Liquidity Crisis, Runs, and Securities Design*

Lessons from the Collapse of the Auction Rate Securities Market

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Abstract

We use the recent collapse of the auction rate securities (ARS) market to study the fragility of financial innovations and systemic risks. We find strong evidence of investor runs and coordination failures among major broker-dealers providing liquidity support. The two forces amplified each other dynamically, resulting in the market's collapse. We also find that, after dealers withdrew their liquidity support, both the likelihood of auction failure and ARS reset rates depend significantly on maximum auction rates. In addition, as predicted by auction theories, there is strong evidence of underpricing. Finally, we find that liquidity in the non-auction secondary market may lead to more severe underpricing.

JEL Classifications: G01, G12, G24, D44, H74

Keywords: Auction rate securities, liquidity crisis, uniform-price auctions, underpricing, securities design, market microstructure, municipal bond pricing

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Abstract

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1 Introduction

In the summer of 2007, increased concerns over losses on subprime mortgages caused an overall revaluation of complex structured securities. As risk spreads soared and liquidity dried up, various markets that had flourished in a liquidity-rich environment experienced substantial disruptions. Amid the crisis, Northern Rock, one of the largest mortgage lenders in the United Kingdom, experienced a classic bank run. The market for asset-backed commercial paper (ABCP), which conduits and structured investment vehicles (SIVs) rely on, shrank considerably. The market for auction rate securities (ARS)—debt instruments whose interest rates are reset periodically through auctions—collapsed.

The liquidity crisis raised important issues concerning systemic risks and the fragility of financial innovations. In this paper, we use the ARS market as the laboratory to shed light on these issues. Importantly, the institutional setting of the ARS market provides a unique environment to study the dynamics of the strategic interaction between investors and broker-dealers in response to systemic shocks and the critical role of securities design in financial stability. We achieve these goals by analyzing comprehensive data on auction results and intraday transactions of ARS issued by municipalities (MARS), which make up about half of the overall ARS market.

We find that in mid-February 2008, two dynamic forces—investor runs and coordination failures among major auction dealers providing liquidity support—amplified each other and resulted in the collapse of the ARS market. An unusually large number of bondholders rushed to sell their holdings, driven by both panic and concern that auctions may fail. The runs resulted in sharp increases in auction dealers' inventory, stressing their balance sheets at a time when the short-term funding markets have already experienced substantial disruptions. Meanwhile, coordination failures among broker-dealers, triggered by an unexpected first-mover that withdrew liquidity support for all of its auctions, led to a simultaneous withdrawal of liquidity support by other major auction dealers. Investor runs and dealer coordination failure amplified each other dynamically: Investor runs made it increasingly difficult for auction dealers to support auctions, and the liquidity withdrawal by auction dealers reinforced investors' beliefs and induced more selling.

The unraveling of the strategic interaction between investors and auction dealers revealed a key flaw of the ARS design: Auction dealers are implicitly assumed, but not contractually obligated, to provide liquidity support in auctions.[1] Dealers' willingness to provide liquidity in auctions depends on the value of their reputation as a market maker to both the bond

[1] Similar to ARS, the liquidity provision for SIVs is also implicit. However, sponsors of SIVs generally took the underlying assets back to their balance sheets when the short-term debt failed to roll over, likely because the interests between sponsors and the issuers are better aligned.

issuers—often clients of their underwriting business—and the ARS investors—often clients of their wealth management business. The relative value of the dealers' reputation diminished sharply as taking on additional inventory would threaten their own survivals, because the other part of the dealers' balance sheets had also been hit hard by systemic shocks. Consistent with Gorton and Souleles (2006), auction dealers would optimally stop providing liquidity support for their auctions under such circumstance.

More importantly, the value of one dealer's reputation depends on the actions of other dealers. Loss of reputation is costly only if other dealers continue to provide liquidity supports. With this externality, the equilibrium of the reputation game played among major dealers can switch quickly from all-support to all-withdrawal after a slight perturbation. Thus, the implicit liquidity support is fragile. The fragility of liquidity observed in the MARS market is particularly remarkable because, despite concerns over the health of monoline insurers of municipal bonds and state and local government budget deficits, the underlying credit risk of municipal issuers had been widely believed to be very low.

Our other findings provide additional evidence on the importance of securities design in market functioning. First, in the pre-crisis period when dealers acted as the bidder of last resort, the likelihood of *any-failures*, defined as when total sell orders exceed total buy orders placed by investors, was mostly driven by exogenous liquidity shocks that were not correlated with bond fundamental values and auction characteristics. However, in the post-crisis period when dealers stopped supporting the auctions, the likelihood of any-failures was significantly related to both fundamentals and auction design. In particular, the likelihood of any-failure decreases 17 percentage points if auction maximum rate increases by one standard deviation. These results corroborate the predictions of the existing auction theories that uniform-price auctions, as those used in all ARS that apply the same clearing rate to all winning bids, are more likely to fail when maximum rates are too low.

Second, significant underpricing occurred in the post-crisis period, with the observed reset rates in the successful auctions averaging 60 percent higher than their estimated fundamental values. In addition, the reset rates are related only weakly to fundamentals but strongly to auction design. In particular, reset rates increase with the maximum rates. In contrast, in the pre-crisis period, reset rates are related strongly to fundamentals but weakly to auction design. These contrasting results are consistent with the predictions of auction theories for the uniform-price auction with fixed supply and endogenous supply, respectively. Theories predict that for auctions with fixed supply, which correspond to auctions without dealers' liquidity support, there exist multiple equilibria. The clearing rates can deviate from their fundamental values, and can be arbitrarily close to the maximum rates. For uniform-price auctions with endogenous supply, which correspond to auctions with liquidity support, theories predict more competitive bidding.

Despite the warnings in existing auction theories, the design of ARS contracts did not try to address the issue of tacit collusion in bidding and the resulting underpricing. Indeed, with so much media coverage on the ARS crisis, little attention has been paid to the pricing (in)efficiencies of such auctions. Our finding provides guidance in improving the design of ARS and auctions used for Treasury securities or troubled assets.

Third, we find that auction reset rates increase with the dealer's cumulative inventory. It is likely that auction dealers may have bid up the clearing rates to compensate for higher inventory risk, make the bonds easier to offload in the non-auction secondary market, or make a profit on their market power. These results highlight the active role that dealers play in price discovery, which can potentially lead to conflict of interests. Issuers, the ultimate bearer of interest costs, always prefer lower interest rates, but they have no role in the auctions once the bonds are issued.[2] Dealers, who can observe all investors' bids and place their own bids in the auctions, may prefer higher reset rates if they hold large inventory, and therefore bias the prices.

