CDS Credit-Event Auctions[1]

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September 1, 2011

[1]Our thanks to many market participants for conversations about the mechanics and working of credit event auctions, particularly Hugo Barth, Karel Engelen, Bjorn Flesaker, David Mengle, Arvind Rajan, and two others who wished to remain anonymous. A very special thanks to Joel Hasbrouck for several valuable discussions concerning the analysis in this paper and especially for suggesting procedures to overcome data deficiencies and anomalies. Much useful input was also provided by participants at conferences where earlier versions of this paper were presented: the Nasdaq OMX Derivatives Research Day at NYU (February 2011), the Moody's-LBS Credit Risk Conference in London (May 2011), and the ISB Research Camp in Hyderabad (July 2011).

Abstract

Credit-event auctions were introduced in 2005 to facilitate cash settlement in the credit default swap market following a credit event. The auctions have a novel and complex structure that makes them distinct from other auction forms. This paper studies outcomes in credit-event auctions over the period 2008-10. We find that the auction price has a significant bias relative to the pre- and post-auction market prices for the same instruments, and that volatility of market prices often *increases* after the auction; nonetheless, the auction generates valuable information for post-auction market price formation. We find strong evidence that "winner's curse" concerns and strategic considerations significantly affect liquidity provision in the auction. Bidders' updating of their private information based on the public information revealed during the auction is significantly affected by the possibility of winner's curse. Lastly, under assumptions that enable us to focus solely on the second stage of the auction, we carry out a structural estimation to recover the underlying distribution of signals. Using these estimates, we find that the alternative auction formats could reduce the amount of bias in the auction final price.

1 Introduction

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. A CDS is akin to an insurance contract that offers protection against the default[1] of a specified reference entity; the objective is make the protection buyer "whole" following a default. This paper investigates the novel auction mechanism that is used to settle these contracts in the event of a default.

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. Physical settlement has the attractive feature that the protection buyer is made whole without the need to identify a fair price for the defaulted instrument.

However, the extraordinary growth of the CDS market in the early 2000s led to a problem: the volume of CDSs outstanding far outstripped, in many cases, the volume of deliverable bonds. A particularly dramatic instance was Delphi Corporation, which at the time of its bankruptcy in 2005 had an estimated \$28 billion in CDSs outstanding against only \$2 billion in deliverable bonds (Summe and Mengle, 2006). Such mismatches created the obvious problem of a squeeze following a default as long positions scrambled to find bonds that could be delivered.

To address the situation, the International Swaps and Derivatives Association (ISDA) instituted in 2005 an auction procedure for identifying the fair price of the defaulted instrument. CDS contracts are then "cash settled" using this price, with the protection seller simply paying the protection buyer par minus the auction-identified price.[2] With a structure that is unique in many ways, credit-event auctions present several fascinating areas of inquiry, theoretical as well as empirical. The current paper represents one such effort: it investigates behavior in and outcomes of CDS credit-event auctions over the period 2008-2010. The paper is, to our knowledge, the first detailed empirical investigation of these auctions.[3]

[1]The contingency that triggers payment under a CDS is referred to as a *credit event*; it includes, but is not restricted to, traditional default definitions (e.g., failure to pay or bankruptcy); in European corporate CDS contracts, for example, restructuring also constitutes a credit event. Nonetheless, for simplicity, we will use the term 'default' interchangeably with 'credit event.'

[2]The original auction procedure was modified in mid-2006 and it is that modified procedure that is described below and is the subject of this paper. 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. After the "Big Bang" of April 2009, the auction mechanism is hardwired into all CDS contracts worldwide, and is the default settlement mechanism for CDS contracts issued after that date.

[3]The literature on CDS auctions is discussed in Section 2.

CDS Credit-Event Auctions: A Brief Description

CDS credit-event auctions are two-stage auctions. Stage 1 identifies an indicative price, called the *initial market mid-point* or IMM, for the defaulted instrument, while Stage 2 identifies the definitive price to be used for cash-settling CDS contracts. The auction has the unusual feature that both the amount auctioned in the second stage, and whether that quantity is for *sale* or *purchase*,[4] are endogenously determined from the participants' first-stage submissions. We provide a sketch of the auction structure here; a detailed description is in Section 2.

In Stage 1 of the auction, dealers make price and quantity submissions. The submitted prices are two-way prices at which dealers are willing to make markets in the defaulted instrument. They are for a pre-specified quotation amount (say, $5 million in face value) and are subject to a specified maximum bid-offer spread (typically $2 per $100 face value). After eliminating crossing bids and offers, the IMM is identified from these prices using a simple averaging procedure described in Section 2. The price submissions are also carried forward to Stage 2 as limit orders, as described below.

The quantities submitted by dealers in Stage 1 are called *physical settlement requests* or PSRs, and represent amounts they undertake to buy or sell *at the auction-determined final price*. PSRs can be made by dealers on behalf of themselves and/or their customers, but there are some restrictions. . Only dealers or customers with existing net CDS exposures are allowed to submit PSRs. Sell-PSRs may only be submitted by dealers/customers who are net long protection, and buy-PSRs by those who are net short protection. Further, the submitted PSRs cannot exceed the size of the existing net CDS exposures of the dealer/customer. Given the PSR submissions, buy-PSRs are netted against the sell-PSRs to identify the auction's *net open interest* or NOI.

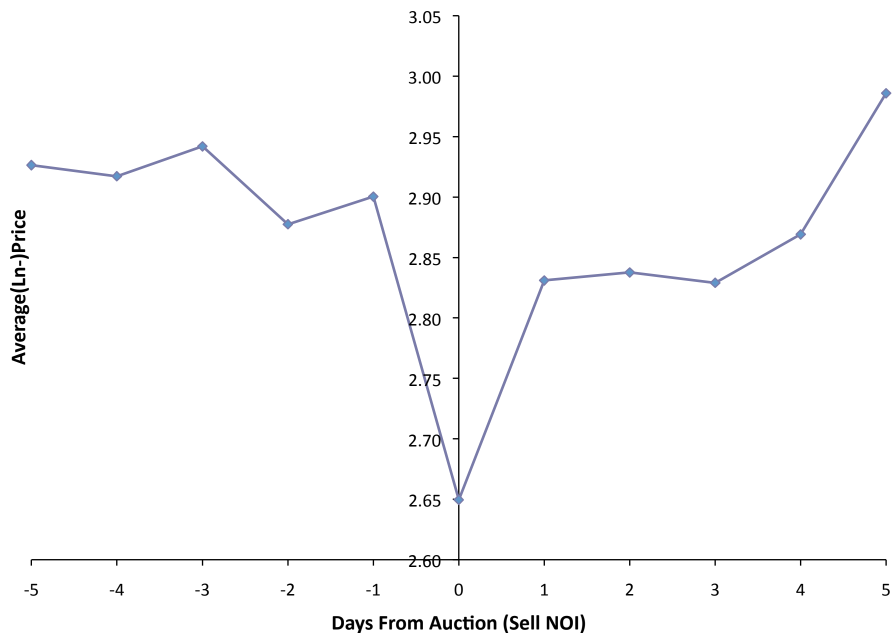
In the second stage of the auction, a standard uniform-price auction is held for the NOI. Importantly, since the NOI could be to buy or to sell, both the *magnitude* of the second stage auction (the quantity on offer) and its *sign* (whether the auction is to buy or sell) are endogenous consequences of first stage behavior. Given the NOI, dealers submit limit-order prices and quantities on behalf of themselves or their customers; the (appropriate side of) Stage 1 price submissions are also carried forward as limit orders for the specified fixed quotation amounts. The price at which the NOI is satisfied is the auction's final price.

