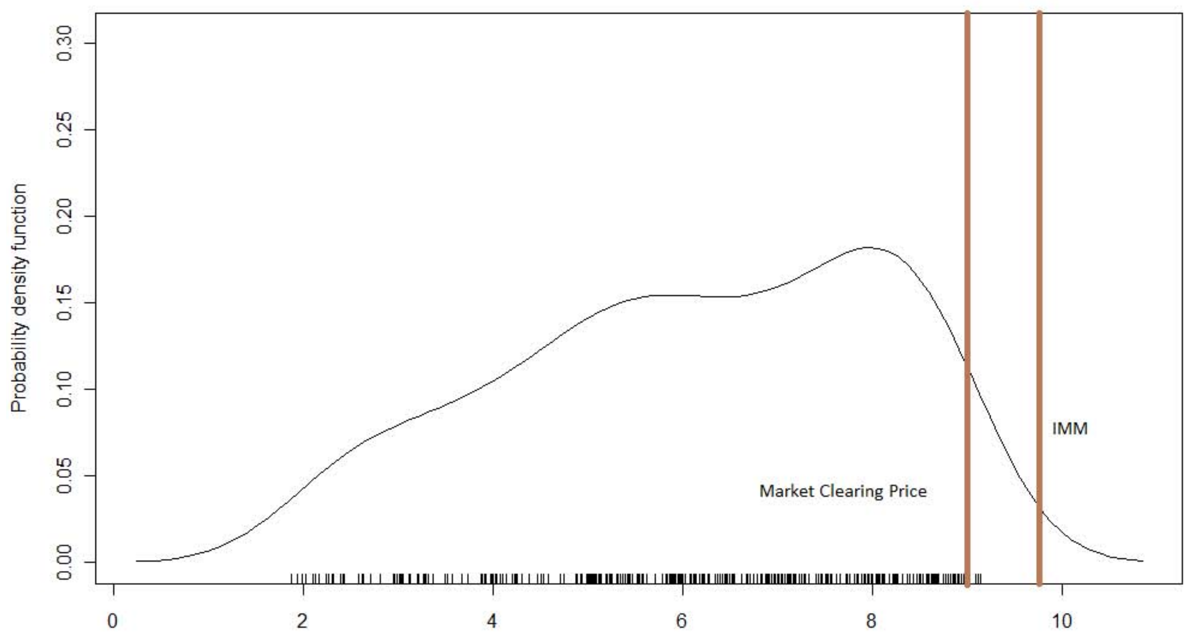
The estimation procedure estimates each bidders estimate of marginal valuation. In Figure 8, we illustrate the resampling procedure in the Lehman auction. In this auction all the 14 dealers participated. The initial market midpoint was \$9.75, the net open interest was to sell \$4,920 million. The auction's final price was \$8.625. The dotted red line in the figure is the actual demand curve submitted by the Goldman Sachs in Stage 2 of the Lehman auction. Thirteen other demand curves were drawn with replacement 1000 times from the actual demand curves submitted by the dealers in round 2 of this auction. The solid blue line is a subsample of the consolidated demand curve based on all other dealers demand curves. The residual supply curve net of others' demand would determine the filling rates of each points of Goldman's demand curve.The probability of getting filled for each point of the Goldman Sachs demand curve is computed based on the number of times each of them got filled in the entire simulations divided by 1000.