Finally, perhaps counter intuitively, in the post-crisis period, reset rates increase with liquidity in the non-auction secondary market. This is possible because investors may bid less competitively if the bond is more easily available outside auctions. Thus, the ARS market provides an interesting example in which more liquidity in the secondary market hinders proper price discovery in the auction market, because of the substitutability of the two markets.

Our paper presents new evidence of liquidity runs and coordination failure in a financial crisis. A large literature has studied runs on depository institutions and currency crises (Diamond and Dybvig, 1983; Calomiris and Gorton, 1991; De Bandt and Hartmann, 2002; among others). Several new studies analyze runs during the recent crisis. For example, Covitz, Liang and Suarez (2009) and Gorton (2009) study runs in the ABCP and repo markets, respectively, during the financial turmoil in 2007. Also related, Chen, Goldstein and Jiang (2009) find supporting empirical evidence that the strategic complementarities among investors generate fragility in financial markets. The collapse of the ARS market provides a new angle to this important issue. Our study finds that flawed securities design can be a key reason for the market's vulnerability to systemic liquidity shocks.

We also provide new tests on the theories of uniform-price auctions (Wilson, 1979; Back and Zender, 1993; Goldreich, 2007; McAdams, 2007; among others). Most existing empirical studies look at either Treasury auctions or auctions used for initial public offering of equities.

[2] It is only until late March 2008 when the SEC allowed issuers to bid in their own auctions (with a public announcement of their intention before the auction date).

The ARS market presents a new venue to test and extend the existing theories. Importantly, ARS auctions differ from the standard uniform-price auctions in a number of ways. For example, ARS auctions are repeated while the existing studies consider only single auctions. Moreover, while the ARS auctions are themselves a secondary market, there exists an active non-auction secondary market facilitating the exchanges of ownership in the securities. Our analysis suggests that these special features have important implications for auction results.

Last, this paper provides a comprehensive study on the ARS market. Existing studies on ARS are scant, mostly with limited data on auction rate preferred stocks (Alderson, Brown and Lummer, 1987; Winkler and Flanigan, 1991; Alderson and Fraser, 1993).[3] An exception is McConnell and Saretto (2009), who analyze ARS auction failures and reset rates during the recent crisis. They argue that auctions fail simply because the market clearing yields are above the maximum rates, and that there is a risk-return trade-off in the ARS pricing in that the risk of auction failures is compensated by higher reset rates.

A key drawback of McConnell and Saretto (2009) is that they ignore the role of broker-dealers in the collapse of the market. In contrast, we examine comprehensively the strategic interactions between investors and broker-dealers and find that dealers played a critical role in the functioning of the ARS market. In addition, their claim of risk-return trade-off in the ARS pricing cannot reconcile their own findings that while reset rates increase with maximum rates, the likelihood of auction failures decreases with maximum rates. Such seeming contradiction is due to their failure to take into account the impact of auction design on the ARS pricing. We argue that, as predicted by the large existing literature on uniform-price auctions, the bidder-preferred equilibrium generally deviates from the market clearing rates and may be arbitrarily close to the maximum rate.

The rest of the paper is organized as follows: Section 2 briefly introduces ARS and documents the recent collapse of the ARS market; section 3 describes our data and sample statistics; section 4 analyzes investor runs and dealer-coordination failures during the ARS crisis; section 5 examines ARS pricing; and section 6 concludes.

2 ARS and the Collapse of the ARS Market

2.1 What Are ARS?

ARS are long-term debt instruments whose interest or dividend rates are reset through periodical auctions, typically every 7, 28, or 35 days. ARS may be issued by municipalities

[3] Alderson et al. (1987) look at the structural characteristics and return behavior of ARPS during its vintage era; Winkler and Flanigan (1991) compare the risk premia on ARPS and commercial papers; and Alderson and Fraser (1993) study the growth and contraction of the ARPS market in the late 1980s.

or their authorities in the form of tax-exempt or taxable bonds (municipal ARS, or "MARS") or by corporations or closed-end mutual funds in the form of preferred stocks (auction rate preferred stocks, or "ARPS"). Buyers of ARS are predominantly corporate treasurers and high-net-worth investors.

The first ARS was an ARPS marketed in 1984 as an improvement over adjustable-rate preferred stocks (Dow Jones Newswires, 1984; Alderson et al., 1987), and tax-exempt MARS debuted in 1988 (*The New York Times*, 1988). Auctions were supposed to provide better price discovery than adjustable-rate securities because auction reset rates may reflect more timely the changes in issuer's credit risk. Consequently, ARS transfer idiosyncratic credit risk to issuers. ARS were also supposed to be more liquid as auctions provide a focal venue for exchanging ownerships with implicit liquidity support from broker-dealers. In addition, because ARS enable issuers to sell long-term debt but pay short-term rates, they are particularly attractive to municipal bond issuers due to generally steeper term structures of the municipal bond yields (Green, 1993).[4] As shown in Figure 1, issuance of MARS soared in 2002 when short-term interest rates on municipal bonds became particularly low comparing to long-term interest rates. Issuance of MARS had remained strong until the first quarter of 2008 since when it abruptly stopped.[5]

The total size of the ARS market reached $330 billion at the end of 2007, roughly one-half of which is accounted for by MARS, and the bulk of the rest are ARPS issued by closed-end funds and ARS issued by student loan authorities (or SLARS).

2.2 Auction Procedure

The auction process serves two purposes—setting the interest rate paid by the issuer until the next auction (price discovery) and facilitating the transfer of ownership (liquidity). The interest rate is reset periodically through a Dutch Auction. In the auction, existing bond owners can place three types of orders: (a) hold order, the par amount of the securities they wish to continue to hold, regardless of the clearing rate; (b) limit sell or "hold-at-rate" order, the par amount of securities they will hold as long as the clearing rate is no lower

[4] State and local governments are generally prohibited by law to issue short-term debt to finance long-term projects. The two main types of short-term debt are tax anticipation note and revenue anticipation note—obligations issued in anticipation of, respectively, the collection of future taxes and revenues (usually inter-governmental aid). These debts have to by repaid within one calendar year. State and local governments may also issue bond anticipation note with somewhat longer maturity to finance capital purposes in anticipation of issuing long-term bonds, or issue budget note to finance unforeseeable or other expenditures for which an insufficient provision was made in the annual budget.