This Paper

In this paper, we investigate behavior and outcomes in the auctions conducted from 2008-2010. Our analysis is in three parts. Section 4 examines the efficiency of the price discovery process in the auction. Section 5 looks at bidder behavior in the auctions, including (a) the impact of "winner's

[4] In the language of the auction literature, whether the second-stage is a "standard" or "reverse" auction.

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 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 average is taken over all the firms in our sample that had a sell-NOI and on which market bond prices were available for all 10 days in the horizon. The data is described in Section 3 below and the calculation of average prices in Section 4.

curse" and strategic considerations on liquidity provision in the auction, and (b) intra- and inter-auction learning dynamics. Finally, Section 6 carries out a limited structural estimation of the auction and use it to examine the impact of alternative auction formats. The auction data we use is obtained from `http://www.creditfixings.com`,[5] and includes dealer-level information on price and quantity submissions. Pre- and post-auction market price data on the instruments that are deliverable in the auction comes from TRACE.

Price Discovery Our study opens in Section 4 with what is possibly the most important intended contribution of the auction: price discovery. 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 constitute the vast majority of auctions in the data), both pre-auction and post-auction

[5] The site is run by Creditex, one of the two co-adminstrators of the credit-event auctions (the other is Markit).

market prices are sharply higher than the auction-determined final prices (see Figure 1).[6]

It is tempting to conclude from Figure 1 that the auction does not work well, but economic theory has suggested many reasons why auctions may result in underpricing. So, to get a better feel for the informativeness of the auction, we turn to econometric analysis. We find, in contrast to the impression given by Figure 1, that information revealed in the auction—in particular, the auction's final price—is a key determinant of post-auction price behavior. Indeed, once auction-related information is introduced, *no* pre-auction price or quantity information is significant in explaining post-auction price behavior.

What then could explain the observed pricing bias? An obvious suspect is the winner's curse[7] problem that may induce conservative bidding (see, e.g., Nyborg and Sundaresan, 1996). A second and more subtle possibility, suggested by the theoretical work of Wilson (1979) and others, is strategic behavior by bidders. Yet a third possibility, raised by Bajari and Hortacsu (2005), is risk-aversion on the part of bidders. In Section 5, we return to these issues and show that the winner's curse and strategic behavior indeed have significant impacts on auction outcomes.

In Section 4, we also examine a second, indirect, test of market informativeness, this one using pre- and post-auction market price *volatilities*. Intuitively, if the auction were fully (or even considerably) informative in identifying the "fair" price of the defaulted instrument, one might expect that post-auction volatility of market prices be lower than pre-auction volatility. We find that this is not the case. To the contrary, we find that price volatility actually goes *up* after the auction, both on average and for over two-thirds of individual names. This finding is puzzling and difficult to reconcile with efficient price discovery. One possible explanation, suggested by our conversations with market participants, is that many informed and specialized traders (hedge funds, firms with workout desks, vulture investors) enter the market only after the auction; consistent with this possibility, we find a sharp increase in the volume of trading post-auction.

Bidder Behavior In Section 5, we turn our attention to bidder behavior in the auctions. We begin with liquidity provision in the auction and the factors that affect it. We proxy the liquidity provided by a dealer using the slope of the demand curve submitted by the dealer in the second stage uniform-price auction: intuitively, the steeper the submitted demand (or supply) curve, the lower the level of liquidity provision. We examine two questions in this context. First, how is liquidity provision affected by the possible winner's curse effect? Second, how is liquidity provision affected by *strategic* considerations, i.e., by the behavior of other dealers in the auction?

[6]Buy-auctions do exhibit the opposite bias on average, but there are only four such auctions in our data.

[7]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 of the item conditional on the combined information of all the bidders will generally be less than the winning bid. For more details and a formal analysis, see, e.g., Milgrom and Webber (1982).

Section 5.1 looks at the impact of the winner's curse. In principle, more dispersed information entering the auction should lead to a greater anticipated winner's curse effect, in turn causing dealers to bid more cautiously, i.e., to submit steeper demand curves. To proxy pre-auction information dispersion, we use the variability of the first-round inside-market price submissions. We find a strong and significant effect exactly along the expected lines: that a higher level of information dispersion leads to steeper demand curves. Motivated by this, we revisit the pricing bias issue in Section 5.3. We find that the most significant explanatory variable for underpricing is indeed our winner's curse proxy, and, indeed, it is the only price or quantity variable that is significant across the board.

Section 5.2 examines the importance of strategic considerations. That such considerations should affect the slope of the submitted demand (or supply) curves has been pointed out by Wilson (1979) and Back and Zender (1993), among others. Using a suitable instrumentation approach, we find that the data strongly confirms the Wilson-Back-Zender models, viz., that there is a strong positive relation between the slope of the demand curve submitted by a dealer and the slopes of the aggregate curve obtained from the others' submissions.

Sections 5.4 and 5.5 then turn attention to learning dynamics *within* and *across* auctions. In Section 5.4, we look at how information revealed in the first stage of the auction affects how much a bidder deviates from its own first round bid. Loosely, greater deviation from own first-round bid indicates more weight being placed on the "public" information revealed compared to the "private" information reflected in the first-round bid. The findings are subtle with a key and interesting role played by winner's curse considerations. In Section 5.5, we examine how past wins and inventory affect current bidding; we find that more past wins leads to less aggressive current bidding.

Structural Estimation In the final part of the paper in in Section 6, we carry out a limited structural estimation of the auction aimed at uncovering 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 result under truthful bidding (e.g., under a Vickrey auction). We find that the extent of underpricing in equilibrium would be reduced substantially. Under (much) stronger assumptions, we find that switching to a discriminatory auction format too would reduce the auction's underpricing, albeit by a smaller amount.

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 details of the data obtained. In Section 4, we test the efficiency of the auction's price discovery process, while Section 5 looks at liquidity provision 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

The Introduction provided a brief introduction to credit event auctions. This section presents a detailed description. As noted above, the credit event auction has two stages. Stage 1 identifies an indicative price (the initial market mid-point or IMM) for the underlying defaulted instrument, while Stage 2 identifies the definitive price (the "final price") for CDS contract cash-settlement. Prior to the auction, a "cap amount" is specified which limits how much the final price may differ from the IMM. The cap amount is typically set at 1% ($1 per face value of $100).

Stage 1 of the Auction

All submissions to the auction in either stage must go through dealers. In Stage 1, dealers make two sealed-bid submissions:

1. Two-way prices (i.e., bid and ask), called "inside-market prices," for the underlying deliverable obligations.
2. Physical settlement requests (PSRs) on behalf of themselves and their customers.

Each of these submissions is subject to certain conditions. There are two conditions on the submitted prices. First, they are for a specified quotation amount which is announced ahead of the auction. If the quotation amount is (say) $5 million, then the dealer is undertaking to buy up to $5 million at the submitted bid price or to sell up to $5 million at the submitted ask price. The quotation amount may vary by auction; for example, it was $10 million in the case of Washington Mutual in 2008, and $5 million in the case of CIT in 2009. Second, the bid-offer spread in the submitted prices are required to be less than a pre-specified maximum amount. This maximum too varies 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 must also obey two constraints, one concerning the sign (i.e., buy/sell) and one concerning the magnitude. First, the PSRs must be on the same side of the market that would be used to physically settle a dealer's trades. That is, a dealer who is net long protection can only submit *sell*-PSRs, since the dealer would have been required to *deliver* bonds under physical settlement. Similarly, a dealer who is net short protection can only submit buy-PSRs.