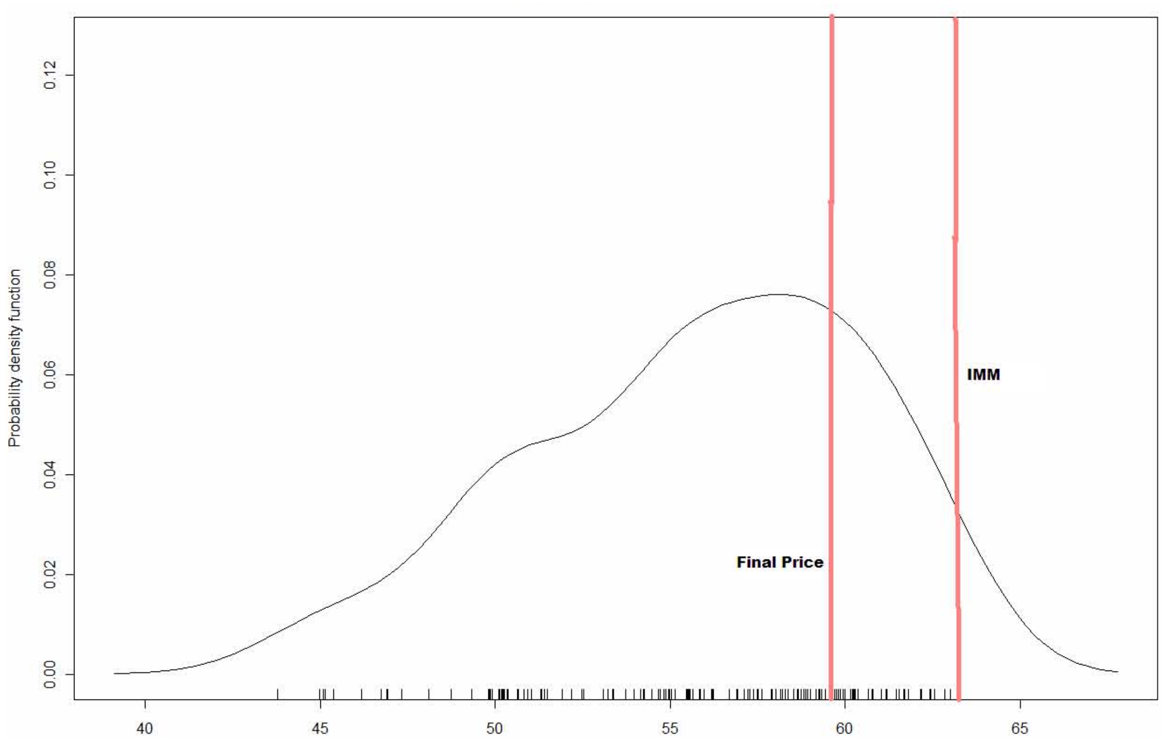
The distribution of the signals of valuations estimated via the procedure in the Lehman case is described above is given in the upper panel of Figure 9. The auction's final price and the IMM are also shown in the figure. The density is unimodal and left-skewed with a mean of 6.16. Similar densities were estimated for each auction in our data set; see the lower panel of Figure 9 for the distribution of signals in the Washington Mutual auction.

Counterfactual Experiments

We conduct two counterfactual experiments in this section with the objective of identifying the stop-out prices that would have resulted under alternative auction formats for the second stage. We examine two formats: a Vickrey auction and a discriminatory auction. In either case, we assume that the first-stage price submissions (leading to the IMMs) are unaffected. This is a non-trivial assumption mainly because of the auction rules linking bounds on the final price to the IMM, but perhaps less likely so in the context of Vickrey auctions which involve truthful second-stage bidding in equilibrium (see below).

Figure 9: Lehman and WaMu: The Estimated Density of Signals





This figure describes the probability density plot of the signals in the Lehman (upper panel) and Washington Mutual (lower panel) auctions obtained using the method described in the text. The auctions' final prices and the IMMs are both shown in the figures.

Table 11: Counterfactuals: Comparison to Other Auction Formats

This table describes the percentage by by which the auction's final prices would increase in two situations: if the second stage involved a Vickrey auction (i.e., truthful bidding of signals) and if it involved a discriminatory auction. The assumptions under which the numbers are derived are described in the text.

	Percentage Increase under a	
	Vickrey Auction	Discriminatory Auction
First Quartile	0	-19
Median	$+14$	-5
Mean	$+20$	$+0$
Third Quartile	$+39$	$+18$

In a Vickrey auction, a winning bidder pays the opportunity cost of the items won. For example, in a discrete multi-unit Vickrey auction, if a bidder wins k units, then she pays the sum of the k highest losing bids made by the remaining bidders. A key feature of Vickrey auctions is that truthful bidding—bidding in which all dealers bid their true valuations—is an equilibrium. Thus, the stop-out price in a Vickrey auction is equal to that which would result in a uniform price auction with truthful bidding. Figure 10 and Table 11 describe the difference between the actual final price and the stop-out price that would have resulted in a hypothetical Vickrey auction under our assumptions. The numbers show that the impact is small in some cases but substantial in others; the prices would, on average be around 20% higher with a median value of 14%.