[5] Data on ARPS issuance are not available. However, Alderson and Fraser (1993) suggested that after rapid growth, ARPS contracted substantially in the early 1990s when concerns over corporate credit quality caused a steep rise in auction reset rates.

than a specified rate; and (c) market sell order, the par amount of securities they wish to sell irrespective of the clearing rate.

Potential buyers can only submit a buy-at-rate type of limit order, in which they specify the par amount of the securities they wish to buy if the clearing rate is no lower than a specified rate. All orders are submitted to the auction agent through broker-dealers, often called "auction dealers." Importantly, auction dealers can submit their own orders in the auctions *after* observing all customer orders submitted to them. In addition, before the auction starts, the auction dealer provides interested parties with "price talk," which entails the range of fair interest rates at which the dealer expects the auction to clear.

The auction agent—the firm that runs the auctions—ranks sell and buy orders by rates. Note that hold-at-rate orders from existing holders appear on both the bid and sell sides of an auction. Bids with successively higher rates are accepted until all the securities being auctioned are sold. The clearing rate, which applies to all accepted bids as in other uniform-price auctions, is the lowest rate at which bids are sufficient to cover all the securities for sale in the auction. Multiple bids at the clearing rate are filled on a pro rata basis.

If bid orders are not sufficient to cover all sell orders, the auction will fail. In failed auctions, interest rates are reset at maximum rates pre-determined according to the rules specified in the bond prospectus, and sell orders are filled pro rata. Sellers have to hold on to their unfilled orders until the next auction. They are generally compensated for by a higher maximum rate.[6]

If all existing bondholders decide to hold all their holdings irrespective of the interest rate, the auction outcome is called "all hold," and the interest rate is reset at an "all-hold rate," usually a low rate pre-determined by the rules specified in the bond prospectus.

2.3 The Role of Auction Dealers

Auction dealers play two important roles in the auctions. First, they can affect price discovery through their price talk, or direct order placement. Second, and more importantly, they may act as the bidder of last resort to help clear the auctions. To illustrate, see a hypothetical auction shown in Figure 2. The aggregate bid or bond demand curve is the solid step function. If the total sell or bond supply curve is the vertical line A, which crosses the bid curve, the auction is said to have "cleared," and the clearing rate is the lowest rate at which

[6] Maximum rates are generally high for non-student loan ARS. For example, some ARS issued by the Port Authority of New York were reset to 20 percent after their auctions failed in mid-February 2008. For SLARS, their maximum rates are generally designed to keep the issuer's interest payments below the expected rates of cash flows from the underlying student loans, a requirement by rating agencies for obtaining a high credit rating. For example, some bonds cap total interest payments within an extended period, resulting in very low maximum rates, sometimes zero, after their auctions have failed a few times.

total bids are greater than total supply, which is 6 percent in the example.

What happens if the total supply is instead the vertical line B, which does not cross the total bid curve? In this case, the auction dealer can submit its own bids to move the demand curve to the left. Because the auction dealer submits its bids after seeing all customer orders, not only can it prevent the auction from failing but also dictate the clearing rate. In the example, the bid curve is extended by the auction dealer to clear the auction at 5 percent. If, however, the auction dealer lets the auction fail, the rate will be reset at the maximum rate, which is 10 percent in the example.

It is important to note that auction dealers are not contractually obligated to provide liquidity in auctions. However, they may have strong incentives to keep the auctions successful and the prices competitive. Auction dealers are frequently the underwriters of the ARS at issuance and have ongoing business relationships with the issuers. Loss of reputation or credibility caused by failed auctions or extraordinarily high interest rates may threaten dealers' underwriting businesses. In addition, many of the ARS investors are the clients of the dealers' wealth management desks. Lack of liquidity in these markets may result in the loss of these clients.

Indeed, with auction dealers committed to liquidity provision, auction failures have been rare until the recent financial turmoil. The opaque nature of the support may have created a false sense of safety among ARS investors. In fact, the sales departments of those same banks typically promoted ARS as safe and liquid, and the possibility of a failed auction was heavily discounted.

2.4 The Collapse of the ARS Market

The subprime mortgage crisis in the summer of 2007 caused an overall revaluation of complex structured securities and general corporate credit risk. Investors started to raise concerns about the credit quality of some ARS, especially those insured or issued by troubled bond insurers such as Ambac Financial Group, Inc., MBIA Inc., and Financial Guaranty Insurance Company (FGIC). In late 2007, auction failures started to occur for some ARPS, including those issued by troubled bond insurers (Quint, 2007).

Moreover, exposures to the credit crisis put significant strains on auction dealers' overall balance sheets, and liquidity provision and market making became increasingly expensive across all over-to-counter markets (Froot, 2009). On January 22, the first day when bond investors could react to Fitch Ratings' downgrade of Ambac, a major bond insurer, Lehman Brothers Holdings, decided not to bid on two auctions it ran, resulting in the first MARS failures since 1991.[7] While Lehman's action did not spillover to other broker-dealers perhaps due to its selective nature, it did intensify the concerns about possible withdrawals of liquidity support by other dealers. See Braun (2008*b*). However, on February 12, news broke out that Goldman Sachs had withdrawn liquidity supports on all auctions it ran and that Citigroup had also done so for a selected set of its auctions (Braun, 2008*a*). On the following days, other major investment banks, including Citigroup, Lehman Brothers, Merrill Lynch, and UBS, reportedly all stopped supporting their auctions (Williams and Weiss, 2008). As the words of the dealers' withdrawal and auction failures spread in major news outlets, auctions began to fail en masse. For example, on February 13, the auction failure rate reportedly peaked to more than 80 percent. Since then, failure rates have declined somewhat but have remained frequently above 60 percent. Among other responses to the ARS market failures, SEC on March 14, 2008 allowed municipal bond issuers to bid in their own auctions (Securities and Commission, 2008).

The collapse of the ARS market led to serious consequences. ARS investors, including big corporations such as Bristol-Meyers Squibb, Jet Blue, and Palm, Inc., and many high-net-worth retirees, suddenly found their "cash equivalent" investments virtually inaccessible. ARS issuers struggled to pay interest rates as high as 20 percent. Auction dealers, who withdrew their liquidity support during the crisis, are still in costly lawsuits for mis-representing the product as safe and liquid. Although these issues have captured headlines in the media, our concerns in this paper are broader and deeper. We are interested in the economic forces behind the collapse of a market that was more than 20 years old. We argue that the design flaws of the ARS market, especially implicit liquidity support, made it vulnerable to runs. Moreover, the price setting mechanism itself—the uniform-price auction—is subject to underpricing, imposing additional costs to bond issuers.