Second, the size of the PSR can be no more than 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. 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.)

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, all crossing (or touching) bids and offers are first eliminated from the given list. (A bid b is crossing or touching with an offer o if $o \leq b$.) From the remaining bids and offers, the best halves—highest bids and lowest offers—are chosen to calculate the IMM. The IMM is just the arithmetic average of these best halves. Thus, if there are n bids and offers remaining, the highest $n/2$ bids and the lowest $n/2$ offers are averaged to obtain the IMM. (If n is odd, the best $(n+1)/2$ bids and offers are used.)

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.

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. To compute the adjustment amount, the difference between the submitted price and the IMM is applied to the quotation amount. For example, suppose the IMM has been determined as 50.00 and there is a net open interest to sell. Assume the quotation amount is $2 million. Then, a dealer who submitted a bid of (say) 52.00 pays an adjustment amount of

$$\$(0.02 \times 2,000,000) \ = \ \$40,000.$$

This penalty is *not* levied if the bid or offer in question did not cross with another offer or bid.

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 (as has been the case in every auction to date), then the auction moves to Stage 2.

Stage 2 of the Auction

In Stage 2, a uniform-price auction is held to fill the NOI. Dealers may 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. (Recall that the submitted prices were for specified quotation amounts.) Since customer orders are routed through dealers, it is not possible to disentangle the two and to identify which of the (new) limit orders originate from the dealer and which from the dealer's customers.

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 in the obvious way as the price that fills the NOI. There is 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.

Comments from Market Participants

An important conflating feature of the data is the mixing of customer orders with a dealer's own orders. Since detailed data on dealers' pre-auction CDS positions or on market participation by non-dealer customers is lacking, we spoke to a number of major market participants (dealers, customers, and administrators) to get a better feel for the auction process. We summarize their consensus opinions here.

First, concerning net dealer positions entering an auction, it is generally believed that dealers are, broadly speaking, "net flat" entering the auction, i.e., that their long and short CDS positions generally offset. The PSRs submitted in the first round do not, then, generally originate from dealers; rather, they are pass-throughs from customers. What types of customers? One major source of sell-PSR orders are believed to be "basis traders," investors who are long protection and long the underlying deliverable instrument. Sell-PSRs enable such investors to replicate the outcome from cash settlement.[8] Buy-PSRs may have multiple origins, from investors with

[8] Letting P denote the auction's final price, the basis trader receives $100 - P$ from the cash-settlement on the

correlation desks dealing with indices/structured products to ones with workout desks looking to take speculative postions. In the data, auctions with sell-NOIs outnumber auctions with buy-NOIs by almost 3-to-1.[9]

Finally, regarding the "adjustment amounts." While these penalties are not large in dollar terms, major dealers told us that they have a far greater impact than the immediate monetary value because of the reputational consequences of being seen to be off-market. Combining this with their net-flat positions, it appears that dealer price submissions in the first round have something of the flavor of a "coordination game," i.e., there is a positive incentive to herd with other dealers in the price submissions. Of course, the price submissions are not a pure coordination game since penalties are only levied under some conditions, and, more importantly, the submissions have payoff consequences since the quotes are transferred to Stage 2 of the auction as limit orders.

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 significantly more complex than most. We have already highlighted its key feature, the endogeneity of the second-stage auction. In contrast, most auctions in practice, as also most auctions studied in the academic literature, deal with a fixed quantity on offer that is specified in advance as being for sale or purchase. The objective of the auction correspondingly differs. In theory and practice, an important focus of fixed-quantity-for-sale auctions has been on identifying the "optimal" auction form that maximizes the auctioneer's (seller's) revenue. There is no analog of this situation in credit event auctions; rather, price-discovery and smooth CDS market settlement are the key goals.

From a theoretical standpoint, there are two kinds of auctions to which credit event auctions bear similarity. One is the class of two-stage auctions that are employed to sell complex and high-valued assets. The other is the category of auctions used in the context of Treasury securities worldwide.

Two-stage auctions are studied in Ye (2007). Like CDS credit event auctions, they have a first-stage of bids which are used to identify an indicative price, and a second round that identifies the definitive final price. However, there are important differences. Two-stage auctions are commonly single-unit auctions with a single winning bidder. The auctioned quantity is also

CDS, and P from the delivered bond, so net is left with the par value of 100, the same outcome as under physical settlement. An alternative is to receive $100 - P$ from the CDS cash settlement and sell the bond in the market, but this leads to a risky cash flow since the market price may not match the auction's final price.

[9] Since there is a positive supply of bonds but a zero net supply of CDSs, it is plausible that some of the long protection CDS positions go to hedge existing long bond positions, while the corresponding short protection positions are naked. Thus, it is natural to expect sell-PSR orders to dominate buy-PSR orders on average.

exogenous: there are no first-stage quantity submission decisions to be made by the participants. Perhaps most significantly, 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 US Treasury securities, as also other Treasury auctions worldwide, resemble the second stage of the credit-event auction, at least those with a sell-NOI. There is a given quantity of a divisible good being auctioned, bidders submit limit orders, and the final price is determined by matching the aggregate demand curve to the available supply. What especially differentiates the credit-event auction is the endogenous determination of the nature of the second-stage auction; Treasury auctions are only for *sale* of an *exogenous* quantity of Treasury securities. 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 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 various 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, Washington Mutual, CIT and Thomson, as well as Fannie Mae and Freddie Mac. Their focus is more on the functioning of the market in stressful times, though they also provide some documentation on the behavior of prices including the bounce-up 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 both theoretical models of CDS credit-event auctions developed in the spirit of Wilson (1979). Both papers take the distribution of post-auction values to be exogenous and common knowledge; the focus in each case is on how the auction-determined price compares to this exogenously-specified fair price. Taking the first stage outcomes as given and assuming only dealers participate in the auction, Du-Zhu model solely the second stage of the auction. They show that there are equilibria of the second stage in which the prices will be 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.) Chernov, Gorbenko and Makarov too take the NOI being auctioned as exogenously specified, but they otherwise study a full two-stage game with both dealer and non-dealer participants. They show that if the NOI is "large," there are equilibria with the opposite property to Du-Zhu, viz., that sell-auctions result in prices that are too low relative to fair price, while buy-auctions result in prices that are too high. (Again, taking sell-auctions as the reference point, we call these "underpricing" equilibria.) Our price-bias findings in Section 4 are consistent with the underpricing equilibrium patterns, but not with the overpricing equilibria; however, we do not generally find a significant role for the size of the open interest in our empirical analysis.

3 The Data and Descriptive Statistics

We collected data on the auctions from `http://www.creditfixings.com`, a website run by Creditex, one of the two co-adminstrators of the ISDA credit-event auctions. (The other is Markit.) 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,[10] 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 low of a single deliverable bond (in 5 different auctions) to a high of 298 deliverables (in the case of CIT). The median number of deliverable bonds was 5.5, with 6 auctions having more than 100 deliverable bonds (all financial firms).

Panels B-D of Table 2 deal with dealer participation in the auction. On an average, 12-13 dealers participated in each CDS 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

[10] 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**

same regardless of whether the auction turned out to have a buy NOI or a sell NOI. However, as Panel D shows, participation in the second round did vary considerably depending on the sign of the NOI. While, on average, auctions attracted 62 second-round limit orders, auctions with a sell NOI to attracted around 70 limit orders on average compared to 38 for auctions with a buy NOI.

Lastly, Panel C of Table 2 describes the penalties (adjustment amounts) for off-market first-round price submissions. On average, 1.2 firms got penalized (levied adjustment amounts) 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 NOI to buy) and the remaining are "sell" auctions.