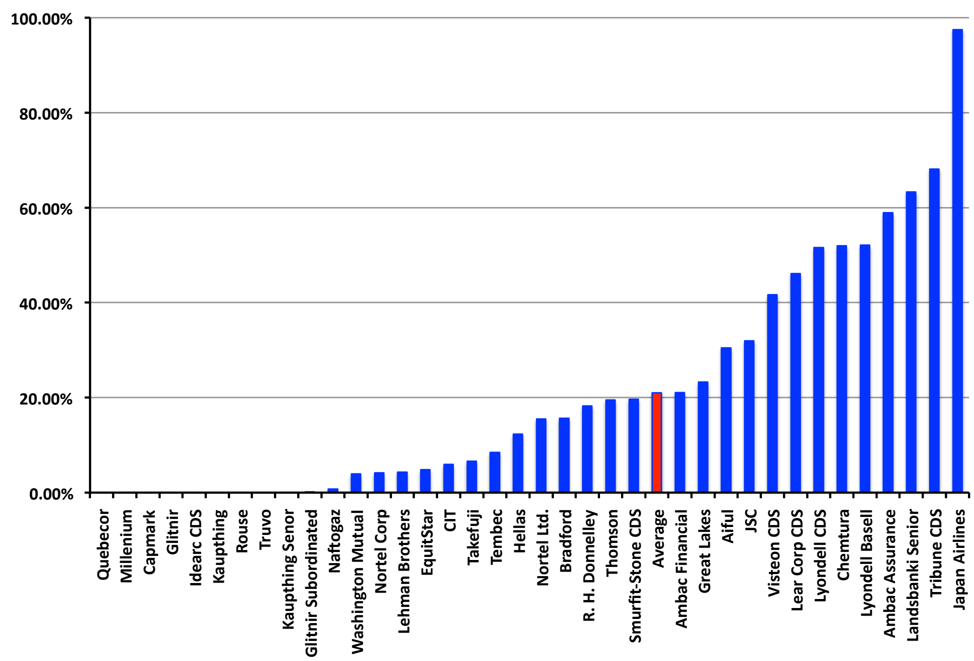
The second comparison point of a discriminatory auction format for the second stage involves an additional (and significantly stronger) assumption. In the same notation as this section, it can be shown that the equilibrium bidding condition under a discriminatory auction format can be written as

$$p \;=\; s - \frac{H(p, x(p,s))}{H_p(p, x(p,s))}.$$

We need to identify the predicted bids under the discriminatory format. To do this, and thence to identify the implied stop-out price, we need the elements of the right-hand side of the above equation in a discriminatory auction equilibrium. The structural estimation of the current auction format estimated the distribution of the underlying marginal distribution of signals s. We can evaluate that estimated marginal distribution at the signals corresponding to the values consistent with the actual bids in the current uniform price format. This would give us the first element of the left had side of the first order condition. If we make the strong assumption that the

Figure 10: Counterfactual I: The Impact of Vickrey Auctions

The figure presents the estimated percentage increase in prices that would result for each auction if the second-stage of the auction involved truthful bidding.



function $H(\cdot)$ is the same under the two formats, then we can use our current estimated of H and H_p through the resampling procedure described before to arrive at the predicted bids under the discriminatory format. Carrying this out and examining the impact, Table 11 shows that on average there is no impact (0%), while the mean impact is -5%.

7 Conclusion

This paper provides the first detailed empirical analysis of the auction mechanism used to settle credit default swaps after a credit event. We find that the auction price has a significant bias relative to the pre- and post-auction bond prices. Nonetheless, econometric analysis shows that auction-identified information, and in particular, the auction's final price, is critical to post-auction price formation. Bidder behavior and auction outcomes are significantly affected by winner's curse and strategic considerations, providing at least a partial explanation of the observed price bias. Somewhat surprisingly, and at first sight, inconsistently with price discovery, we find that volatility of bond prices actually increases after the auction, but this may just indicate the presence of new informed investors who enter only post-auction. Finally, we also carry out a limited structural estimation of the auction aimed at uncovering the distribution of signals that guides auction behavior; under some (relatively strong) assumptions, we use the identified signals to see the potential price effects of changing the auction format.

Several interesting avenues of research remain to be investigated. One is the development of a complete theoretical model of credit-event auctions. Promising bases have been laid in this direction by the work of Du-Zhu (2010) and especially Chernov, et al (2011); an important issue that remains is to incorporate asymmetric information aspects into the model. A second, coming out of the first, is a more complete structural estimation of the auction. And finally, building on both of these, is the identification of potentially better auction mechanisms.

A Definitions of Variables

Variable Name	Definition
Avg_CompSlope	Average of the slopes of demand curves of all competitors in an auction
AvgPrice_Pre	Average value-weighted price for the day prior to auction
AvgQty_Pre	Average daily quantity traded on the day prior to auction
Dealer_PSR	Dealer's physical settlement requests
Dealer_PSRNorm	Dealer's PSR normalized by Total_PhySett
EstPrices_Pre	Estimated price 1 day prior to auction computed using the regression (1)
FinalPriceNorm	Final auction price normalized by the AvgPrice Pre/(EstPrices_Pre)
FracFilledCarryOver	Fraction of NOI filled by carried-over bids/offers from Round 1
LogFinalPriceNorm	Log of FinalPriceNorm
OIDummy	Dummy variable, = 1 if Open Interest is to buy, 0 otherwise
OpenInt_Norm	NOI normalized by the dollar value of trades on the day prior to auction
OpenIntAmtNorm	NOI normalized by the dollar value of trades on the day prior to auction
RecessionDummy	Dummy variable, = 1 if auction is held 1-Oct-08 and 1-Oct-09.
Ret_1Day_Pre	Nomal daily return on the day prior to the auction
Rnd1DevIMM_Sq	Squared Deviation of Round 1 bid from IMM for each dealer
Round2QS	Round 2 quotation size
Total_PhySett	Sum of all PSRs on the same side as the NOI
Trades_Pre	The total number of trades on the day prior to auction
Var_Rnd1Bid	Variance of bids placed in round 1 of the auction
Var_1day_Pre_EstP	Variance of residuals in regression (1) estimated 1 day prior to auction
Var_1DayPre	Variance of value-weighted prices 1 day prior to auction
Var_CompPhysSett	Variance of Competitors' PSRs on the same side as Net Open Interest
Var_PhySett	Variance of PSRs on the same side as Net Open Interest
Var_Rnd1Bid_Norm	Variance of Round 1 bids normalized by the auction final price