3 Data and Sampling

Our overall sample consists of all MARS whose auctions are run by three major auction agents and which are also subjected to the transaction report requirement by the Municipal Securities Rule Making Board (MSRB). Below, we describe the data on auction results, intraday transactions, and bond characteristics.

[7] The very first MARS failure was in 1991, Pima County industrial development bond, Tucson Electric Power. The bond had 16 consecutive failures until the Bear Stearn Companies, Inc. converted it to fixed-rate bond.

3.1 Data on Auction Results

We obtained proprietary reports of daily auction results from three major auction agents, including Wilmington Trust, Bank of New York Mellon, and Deutsche Bank.[8] For each auction, the following information was reported: the auction date, bond CUSIP number, lead manager/auction dealer, auction frequencies, auction status (failed, succeeded, or all hold), reset interest rate, benchmark rate (for example, 30-day LIBOR or 7-day commercial paper rate), and bond insurer. The auction results we use in this paper start on July 1, 2007 for Wilmington Trust and Bank of New York Mellon and on January 1, 2007 for Deutsche Bank, but all end on April 21, 2008.

The securities in the auction reports consist of all types of ARS. We focus our study on only the bonds that have also appeared in the MSRB intraday transaction data. These bonds consist of MARS issued by state and local governments, as well as a small portion of SLARS issued by student-loan authorities. Since these SLARS also fall into the MSRB's reporting requirements, we treat them as municipal bonds.

3.2 Intraday Transactions Data

Municipal securities dealers are required by the MSRB to report almost in real-time each purchase and sale transaction. This reporting system is called RTRS (Real-Time Reporting System). Transactions of municipal ARS, either through regular auctions or intermediated by dealers outside auctions, are subjected to the same reporting requirements.[9] Since auctions occur frequently, restricting our sample to those that appeared in RTRS is unlikely to omit bonds due to lack of trades.

The transaction data allow us to estimate the amount of buys and sells filled in auctions, a piece of information not available in the auction results. Although the transaction data don't have an indicator for whether the trade happened in or outside an auction, we can generally classify trades on auction dates as "auction trades" and those between auction dates as "non-auction trades."[10] Moreover, the trade reports also identify the direction of each trade. Sales by existing bondholders and purchases by new bondholders are reported as dealer "purchases from customer" and "sales to customer," respectively.

We use the RTRS data to estimate the supply and demand in the auctions. In addition,

[8] Auction agents differ from auction dealers in that auction agents only run the physical operations of the auctions just like auction houses. They don't interact with investors directly.

[9] Specifically, Rule G-14, (a)(ii)(B) states that "a dealer effecting trades in short-term instruments under nine months in effective maturity, including variable rate instruments, auction rate products, and commercial paper, shall report such trades by the end of the RTRS Business Day on which the trades were executed."

[10] This method may underestimate the amount of trades outside auction because trades that happen on auction dates, but prior to auction opening or after auction deadline, are actually non-auction trades.

the transaction data allow us to reconstruct dealer's inventory and examine the interaction between the non-auction secondary market and the auction market.[11]

3.3 Data on Bond Characteristics

Both the auction reports and the trade reports have only limited information on bond characteristics, such as the auction dealer, auction frequency, and benchmark rate. We obtained from Bloomberg additional bond description data, including bond type (general obligation (GO) or revenue bond), tax status (tax-exempt or taxable), credit enhancement (insurance), underlying credit rating (that is, the issuer's credit rating in the absence of credit enhancement), dates of issuance and maturity, and par amount outstanding. However, the information on a key variable, the auction maximum interest rate, is only partially available: The maximum rates are the same as the reset rates for failed auctions, but they are not readily available for successful auctions in any data sources.

Maximum interest rates are determined according to the rules specified in debt contracts. Broadly speaking, the rules are either fixed or floating, and, among floating rules, the rules may be multiplicative, additive, or complex. We classify these rules as follows: fixed, for example, 15 percent; multiplicative, a multiple of a benchmark rate; additive, a markup plus a benchmark rate; and complex, usually a combination of the above types possibly linked to interests paid in the past.[12] Often, the multiples or markups vary with bond's overall ratings (credit ratings after taking into account credit enhancement).

Instead of reading through all bond prospectuses, we first use a statistical method to infer the rules used to calculate maximum rates. First, because maximum rates are linear functions of benchmark rates in fixed, multiplicative, and additive rules, we can infer the rule accurately using data from at least two failed auctions. Second, for bonds that have failed only once over the entire period, we infer the rule based on the following criteria: The rule is fixed if the auction rate is a multiple of one percent; the rule is multiplicative if the ratio of the maximum rate to the benchmark rate, rounded to one percent, is a multiple of 25 percent; and the rule is additive if the difference between the maximum rate and the benchmark rate, rounded to 1/1000 of a percent, is a multiple of one-half of a percent.

The potential issues with the above statistical method are the following: (i) the method does not work if the rule is complex or if the bond had never failed; (ii) for bonds with only

[11]Strictly speaking, both auctions and non-auctions are secondary markets. Thus, we use "non-auction secondary market" to distinguish trades that occurred outside auctions from those that occurred in auctions.

[12]This "look-back" feature is usually seen in SLARS. As witnessed in the current crisis, these ceiling restrictions have resulted in zero maximum rate. This happens when the cap on, for example, a 90-day rolling average interest rate is relatively low and the rates were set high consecutively for several auction periods due perhaps to auction failures.

one failed auction, we identify the rules with some tolerance of error; and (iii) errors may also occur if the issuers changed the rules after auction failures, which does happen, but very rarely.

Leaving out bonds in (i) may potentially induce selection bias to our analysis. To address the selection issue, we manually collect information on bonds whose maximum rate rules are not identifiable using the above statistical method. To check the estimation errors in (ii) and (iii), we look up the bond prospectus for a randomly selected sample of bonds whose maximum rate rules are determined using the above statistical method, and we find fairly low errors.

3.4 Sampling and Summary Statistics

Table 1 shows how our analysis sample is constructed. There are 4,945 ARS in all reports from the three auction agents (line 1), of which 3,709 are municipal securities as they appear at least once in the MSRB's trade report (line 2). For 3,567 of these municipal securities, information on their bond characteristics is available through Bloomberg (line 3). For our analysis, we also remove bonds with reset periods shorter than 7 days or greater than 35 days. This leaves us with 3,526 bonds, which we label as our "overall sample" (line 4). As shown on line 5, for 2,845 bonds in the overall sample, we are able to identify the types of their maximum rate rules and compute their maximum rates using either a statistical or a manual identification method.