Summary statistics on the frequency and size of trades is presented in Table 3. The upper panel deals with the total number of trades and the lower with 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). The table shows that (a) trading frequency across auctions varies greatly, and (b) the number of trades increases sharply after the auctions. For example, Panel A shows that the average number of trades per day (of all the deliverable bonds in that auction combined) in the 5 trading days preceding an auction was 73, but the distribution is highly skewed with a median of only 8 trades a day. Trading volume creeps up before the auction, with the mean and median number of trades in the deliverable bonds on the day before the auction reaching 87 and 11, respectively. After the auction, trading volume increases sharply, with mean and median number of trades on the day after the auction of 157 and 37, respectively. 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.

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 only pertain to 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.

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

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 do market-price volatilities of the defaulted instruments behave pre- and post-auction? Is there any information in the PSR quantities submitted in the auction? For example, do the NOI or other PSR-related information affect post-auction market prices? What about the limit orders submitted in the second stage of the auction? Does, for example, the dispersion of limit orders affect post-auction behavior? And so on. 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 in the analysis, we need to identify a candidate price for each bond on each day in the horizon using the traded market prices of the deliverable instruments. There are two problems that confront us here. The first is the existence of clearly erroneous points in TRACE data (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). This problem is relatively easy, if labor-intensive, to handle: we simply eyeball the prices and throw out all data points that are clearly egregious errors. The remaining analysis is carried out on the cleansed data set.

The second problem is more subtle and concerns the existence of issue-specific effects in the bond prices. Recall that several auctions admit multiple deliverable instruments. For some companies, we found that certain issues of deliverable bonds tended to trade at systematically different prices from other issues. An extreme example is Charter Communications, whose auction-determined final price was \$2.375. Some of the 19 deliverable obligations for Charter (e.g., the obligation with ticker CHTR.HM) tended to trade in the pre-auction market at prices of \$9-\$10, while the other deliverables traded at prices around \$2-\$3, close to the auction's final price. This suggests that there may be issue-specific influences on the prices.

There are two different methodologies we use to extract a "representative" market price from the data given this problem. The first is manual: we eyeball the data, and eliminate all those deliverable issues whose prices exhibit systematic differences (e.g., the CHTR.HM ticker mentioned above) from other deliverables on the same name. 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 to give large trades more importance. Our results are unchanged if we use an equally-weighted average.)

This second approach looks to use all the data. 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

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

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).[11] 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."

Happily, both approaches yield very similar results for our analysis. While we do not report the numbers here, the levels of the prices estimated under the two methods are very close, and, in many cases, almost identical.

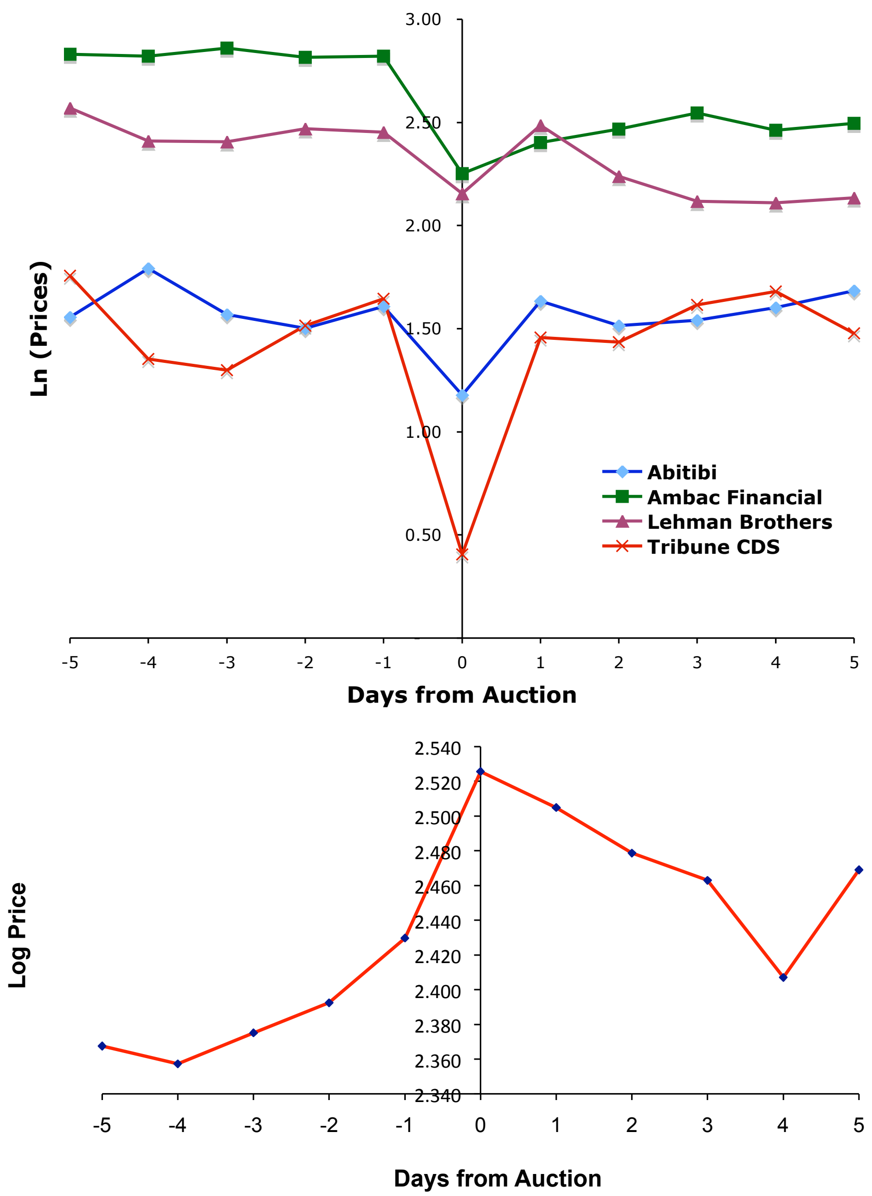
Preliminary Evidence: The Price Patterns

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.[12] Most individual sell-auctions exhibit this broad pattern; the upper panel of Figure 2 illustrates with four specific cases. While we have only four buy-auctions in this sample (Cemex, General Motors, Six Flags and Station Casino), three of them display broadly the opposite pattern to buy-auctions; the lower panel of Figure 2 describes the behavior of General Motors' prices.

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

[12] The average (log-)price in the figure is calculated by taking the log of the weighted-average price on each day as in the first approach described above. The figure uses all the sell auctions for which we have prices on all 10 trading days under this approach.

Figure 2: Average Prices Pre- and Post-Auction



The upper panel of the figure presents the average (log-)price of the deliverable instruments in the CDS credit-even auctions 5 trading days before and after the auction date for four firms: Abitibi, Ambac Financial, Lehman, and Tribune. The lower panel presents the same data for General Motors. Day-0 is date of the auction and the day-0 price is the auction's final price.

Econometric Analysis

Figures 1 and 2 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 amount as well as 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 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 from 0 to 73.5%; while excluding it, and including all other auction-generated information produces an adjusted R^2 of only 12.5%. In short, the regressions provide very strong evidence that the auction generates valuable information (particularly, the final price) that is incorporated into future market prices.