B Within-Auction Learning Dynamics

Between Rounds 1 and 2 of the auction, bidders receive information on Round 1 bidding. Two pieces of information are of especial interest: how far a dealer's own bid was from the IMM, and the variability of the Round 1 inside-market price submissions. The question of interest is: How does the information revealed determine how far a dealer deviates in Round 2 from its own first-round submission?

The a priori expectation of either variable's impact is not unambiguous. The extent of

Table 12: Round 2 Deviations from Round 1 Bids

This table presents the results of regressing the round 2 deviations from round 1 bids of a dealer for each auction on variability of round 1 bids (Var_Rnd1bid) and how far bidders' own bid was different from the summary information as measured by the IMM.

Dependent Variable: (Round2Bid/Round1Bid - 1)^2

	Spec 1		Spec 2		Spec 3	
Intercept	-2.27	**	-2.29	**	-2.23	**
	(0.89)		(0.89)		(0.89)	
Rnd1DevIMM_Sq	52.17	***	51.9	***	51.91	***
	(2.5)		(2.5)		(2.5)	
Var_Rnd1Bid	1.07	***	1.05	***	1.06	***
	(0.33)		(0.33)		(0.33)	
Rnd1DevIMM*VarBid	-64.32	***	-64.18	***	-64.49	***
	(7.19)		(7.19)		(7.19)	
Dealer_PSR			0.001			
			(0.0089)			
Dealer_PSRNorm					0.98	
					(0.76)	
Tot_PhySett	0.0023	**	0.002	*	0.0022	**
	(0.001)		(0.001)		(0.001)	
Var_PhySett	-0.00007	**	-0.00006	**	-0.00006	**
	(0.00003)		(0.00003)		(0.00003)	
OpenIntNorm	-0.03		-0.03		-0.03	
	(0.04)		(0.04)		(0.04)	
Round2QS	-0.00012		-0.0001		-0.0001	
	(0.00056)		(0.0006)		(0.0006)	
Recession Dummy	0.08		0.12		0.08	
	(0.62)		(0.62)		(0.62)	
No of Observations	1821		1821		1821	
R-sq	22.23		22.33		22.30	
Adj R-sq	21.88		21.94		21.91	

deviation of a dealer's second-round bids from its own first-round bids depends, loosely speaking, on the weight accorded to the public information revealed in Round 1 compared to the private information incorporated and reflected in the dealer's own first-round bid. So, for example, a greater weight accorded to private information would reduce the dealer's deviation from its own first-round bid, while a higher weight accorded to the revealed public information would increase this deviation.[14]

To gauge the impact of the variables of interest, we regress the deviations of dealers' Round 2 bids from Round 1 bids on a range of variables that includes the two of interest, the deviation of

[14] This is related to the point made by Milgrom and Webber (1982b) that the impact of release of public information on bidding behavior depends on the complementarity or substitutability of public information with the bidders' private information.

a dealer's own Round 1 bid from the IMM, and the variability of first-round bids, as well as an interaction term between the two. Our findings, reported in Table 12, point to effects that are both subtle and interesting.

On the one hand, the coefficients on both terms, the Round 1 deviation of one's own bid from the IMM and the variability of Round 1 bids, are both positive and highly significant. This likely signifies the the incorporation of and greater weight accorded to public information into second-round bids. (For example, a higher deviation of a dealer's own bid from the IMM leads to increased weight on the revealed public information will lead to a higher deviation of the dealer's second-round bid from the first-round bid.) On the other hand, the coefficient on the interaction term is *negative*, and is also large and significant. This means that the marginal impact of (say) the Round 1 deviation from IMM depends on the variability of Round 1 bids, and so the possibility of a winner's curse effect. For example, if we evaluate this marginal impact at the first quartile of variability bidders' Round 1 bids, we find that the overall impact is positive; bidders adjust their Round 2 bids based on the consensus. However if we do the evaluation at the median variability level of Round 1 bids (roughly, 0.7), then the overall impact is *negative*. Intuitively, the increased winner's curse impact causes bidders to put more weight on their private information and not deviate too much from their own first-round bids.

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