Table 2 shows summary statistics. Our overall sample consists of 2,463 bonds issued by non-student loan municipalities with total par outstanding of $137 billion, or 83 percent of the entire non-student loan MARS market, and 1,063 bonds issued by student loan authorities with total par outstanding of $52 billion, or 61 percent of the entire student loan ARS market.[13]

In our overall sample, only about 1.5 percent of the bonds are GO bonds, and 17 percent are taxable. Most of the bonds have reset periods at 7, 28, and 35 days (45, 18, and 37 percent, respectively). Roughly 41 percent of the bonds are not rated, and among those rated, more than one-half have an underlying rating of A or better. Among all bonds, 41 percent are insured by "weak insurers" — those under review for downgrades during the sample period, including Ambac, MBIA, FGIC, CFIG Guaranty, and XL Capital Insurance (XLCA); 11 percent insured by " strong insurers," including Financial Security Assurance (FSA) and Assured Guaranty; and the rest are either insured by other small insurers (20

[13]According to Merrill Lynch estimates, at the end of 2007, total outstanding of bonds issued by non-student loan municipal issuers is $166 billion, and total outstanding SLARS, issued by either municipal authorities or private companies, is $86 billion.

percent) or not insured (28 percent). About 28 percent of the bonds have multiple broker-dealers running their auctions. As lead managers, Citigroup, UBS, and Morgan Stanley together account for about one-half of the bonds (22, 18, and 10 percent, respectively), and the top 5 broker-dealers account for close to two-thirds of the bonds. On average, the bonds have $54 million of par outstanding, $40,000 minimum bidding size, and 24 years to maturity. In general, the above summary statistics change only slightly when we restrict our sample to bonds with known maximum rates.

Table 3 shows statistics on maximum rates.[14] As shown in panel A, among the 2,845 bonds with known maximum rate rules, 1,143 or 40 percent have fixed maximum rates. Most of the bonds with floating rules (1,404 of 1,702, more than 80 percent) have the multiplicative/floating rules.

Bonds with fixed maximum rates tend to have higher maximum rates, and are less likely to fail. About three-fourths of bonds with a fixed rate-cap have never failed during the sample period, while more than 90 percent of bonds using a floating cap had failed at least once. As shown in panel B, the average maximum rate on bonds with fixed rules is about 14 percent, significantly higher than that on bonds with floating rules, under 7 percent. The distributions of maximum rates also differ significantly by their calculation rules. As shown in Figure 3, while the maximum rates of bonds with floating rules distribute fairly continuously in their ranges, those bonds with fixed calculation rules mostly concentrate on 12 percent and 15 percent.

We break the sample into three periods. The pre-crisis period starts from July 1, 2007 to December 31, 2007. The crisis period starts from February 11 2008 to February 19, 2008. The post-crisis period starts from February 27, 2008 to March 19, 2008.[15]

4 Investor Runs and Dealer Coordination Failures

What happened during the week of February 11, 2008? Why did a market with nearly two decades of stability collapse almost overnight? In this section, we first show concrete evidence of "runs" for liquidity by investors. The runs were partly sunspot-driven, as a significant portion of them cannot be explained by fundamentals. We then look at the role

[14] We identify the maximum rate rules for 90 percent of bonds that had never failed or failed only once during our sampling period (982 of 1,094 and 332 of 364, respectively) and for 75 percent of bonds that had two or more failed auctions (1,542 of 2,068).

[15] Our results are robust if we use July 1, 2007 to January 21, 2008 as the pre-crisis period and February 20, 2008 to March 19, 2009 as the post-crisis period. We chose these alternative cutoff points because as mentioned earlier January 22, 2008 marked the first MARS auction failure, February 12 the first overall withdrawal of liquidity support by a major auction dealers, and March 20 marked the start of issuer participating bidding and of significant refinancing and conversion of the ARS by issuers.

of broker-dealers. Evidence suggests that implicit liquidity support is vulnerable to systemic shocks and that coordination failures to provide liquidity support occurred in a reputation game among major broker-dealers. Our analysis shows that the two forces, investor runs and dealer-coordination failures, amplified each other, resulting in the collapse of the ARS market.

4.1 Investor Runs

4.1.1 Definition and Measurement

We start with a definition of investor runs in an auction setting. Ideally, runs should be measured by the sudden surges in net liquidity demand ("NLD", equal to demand for liquidity minus supply of liquidity). For banking institutions, NLD corresponds to net deposit outflows.[16] For auctions, we define NLD as

$$NLD = \sum Sell - \sum_{r_j \geq r_{min}}^{r_{max}} Buy@r_j, \tag{1}$$

with $Sell$ denoting the amount of sell order and $Buy@r_j$ the amount of limit buy order at a rate r_j. Although we do not have data on the orders actually placed in auctions, we combine data on intraday transactions and auction results to obtain a reasonable estimate of the *occurrence* of positive NLD (that is, the indicator variable $I_{NLD>0}$).

To see this, note that the sufficient and necessary condition for an auction to clear in the absence of dealer intervention is:

$$\underbrace{\sum_{r_i \geq r_{min}}^{r_{max}} Hold@r_i + \sum_i Hold +}_{Existing\ Holders} \underbrace{\sum_i Sell}_{ExistingHolders} \leq \underbrace{\sum_{r_j \geq r_{min}}^{r_{max}} Buy@r_j}_{Potential\ Holders} + \underbrace{\sum_{r_i \geq r_{min}}^{r_{max}} Hold@r_i + \sum_i Hold}_{Existing\ Holders}. \tag{2}$$

The left-hand side equals to the total amount of bond outstanding. Hold and hold-at-rate orders appear on both the sell and buy sides of the inequality because a hold order is effectively a market sell, and, simultaneously, a market buy order, and similarly, a hold-at-rate order is a combination of a market sell order and a limit buy order. Simplifying (2), we find that an auction would fail in the absence of dealer intervention if

$$\underbrace{\sum_i Sell}_{ExistingHolders} > \underbrace{\sum_{r_j \geq r_{min}}^{r_{max}} Buy@r_j}_{Potential\ Holders}, \quad \text{or,} \quad NLD > 0 \tag{3}$$

[16]For banks, because of the first-come first-serve rule, NLD equals to net deposit outflows until either a suspension of convertibility or bank failure.