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). T-statistics 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	0.07712	-0.38965	0.0319	0.2303	0.8544 ***
	(0.8091)	(0.40061)	(0.5298)	(0.1504)	(0.1043)
avg_vwp_pre	0.00246	0.00086	0.0008		
	(0.00204)	(0.001)	(0.0013)		
var_p_pre	2.20748	6.719 ***	6.933		
	(3.6626)	(1.921)	(4.519)		
ret_1daypre	0.6929	0.61936	0.0946		
	(0.7481)	(0.3642)	(0.5627)		
avgqty_pre	3.452E-08	-4.264E-09	-2.027E-08		
	2.691E-08	1.447E-08	2.151E-08		
trades_pre	0.000054	-0.000016	0.000063		
	(0.00014)	(0.00007)	(0.0001)		
FinalPriceNorm		0.7411 ***	0.8494 ***	0.7716 ***	
		(0.1176)	(0.2462)	(0.1683)	
FPError			0.0056	0.0042	0.04319
			(0.0266)	(0.0173)	(0.0247)
total_physett			-0.00015	-0.00008	-0.000056
			(0.0001)	(0.00009)	(0.00015)
var_physett			0.0000046	0.000004	0.0000024
			(0.000004)	(0.000003)	(0.000005)
OpenIntAmtNorm			0.00353	0.00474 *	-0.00402
			(0.0031)	(0.00255)	(0.00275)
OIDummy			-0.00509	0.00784	0.14365
			(0.0778)	(0.0664)	(0.0970)
RecessionDummy			0.0929	0.03712	0.12113
			(0.0983)	(0.0579)	(0.0897)
Fracnfilledcarryover			0.14717	0.06642	0.01806
			(0.1634)	(0.1346)	(0.2191)
No of obs	18	18	18	20	20
R-sq	20.95	82.84	92.7	81.01	44.73
Adj R-sq	0	73.48	68.9	67.2	12.48

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). T-statistics 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)
Price_pre	0.00317	-0.000056	0.00059		
	(0.00228)	(0.0014)	(0.0019)		
var_p_pre	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)		
avg_qty_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)	
tot_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)
Fracnfilledcarryover			-0.01787	-0.04809	-0.2099
			(0.1452)	(0.1403)	(0.2040)
No of obs	22	22	22	23	23
R-sq	23.74	77.93	81.28	69.32	26.22
Adj R-sq	5.8	71.04	60.68	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 5.80%. Adding the normalized final price (4) alone to the right-hand side variables increases the adjusted R^2 to 71.4%, 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 the light of the finding that auction-generated information is significant for subsequent price formation, a number of explanations suggest themselves for the apparent mis-pricing in Figures 1-2. One comes from the well-known "winner's curse" problem in common-value auctions; we examine the impact of the winner's curse on auction outcomes in Section 5.1. Another is strategic considerations; Wilson (1979) and Back and Zender (1993), among others, have shown that monopsonistic competition in uniform-price auctions could lead to underpricing in equilibrium. The effect of strategic considerations on auction outcomes is studied in Section 5.2. A third possibility that we do not pursue in this paper is risk-aversion on the part of dealers.

The Behavior of Volatilities

Finally, as an indirect test of the auction's price discovery, we examine how price *volatility* behaves before and after the auction. For this purpose, we use the residuals from (1) to estimate the variance. Table 6 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 trad-

Table 6: 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

ing 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.

5 Behavior in the Auction

From price discovery, we now turn our attention to the behavior of dealers in the auction. We begin with an examination of the provision of liquidity by dealers in the second stage of the auction. We proxy a dealer's liquidity provision by the slope of the dealer's submitted demand (or supply) curve; intuitively, the steeper this slope, the lower the liquidity provision, since a given change in quantity creates a larger price effect.[13] In Section 5.1, we examine how the presence of the well-known "winner's curse" effect influences liquidity provision. In Section 5.2, we examine the impact of strategic considerations on liquidity provision, i.e., how is the liquidity provided by a particular dealer affected by the liquidity provision of all other dealers? Building on the findings here, Section 5.3 then revisits the "underpricing" issue identified in the previous section and examines the extent to which this is affected by the winner's curse and other factors.

In Section 5.4, we examine intra-auction dynamics: specifically, how does information revealed in the first stage of the auction affect the extent to which a dealer's second round bids deviate from its first round bids? Finally, in Section 5.5, we study dynamics *across* auctions, namely, the effect of previous wins and inventory won thereby on current beidding behavior.

5.1 Liquidity and the Winner's Curse Effect

It is well-known that under standard conditions common value auctions (such as the second stage of CDS auctions) are subject to a "winner's curse" problem. Loosely speaking, the auction's winners are those who anticipate the highest value for the commodity being auctioned, meaning that the value of the item being auctioned conditional on the joint information available to all participants will be lower than the corresponding value conditioned on only the winner's information. Thus, the auction's winner(s) are likely to make lower profits than they anticipate ex-ante, which is the winner's curse.

[13] To be sure, a dealer's submitted demand curve also includes customer orders, and, as we have noted, it is not possible to disentangle the dealer's own demand from that of its customers. Our use of the expression "dealer's demand curve" should be interpreted broadly.

In this section, we examine how the presence of the winner's curse affects liquidity provision by a dealer in the auction's second stage. Liquidity provisioning is, as noted above, proxied by the slope of the dealer's submitted demand or supply curve. To proxy the the intensity of the winner's curse, we use the variance of the first-round (inside market) price submissions. The justification is obvious: to the extent that the first-round price 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 effect.

Now, as the anticipated winner's cruse effect intensifies, then other things being equal, we would expect liquidity provision to *decrease*. That is, if we ran a regression of the slope of the submitted curve on the winner's curse proxy, we would expect the coefficient on the latter to be *negative*.

This is exactly what we find. Table 7 describes the results of regression analysis with the dealer's slope as the dependent variable and the variance of first-round price submissions as the explanatory variables (along with several controls). In each of the three specifications, the coefficient on the winner's curse proxy is strongly negative as predicted, and indeed, this is the only variable that is significant at the 1%-level across the board.

5.2 Liquidity and Strategic Considerations

Auctions such as the CDS credit-event auctions and US Treasury auctions are *divisible good* auctions unlike the traditional single-unit auctions that have been widely studied in the literature. It was first pointed out by Wilson (1979) that auctions of divisible goods are fundamentally different in their properties from single-unit auctions. Wilson's insights were extended by Back and Zender (1993) who also showed that uniform-price auctions of divisible goods could be dominated (from the seller's expected revenue standpoint) by discriminatory auctions. This result is contrary to the corresponding result in single-unit common-value auctions.[14]

A fundamental insight in the Wilson-Back-Zender 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. For example, if the total demand curve submitted by the remaining bidders is sufficiently steep, then the marginal cost escalates very rapidly for the last bidder. 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. Of particular

[14] See, e.g., Milgrom and Webber (1982) or McAfee and McMillan (1987). See also Kremer and Nyborg (2004) who show that discrete price and quantity spaces reduce the severeity of the underpricing problem identified by Wilson-Back-Zender.

Table 7: Liquidity Provision and the Winner's Curse

This table presents the results of regressing the slope of a dealer's submitted demand curve on a proxy for the winner's curse (the variability of first-round price submissions) as well as other control variables.