When $NLD > 0$, only two scenarios will occur. In the first scenario, the auction dealer intervenes by submitting its own bid so that the auction clears. We call such an auction outcome "pseudo-failure," as the auction whould have failed in the absence of dealer interventions. In the data, this corresponds to the case when the total amount of "dealer purchases from customer" net of "dealer sales to customer" is positive on an auction date. In the alternative scenario, the auction dealer may do nothing and let the auction fail. Therefore, the occurrence of positive NLD is observationally equivalent to either "actual failure" or "pseudo-failure." For the ease of exposition, hereafter, we call the occurrence of positive NLD "any-failure." Accordingly, we define an investor run in the ARS auctions as a sudden surge in the rate of any-failures.

4.1.2 The Surge in the Any-Failure Rates

In Figure 4, we plot the rate of any-failures and its two components in our sample. Before January 22, 2008, any failures consist almost solely of pseudo-failures, because the dealer routinely supported the auctions. The any-failure rate has been largely stationary, averaging about 55 percent with a range of 40 to 70 percent. The need for constant dealer's bidding support highlights the lack of depth in the market.

The any-failure rate crept up steadily after Lehman let two of its MARS auctions fail on January 22 as investors became increasingly concerned about the possible withdrawal of liquidity supports by broker-dealers. See, for example, Braun (2008*b*). On February 12, Goldman Sachs withdrew its support to all of its MARS auctions, and other major auction dealers followed suit on the next day. As a result, the actual failure rate jumped to nearly 60 percent. The rate of any-failures peaked at 90 percent on February 13 and stayed at around 80 percent until February 27 when it dropped to about 70 percent.

The surge in the rate of any-failures from about 55 percent to 90 percent during the week of February 11 reflected the sharp increases in the net liquidity demand in the auctions. Therefore, it is clear that investor runs had occurred.

4.1.3 Demand and Supply of Liquidity During Crisis

The surge in the rate of any-failures may be due to either extraordinarily high liquidity demand by existing holders or a sudden reduction in liquidity supply by potential holders. To examine the source of the runs, we would ideally study separately the sell and buy orders placed in the auctions. In the absence of such data, we use transactions data to separately infer liquidity demand and supply.

Trades reported in the MSRB's transactions data consist of only orders filled in auctions.

In successful auctions, buy orders are truncated. Reported customer buy trades may underestimate buy orders submitted by potential holders in the auction because some buy orders may not be filled. In contrast, customer sell trades may overestimate market-sell orders placed in the auction because some hold-at-rate orders from existing holders may not be filled, resulting in a sell.[17]

These potential biases do not hinder our analysis, as we are interested in the changes in the amount of orders instead of their levels. The amount of sales resulting from unfilled hold-at-rate orders was likely less during the crisis than before the crisis, due to higher clearing rates. This biases against us finding sudden surge in liquidity demand. Similarly, changes in customer buy trades may overestimate changes in customer buy orders, which biases against us finding sudden decrease in liquidity supply.

In failed auctions, buy orders, if there are any, are completely filled. So both the number and the amount of customer-buy trades are equal to those of buy orders. In contrast, the amount of sell orders is truncated because some or all sell orders are not filled. Even so, the number of sells may be preserved in the transactions data because sell orders are filled pro rata when there is at least one buy order.

As shown in the top panel of Figure 5, until early January, the average amounts of customer buy trades and customer sell trades in successful auctions have been steady at low levels. However, both series shot up during the week of February 11, with customer sell trades jumping particularly higher. In the lower panel, we also plot the number of customer sell and buy trades separately. For successful auctions, the number of customer sells was fairly steady at about four trades per bond until mid-January when it started to inch up. It shot up to nearly 40 trades during the week of February 11. The number of customer buys shows no sign of sudden changes. This suggest that the investor runs were driven by increased liquidity demand than decreased liquidity supply.

For failed auctions, the number of customer sells—which is an unbiased estimator for the number of sell orders—was about 15 trades, markedly higher than the average number of customer sell trades in the pre-crisis period. The number of customer buy trades in failed auctions held steady at about the level seen in the pre-crisis period. The results suggest that investor runs were more likely driven by increased liquidity demand rather than decreased liquidity supply.

[17]These potential biases don't exist if auction dealers bid to just absorb excessive sell orders, in which cases, the reported number and amount of customer sell and buy trades should be equal to sell and buy orders submitted in the auction.

4.1.4 Modelling Auction Failures

Our analysis of investor runs above is based the time series of the any-failure rate, which does not control for any factors that may affect NLD. We now use a regression approach to look further into two issues of the runs. First, we provide a rigorous estimation of the significance of the surge in the any-failure rate during the crisis compared to that in the pre-crisis period. Second, we examine whether the runs were at least partially panic-driven. To do so, we need to first construct empirical models for the any-failure rate.

We use auction theories to guide the specifications of our empirical models for the any-failure rate. Specifically, for the post-crisis period, without the broker-dealer acting as the bidder of last resort, the ARS auctions closely resemble the standard uniform-price auctions that are extensively studied in the literature (for example, Wilson, 1979; Back and Zender, 1993). The results of these studies suggest that, all else equal, the likelihood of auction failure decreases with the level of the maximum rate and increases with the fundamental value of the bond yield.[18] If the maximum rate is too low, say, below the lower bound of the fundamental rate, then there will be zero bid and the auction fails for sure. With relatively higher maximum rate, the auction may fail at some nonzero probabilities. See Proposition 1 of Back and Zender, 1993.[19]

Thus, we include maximum rate and the following variables that proxy for the bond's fundamental value as the potential determinants of any-failure: (1) bond characteristics, including bond size, age (time since issuance), remaining maturity, and whether the bond is backed by student loans, a GO bond, issued for the refunding purpose, or taxable; (2) credit risk factors, including indicators for underlying bond ratings and for credit enhancements. Specifically, we indicate whether the bond is insured by strong insurers, including FSA and Assured Guaranty that retained their AAA ratings, and weak insurers, including Ambac, MBIA, FGIC, CFIG, and XLCA who were under review for downgrades and in the headline news in early 2008; (3) other auction design factors, such as interest rate reset frequency, minimum bid size, and whether the auction has multiple remarketing agents. These variables may affect the liquidity of the bond; and (4) municipal bond market conditions, including

[18] Although auction theories almost always focus on the equilibria when auctions clear, they nonetheless provide useful guidance to our analysis of auction failures. To our best knowledge, Back and Zender (1993) is the only study that contains some analysis on the possibility of under-subscription in the uniform-price auctions. See, for example, their Proposition 1 on page 748.