Dependent Variable:	**Bidder_slope**	**Bidder_slope**	**Bidder_slope**
	Spec 1	**Spec 2**	**Spec 3**
Intercept	-8.283	-2.304	-11.8372
	(17.908)	(16.805)	(15.6406)
total_wins_till_bid	0.11579	0.05629	0.1394
	(0.15217)	(0.13916)	(0.1469)
var_rnd1bid	-11.1416 ***	-11.3245 ***	-11.544 ***
	(2.5597)	(2.5522)	(2.8041)
IMM	-0.073	-0.0805	
	(0.1656)	(0.1653)	
IMMnorm			-1.0227
			(5.5572)
dealer_psr	0.00858	0.01633	0.00837
	(0.01708)	(0.01508)	(0.0171)
var_physett	0.00008		0.00008
	(0.00008)		(0.00008)
recessiondummy	-8.552		-5.537
	(11.710)		(10.5446)
var_p_pre		151.56	146.4
		(113.92)	(110.35)
No of obs	166	166	166
R-sq	18.98	18.5	18.9
Adj R-sq	15.39	15.43	15.31

Table 8: Liquidity Provision and 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		
Dep. Variable	**Avg_Compslope**	
Intercept	-1.3119	**
	(0.6284)	
var_comp_physett	0.00000789	***
	(0.00000216)	
var_p_pre	-1.0029	**
	(0.3910)	
No of obs	97	
R-sq	23.14	
Adj R-sq	21.5	
Partial R-sq	1.22	
F	7.42	
Prob > F	0.001	
Endogenous		
Avg_Compslope	Yes	
Weak Instruments	No	
Robust F	13.38	
Prob > F	0.0004	

Second Stage		
Dep. Variable:	**DealerSlope**	
Intercept	-11.6474	**
	(5.5389)	
avg_compslope	4.8868	***
	(1.5948)	
var_p_pre	3.097	**
	(1.3696)	
No of obs	97	
R-sq		

importance from the perspective of the current paper, the constructed equilibria in Wilson/Back-Zender result in underpricing of the auctioned commodity relative to its fair price.

Motivated by the Wilson-Back-Zender arguments, we examine how the slope of the submitted demand curve for one agent reacts to an increase in the slopes of the others' aggregate curve. Since the slopes are jointly determined in equilibrium, we cannot simply regress a dealer's submitted slope on the slope of its competitors, i.e., on the slope of the aggregate (or average) demand curve submitted by the other dealers. 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 pre-auction market prices and the variance of the competitors' physical settlement requests. The role of the pre-auction market prices is obvious: the more this variability, the greater the uncertainty concerning the "correct" price and the steeper should be the submitted demand curves. As an instrument for the average competitor's slope, we need two conditions to be met: that it affect the competitor's slope and that it not affect the dealer's own slope. We use the variance of competitors' PSRs to achieve this end. 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 dealers own slope.

Table 8 presents the findings. The results are sharp: the choice of instrument is strongly backed, and the coefficients come out as expected, with an increase in the competitor's average slope leading to a sharp increase in the dealer's own submitted slope, in line with the equilibria in Wilson (1979) and Back and Zender (1993).

5.3 Auction Underpricing Revisited

The results of this section suggest that the factors commonly cited in the theoretical literature as possible sources of underpricing do, in fact, have substantial effects on auction outcomes. This raises the question: can they directly explain the observed underpricing in the sell-auctions? To answer this question, we regress the amount of underpricing (the price one day after the auction minus the auction-identified final price) on a number of explanatory variables including the variance of Round 1 submissions (a proxy for the winner's curse) and the size of the net open interest (as suggested by Chernov, et al, 2011). The results are summarized in Table 9.

There is very strong across-the-board support for the effect of the winner's curse proxy: an increase in the variance of round 1 submissions increases the degree of underpricing and the coefficient is significant at the 1% level in every specification and is roughly the same size in each case. All the other variables, including surprisingly the size of the net open interest, are insignificant in almost every case. There is one exception: the variance of market prices one day prior to the auction is significant in some specifications, but this is also, in a sense, a winner's

Table 9: The Factors Influencing Underpricing

This table presents the results of regressing the degree of underpricing in sell-auctions on a number of explanatory variables. The dependent variable in all cases is the market price one day after the auction P(+1) minus the auction determined final price FP.

Dependent Variable	P(+1)-FP	P(+1)-FP	P(+1)-FP	P(+1)-FP	P(+1)-FP	P(+1)-FP	P(+1)-FP
Intercept	0.64	0.38	0.29	1.6 ***	-0.1	0.13	1.55 *
	(0.26)	(0.5)	(0.61)	0.4	(0.53)	(0.9)	(0.81)
var_physettsize		3.0E-05	1.3E-05		1.4E-05	1.6E-05 *	
		(9.0E-6)	(9.0E-6)		(8.0E-6)	(9.0E-6)	
OpenIntAmtNorm			0.024	-0.05		0.047	
			(0.08)	(0.08)		(0.079)	
var_rnd1bid	0.61 ***	0.68 ***	0.72 ***		0.75 ***	0.76 ***	
	(0.25)	(0.26)	(0.28)		(0.24)	(0.29)	
var_1daypre					0.1 **	0.11 ***	0.089
					(0.05)	(0.055)	(0.06)
valuetraded1daypre(US$ mn)						5E-11	2E-10
						(1.0E-10)	(1.0E-10)
avgqty1daypre						-1E-07	-2E-07
						(2.0E-07)	(2.0E-07)
trades1daypre						-0.002	-0.0039 *
						(0.002)	(0.002)
No of obs	22	22	22	22	22	22	22
R-sq	0.22	0.3	0.3	0.02	0.42	0.52	0.24
Adj R-sq	0.18	0.22	0.18	0.01	0.33	0.27	0.07

curse proxy—a higher variance suggests a high degree of information dispersion entering the auction.

5.4 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. The first is how far the dealer's own bid was from the IMM, i.e., from the summary statistic of the prices submitted in Round 1. Since the IMM has a significant impact on the auction's final price, dealers would be expected to incorporate this information into their second-round bids. The other is the variability of inside-market price submissions in Round 1. A high level of variability in first-round bids points not only to greater information revelation but also a greater winner's curse effect. How does the information revealed determine how far a dealer deviates from its own first-round submission?

The a priori expectation of either variable's impact is not unambiguous. The extent of 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.[15]

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 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 10, 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

[15] 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.

Table 10: 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	

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.

5.5 Across Auction Dynamics

A second learning aspect of bidding behavior of interest concerns the impact of experience and inventory won through past auctions on the Round 2 bidding behavior. Table 11 describes

Table 11: Round 2 Quotes and Past Wins

This table presents how past win behavior (Wins_till_Bid) affect bidders' bidding behavior in round 2. The dependent variable is Round2Quoted Price/IMM for each dealer's bid for each auctions.

Dependent Variable: Round2QuotedPrice/IMM

	Spec 1 (Winning bids)		Spec 2 (Winning bids)		Spec 3 (All bids)		Spec 4 (All bids)	
Intercept	0.97	***	0.94	***	0.77	***	0.73	***
	(0.01)		(0.009)		(0.01)		(0.008)	
OpenInterestAmt	0.000015	***	0.00001		-0.00003	***	-0.00003	***
	(0.000006)		(0.000007)		(0.000003)		(0.000003)	
Wins_till_bid	-0.02	***			-0.0003	***		
	(0.002)				(0.000009)			
WinSize_till_bid			-0.0002	**			0.000023	***
			(0.00007)				(0.0000008)	
No of Observations	606		606		2708		2708	
R-sq	7.27		0.83		3.47		3.26	
Adj R-sq	6.96		0.51		3.40		3.1	

the results. We find that the number of past wins and the amount of wins in past auction negatively affects aggressiveness of dealers in Round 2. Conditional on other relevant variables, the number of past wins may proxy the amount of learning on how bidder may win without being too aggressive. This variable may also proxy for the exposure to risks associated with defaulted bonds obtained from wins in past auctions. We find that it has a significant negative coefficient pointing to the possibility of impact of inventory and risk exposure.