[19] To illustrate, let us denote the maximum rate of a bond by r_m and its fundamental rate by a random variable r, which has a support $[r_L, r_H]$ and mean $\bar{r}$. Then, the results in Back and Zender (1993) suggest that equilibria with strictly positive bids exist if $r_m \geq c_1$ for some $c_1 \leq r_H$ (see their Theorem 1 and Proposition 1). However, if $r_m \leq c_2$ for some $c_2 \geq r_L$, the only equilibrium is the one with zero bid, and the auction fails for sure (Proposition 1). To see this, note that obviously no one is willing to bid if $r_m < r_L$. When $r_m \in [c_2, c_1]$, the auction is likely to fail because of insufficient bids with the probability of failure depending on both the maximum rate and the distribution of the fundamental rate.

the SIFMA Swap Index and the volatility of swap rate. As shown in Figure 6 where we plot SIFMA Swap Index and SIFMA 7-Day ARS Index, during the normal periods, reset rates on ARS are fairly close to those on VRDOs.[20] While the SIFMA Swap Index is a reasonable proxy for the fundamental value of ARS, the volatility of the swap rate proxies for the range of the ARS rates.

We also take into account features that are unique to ARS auctions. In particular, there exists a secondary market outside auctions in which auction dealers buy and sell ARS at par to provide immediacy for some investors. The conditions in the non-auction secondary market may affect the bidding strategies and valuations in the auctions. To measure the secondary market liquidity, we use the average number of non-auction secondary market trades before each auction and the amount of inventory accumulated by the auction dealer since January 1, 2007. We summarize our discussions with the following linear specification for our probit model of auction failure:

$$\begin{aligned}\Delta Y_{it} = f(&\text{bonds: size, remaining mat., age, taxable, student loan, GO, refunding;}\\ &\text{auction: max rate, reset period, min bid, multi-dealer;}\\ &\text{credit risk: underlying rating, insurer strength;}\\ &\text{munis markets: SIFMA Swap Index, volatility of swap rate;}\\ &\text{non-auction liquidity: dealer's cum. inventory, non-auction trading freq.}).\end{aligned} \tag{4}$$

4.1.5 Significance of the Surge in the Any-Failure Rate during the Crisis

We estimate a probit model of any-failures using the sample of auctions in the *pre-crisis period*, from July 1, 2007, to December 31, 2007. The failure rates predicted by this model for the crisis period are estimates for the would-be failure rates if the market mechanism, especially the assumption of dealers' liquidity support, had not changed. The difference between the observed failure rate and the predicted failure rate measures the significance of the surge in the any-failure rate during the crisis.

The estimated results of the probit model of any-failures for the pre-crisis period are reported in Table 4. Columns (1)-(4) report coefficients of probit regressions with different specifications and Column (5) reports the marginal effect of the full specification in Column(4). The striking finding is that our models can explain only a small fraction of the variation in the rate of any failures in the pre-crisis period. The pseudo-R^2s are only about

[20] The SIFMA 7-Day ARS Indexes are based on reset rates from actual ARS auctions for a sample of high-grade ARS that meet a minimum size requirement and reset every 7 days. The SIFMA Swap Index is a 7-day index composed of high-grade tax-exempt VRDOs. See www.sifma.org for more details on these indexes.

2 percent for all specifications. In other words, the occurrence of insufficient investor bids prior to the crisis was highly random. This low predictability is consistent with our hypothesis that the liquidity supply-demand imbalance in the pre-crisis period is driven mainly by ARS investors' idiosyncratic liquidity shocks that are not correlated with bond fundamental values and auction characteristics. With thousands of auctions being held every day, the market is highly fragmented. As bids are submitted simultaneously and sealed, it is highly likely that demand for liquidity exceeds supply at some auctions.

Other interesting results are as follows. Unless mentioned otherwise, we focus our models with the full specifications in Column (4). First, bonds backed by student loans, with larger size, or with tax-exemption status, are more likely than other comparable bonds to experience any-failures. In particular, the point estimates suggest that the likelihoods of any-failures for student-loan ARS and tax-exempt bonds are, respectively, about 8 and 11 percentage points higher than other comparable bonds. Second, bond insurance does not have any effect on the likelihood of any-failure, and only bonds with underlying ratings equal or better than AA are marginally less likely to experience any-failures in the pre-crisis period. Third, the likelihood of any-failures increases with both SIFMA Swap Index and interest rate volatility. Fourth, the likelihood of any-failures decreases with maximum rate, falling about 3 percentage points for a one-standard deviation increase in maximum rates. Finally, the likelihood of any-failures is weakly positively related to the liquidity in the non-auction secondary market and weakly negatively related to dealer's inventory, perhaps because the investors correctly anticipated during the normal times that broker-dealers would provide liquidity supports in any cases.

In Figure 7, we plot the average likelihood of any-failures predicted by the probit model (4) (the dash line) estimated using the *pre-crisis sample*. The difference between the observed rate of any-failures and the predicted rate of any-failures widened sharply in late January and shot up to its peak to about 50 percent right after February 11. The differences during the week of February 11 are also statistically significant (test statistics are not shown but available upon request). These unusually large rates of any-failures are strong evidence for investor runs conditional on observable factors affecting net liquidity demand.

4.1.6 Information-Based or Panic-Driven Runs

Investor runs may be caused by two different reasons, either new information or self-fulfilling panic triggered by "sunspots" (Cass and Shell, 1983; Diamond and Dybvig, 1983; Gorton, 1985; Jacklin and Bhattacharya, 1988). In our case, information-based run would be driven by sharp changes in key risk factors that affect the ARS valuations. These key risk factors include the expected likelihood that broker-dealers will withdraw their liquidity supports, as well as the credit risk on the bonds. Given that the odds that dealers will abandon the market are bounded by certainty, the probability of any-failures predicted by the model estimated using the *post-crisis sample* should be the upper bound of any-failure rate if the runs are completely information-based. Therefore, the "abnormal failure rate.", the difference between observed rates of any-failures and their predicted upper bounds, is our conservative gauge of panic-driven runs.

Our approach to estimating the abnormal failure rate resembles the standard event studies (see, for example, Campbell, Lo and MacKinlay, 1997). The notable exception is that our estimation window, the post-crisis period, is after the event window (the week of February 11) instead of prior to the event window. A similar approach is used in Calomiris and Mason (2003) in their study of the impact of contagion on bank failures.

We first compute the predicted probability of any-failures using a probit model estimated from the data in the post-crisis period (February 27, 2008 to March 19, 2008). Table 5 shows the results from the probit models. In contrast to the pre-crisis results, our models can explain a large fraction of the variation of failure in the post-crisis period, with pseudo-R^2s close to 45 percent. Thus, any-failures in the post-crisis period are related strongly to fundamental risk factors and auction design.