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 only indicative. Carrying out a structural estimation of the entire auction process involves developing and modeling behavior in a complete two-stage model which would take us beyond the scope of the current paper. Rather what we do is to simplify the process by assuming that the auction has both common-value and private-value components; that the IMM and NOI act as sufficient statistics for the common value component; and that after Round 1, dealers receive private signals on the values of the underlying bonds that, conditional on the IMM and NOI, are independent. These signals are incorporated into the demand (or, depending on the NOI, the supply) curves they submit in Round 2 of the auction. Our estimation extracts non-parametrically the underlying distribution of the privately-observed 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, as reported in 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, mentioned earlier, is self-explanatory. The last part of the assumption helps segregate the influence of others' signals on the value function of the dealer. The existence of a private value component may be justified by appealing to dealers' own risk-management and portfolio considerations that drive their demands for net positions after the auction. 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, the final assumption is a natural condition to impose.

Bidding and Equilibrium

There are n bidders ("players") in the auction. Let the value of the underlying deliverable bond be V. Each player i draws a private signal s_i concerning the incremental value of the bond over the IMM. The draws are independent across players and come from a common distribution. We assume that $E(V \mid s_i) = \text{IMM} \times s_i$. For notational simplicity, we normalize the NOI to unity in this discussion.

Given his signal s_i, each player 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, given the signal s_i. 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.

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

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

Although player i does not know the values of s_j for $j \neq i$, the distribution of signals is common knowledge, so player i can calculate the probability distribution of prices p that will result from the vector of strategies $X = (x_1, \ldots, x_n)$:

$$\begin{aligned} H(\hat{p}; v, X) &= \text{Prob}(p \leq \hat{p} \mid V = v, X, s_i) \\ &= \text{Prob}(\textstyle\sum_{j=1}^{n} x_j(\hat{p}, s_j) \leq 1 \mid V = v, s_i) \\ &= \text{Prob}(\textstyle\sum_{j=1}^{n} x_j(\hat{p}, s_j) \leq 1 \mid V = v) \quad \text{(by independence of signals)} \end{aligned}$$

So the expected profit of player i given the strategies $X = (x_1, \ldots, x_n)$ and the signal s_i is

$$\Pi_i(X, s_i) \; = \; E\left\{ \int_0^{\infty} (V - p) x_i(p; s_i) \, dH(p; V, X) \right\},$$

where the expectation is taken over the distribution of V given the signal s_i. The strategy x_i is a best-response of player i to X_{-i} if for all other strategies y_i and for all s_i, we have

$$\Pi_i((X_{-i}, x_i), s_i) \; \geq \; \Pi_i((X_{-i}, y_i), s_i).$$

A symmetric equilibrium is one in which all players use the same strategy $x(\cdot; s)$. Given the assumed symmetric structure of the game, it is natural to focus on symmetric equilibria.

In a symmetric equilibrium, player i's best-response to all other players using the strategy $x(\cdot;\cdot)$ is to use the strategy x itself. This means $x(\cdot; s_i)$ maximizes

$$\Pi_i((X_{-i,}, y_i), s_i) \;=\; E\left\{\int_0^{\infty}(V-p)y_i(p;s_i)\,dH(p;V,(X_{-i},y_i))\right\},$$

over all possible choices y_i, where, in obvious notation, we use X_{-i} to be the strategy vector in which all players $j \neq i$ use the strategy $x(\cdot;\cdot)$. Appealing to calculus of variations arguments, Wilson (1979) provides the first-order Euler conditions for optimality in this maximization exercise:

$$E\left\{(V-p)H_p(p;V,(X_{-i},x)) + x(p,s_i)H_x(p;V,(X_{-i},x))\right\} \;=\; 0,$$

where $H_p = \partial H/\partial p$ and $H_x = \partial H/\partial x$ are the partial derivatives of H with respect to p and i's strategy x_i, respectively, evaluated at $x_i = x(\cdot; s_i)$.

By assumption, $E[V \mid s_i] = \text{IMM} \times s_i$. Moreover, the partial derivatives H_p and H_x are evaluated at $y = x(p, s_i)$. Hence, the expectation of $H_p(.)$ conditional on s_i: $E\{\partial H(p_F; V, y)/\partial p | S_i = s_i\} = H_p(.)$ only. Similar argument applies for $H_y(.)$. So the Euler condition can then be represented as

$$\text{IMM} \times s_i = p - x_i(p,.)\frac{H_x}{H_p} \tag{5}$$

Identification and Estimation

If the data we observe is generated by the equilibrium of the second stage as described above then the necessary condition for optimality as in the previous equation helps us non-parametrically identify the signals s of the bidders using the observed bids. Let the observed distribution of the residual supply curve facing a bidder be defined as

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

G measures the probability that the quantity demanded x will be less than the (stochastic) residual supply faced by bidder i. This probability can be estimated for all (p, x) pairs if the joint distribution of $\{(x(p, s_j), j \neq i\}$ can be estimated from the data. 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 are identified from the distribution of observed bids. We must emphasize here that in reality bidders probably do not submit a strictly downward sloping demand function and rather submit a step function. In such a case what we identify and estimate here based on the first order conditions are like the bound of the distribution of signals (Hortacsu and Mcadams, 2010). We shall abstract away from these considerations in this paper.

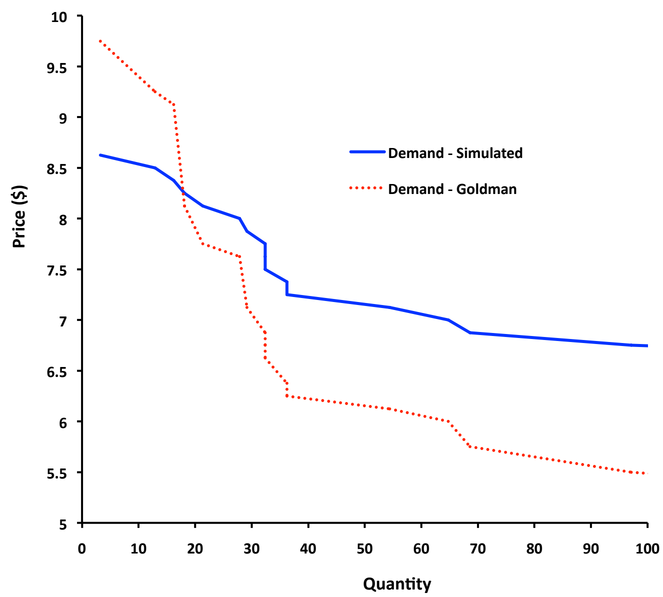
Resampling procedure

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.
- 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.

Figure 3: 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.

Estimation Results

The estimation procedure estimates each bidders estimate of marginal valuation. In Figure 3, 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 solid blue line int he 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 red 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 points 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.

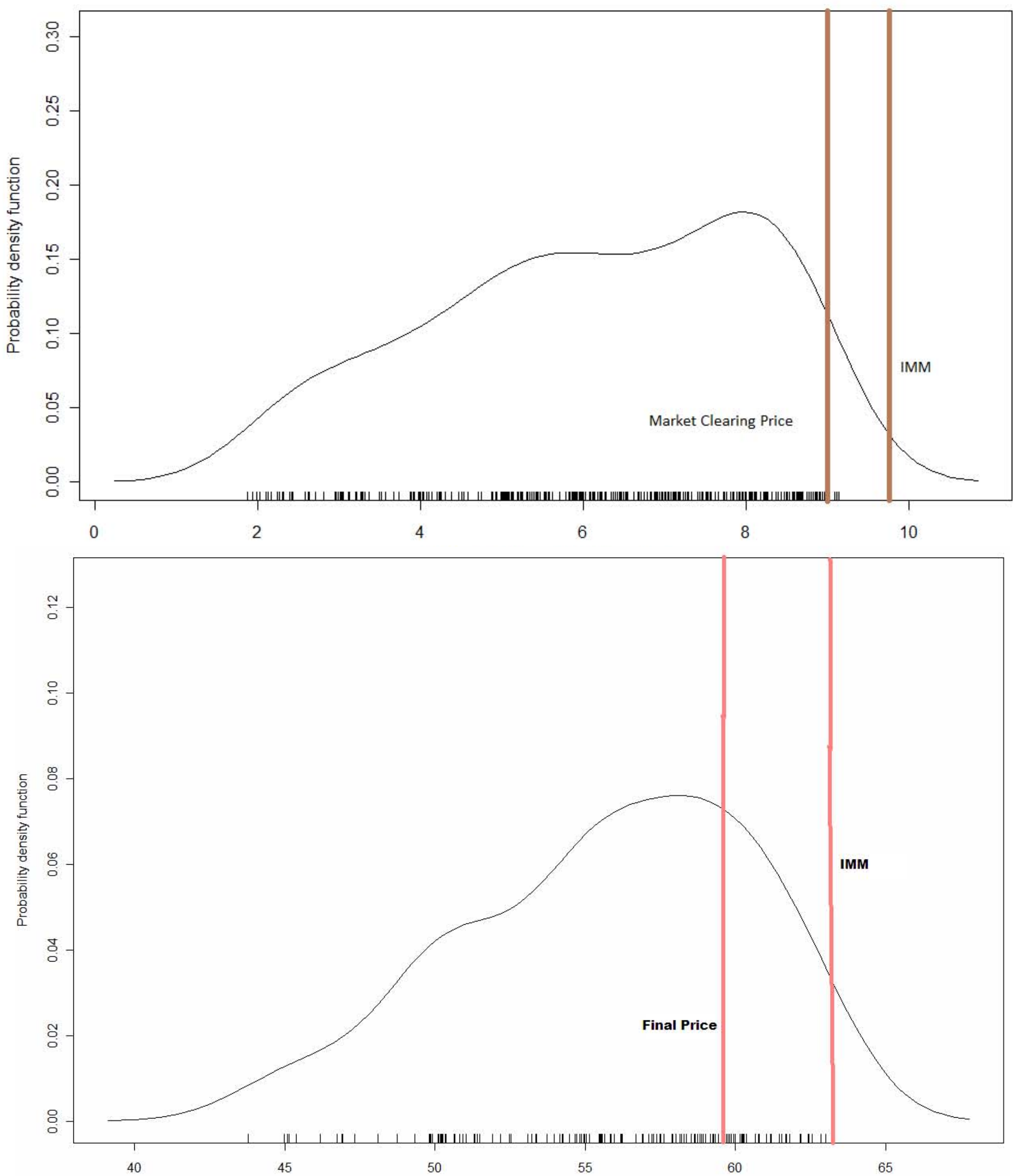
The distribution of the signals of valuations estimated via the procedure in the Lehman case is described above is given in the upper panel of Figure 4. The auction's final price and the IMM are also shown in the figure. The density is unimodal and left-skewed with a mean of 6.16. Similar densities were estimated for each auction in our data set; see the lower panel of Figure 4 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).

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 5 and Table 12 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 21% higher with a median value of 12%.

Figure 4: 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.

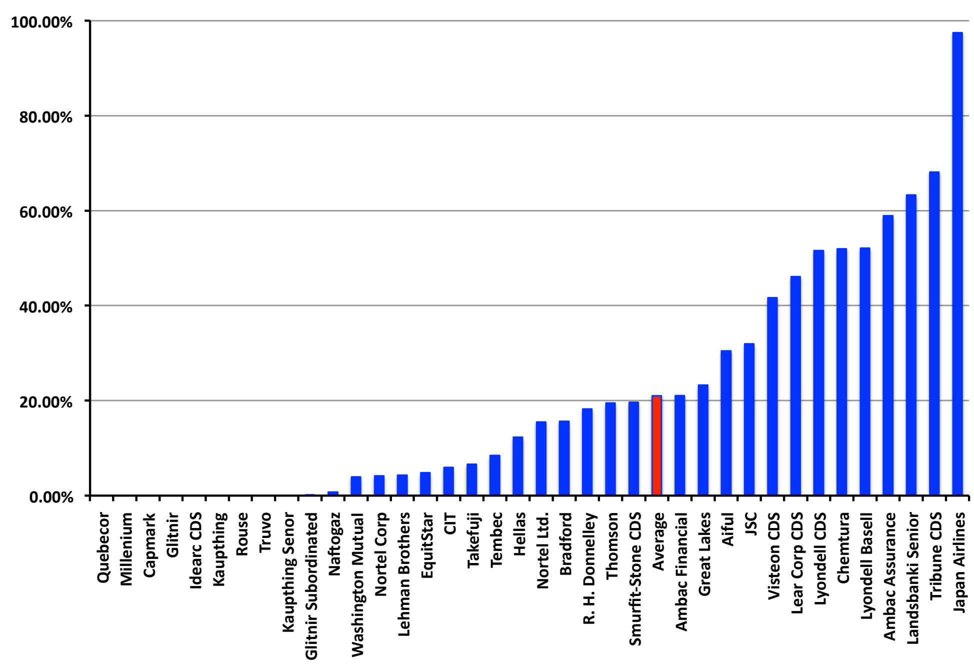
Table 12: Counterfactuals: Comparison to Other Auction Formats

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	$+1$	-2
Median	$+12$	$+3$
Mean	$+21$	$+9$
Third Quartile	$+31$	$+21$

Figure 5: 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.



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 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 12 shows that the average impact is an increase of 9% while the median impact is 3%.

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 Chernov, et al (2011). 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
AvgPrice_Pre	Average value-weighted price for the day prior to auction
Price_Pre	Level of average price 1 day pre computed from the regression
VarPrices_Pre	Variance of AvgPrice_Pre/(Price_Pre) for the day prior to auction
1DayRet_Pre	Nomal daily return on the day prior to the auction
AvgQty_Pre	Average daily quantity traded on the day prior to auction
NoOfTrades_Pre	The total number of trades on the day prior to auction
FinalPriceNorm	Final auction price normalized by the AvgPrice_Pre/(Price_Pre)
FPError	The error terms from the final price regression
TotalPhysSett	Physical settlement requests on the same side as the Net Open Interest
Var_PhysSett	Variance of PSRs on the same side as Net Open Interest
OpenIntAmtNorm	Open Interest normalized by the dollar value of trades on the day prior to auction
OIDummy	Dummy variable which takes a value of 1 if Open Interest is to buy and 0 otherwise
RecessionDummy	Dummy variable which takes a value of 1 if auction is held between 1 Oct'08 and 1 Oct'09
FracFilledByCarryOver	Fraction of net open interest filled by carried over bid/(offer) from round 1
no_of_bids	Number of bids placed in round 1
var_rnd1bid	Variance of bids placed in round 1
CompetitorAvgSlope	Average demand curve slope ofall competitors in an auction
Round1BidNorm	Dealer's Round 1 Bid normalized by IMM
var_rnd1bidnorm	Variance of normalized round 1 bids
dealer_PSR_norm	Dealer's physical settlement request normalized by total physical settlement
PSR_SameAsOI_Dummy	Dummy: 1 if dealer's PSR is on the same side as the Net open interest and 0 otherwise

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