Other main results are as follows: First, the likelihood of any-failures in the post-crisis period is strongly negatively related to maximum rate. The pseudo-R^2s increase from 18 percent in Column (2) to nearly 45 percent in Column (3) once maximum rate is added to our models. Also, the point estimate suggests that, all else equal, the likelihood of any-failures decreases 17 percentage points if maximum rate increases by one standard deviation. Second, bonds that are backed by student loans, taxable, and older are more likely than other comparable bonds to experience any-failures in the post-crisis period. Third, auctions of bonds insured by those other than strong insurers are more likely to experience any-failures in the post-crisis period. Also, bonds with underlying ratings equal to or better than AA are less likely to experience failure. Fourth, auction designs become an important factor for auction clearing in the post-crisis period. In particular, all else equal, the likelihood of any-failures increases with the reset period as less frequent auctions provide fewer chances for liquidity. Finally, the likelihood of auction failure is unrelated to dealer's inventory and the liquidity in the non-auction secondary market.

Table 6 shows our estimated abnormal failure rates. The average abnormal failure rates are statistically significant since January 28 (except January 30). The magnitude of the abnormal failure rates peaks at 26 percent on February 13, which is about 30 percent of the observed rate of any-failures. Because this is a conservative estimate for the portion of the any-failure rates that cannot be explained by information-based runs, we conclude that a significant portion of any-failures in the week of February 11 is due to a self-fulfilling panic or sunspot.

4.2 Dealer Coordination Failure

Unlike what the name "auction dealer" suggests, the role of auction dealers in the ARS market went beyond collecting bids and conducting price talks. We show below that auction dealers effectively acted as market-makers in the pre-crisis periods as they routinely bought undersubscribed bonds at auctions and then sold them in the non-auction secondary markets. All major dealers, however, stopped supporting their auctions almost simultaneously after one major dealer unexpectedly withdrew its support, leading to widespread auction failures. We find that these simultaneous decisions are the result of coordination failure among dealers.

4.2.1 Auction Dealers As Market Makers

Auction dealers effectively played the role of market makers during the normal times of the auction market. In Figure 8, we plot average par amount of dealer net buys on auction dates and after auction dates in the non-auction secondary market. During the pre-crisis period, dealers had been net buyers in auctions and net sellers post auctions. That is, like market makers, they absorbed surplus supply into their inventories by acting as the bidder of last resort during auctions, and unloaded them after auctions in the non-auction secondary market. The liquidity services were provided almost at no extra cost to investors, as almost all trades happened at par value before the crisis. Auction dealers were ultimately compensated by management fees paid by issuers and repeated business in underwriting and wealth management. Such practice is sustainable if total supply and demand in and out of the auctions can be balanced.

Figure 8 also shows that the dynamics of the ARS market changed significantly in late 2007 and early 2008. While broker-dealers were taking increasingly larger amount of bonds in auctions, it became harder for them to unload bonds in the non-auction secondary markets.[21] Average dealers net buys reached their peak at about $6 million per bond on February 11, but average dealers net sells in the post-auction secondary market stayed in their usual range. On February 12, average dealers net buys fell dramatically and eventually to zero in a few days later.

[21] On December 15, 2007, David Shulman (UBS Municipal Finance Director) stated the following in an e-mail to Joseph Scoby (UBS Chief Risk Officer): " (I) will need some guidance from you as well as Marcel in terms of our overall position and philosophy as it relates to continuing to support these auctions . . . What is clear is that fundamental mechanism of the ARCs structure is not working in a liquidity squeezed environment . . . "

As shown in Figure 9, what happened on February 12 is that Goldman Sachs became the first dealer that allowed almost all its auctions with insufficient bids to fail. Citigroup also *selectively* let some of its auctions fail on the same day (Braun, 2008*a*). In the next three days, all other dealers followed suit. Indeed, as shown in Figure 8, average dealer net buys even fell below zero on a number of days since then, suggesting that the dealer became the taker of liquidity in some auctions. At the same time, dealers continued to unload their inventories, though at a noticeably slower pace, in the non-auction secondary market, likely because investors became increasingly unwilling to buy these securities.

4.2.2 The Fragility of Implicit Liquidity Support

Why did major dealers suddenly and almost simultaneously stop supporting their auctions? Can we predict such an outcome based on what we know about the financial conditions of the auction dealers? We argue that implicit liquidity support in the ARS arrangement is fragile to systemic shocks. More importantly, an unexpected first mover triggered coordination failures in a reputational game among major dealers, leading the market into a self-fulfilling all-withdrawal equilibrium.

Let us first put aside the possible strategic complementarities among major dealers and assume that the value of one dealer's reputation is independent on the actions of other dealers. In this case, the implicit liquidity support resembles closely the implicit support for an off-balance sheet debt as in Gorton and Souleles (2006). Using a model of repeated contracts, they argue that the key for sustaining a bankruptcy-remote special purpose vehicle (SPV) is to have the sponsor implicitly commit to "bail out" the SPV when the SPV would otherwise fail. Based on the value of reputation in obtaining future securitization business, the implicit support mitigates the concerns over moral hazard and adverse selection. When the SPV is profitable, the sponsor uses it to subsidize its on-balance sheet assets. However, in the state of the world where a bailout of the SPV would threaten the survival of the sponsor, the sponsor would let the SPV fail. This state most likely occurs when systemic shocks hit both on- and off-balance sheet assets.

Auction dealers are almost always bond underwriters. They also often sell directly to the clients of their wealth management divisions. The value of dealer's reputation hinges on future businesses in both underwriting and wealth management. The theory of Gorton and Souleles (2006) suggests that dealers would withdraw their liquidity support if doing so threatens their survivals. This may happen either when the amount of capital needed for making the market becomes too large so that it threatens their survivals, or when the price of raising additional capital is too high. We now look into these two factors.

4.2.3 Dealer Inventory and Funding Costs

In Figure 10, we plot aggregate inventory accumulated by all dealers since January 1, 2007 (the solid line). Aggregate inventory stayed largely unchanged in the first quarter of 2007. However, dealers started to aggressively pare down their inventory in the second quarter. The level of inventory picked up somewhat temporarily in the summer of 2007 when the financial market turmoil began, but then fell again to reach its low towards the end of 2007. The sharp declines in aggregate inventory during the relatively quiet period in the municipal bond markets are consistent with Gorton and Souleles (2006). That is, dealers may have tried free up capital from the ARS market to subsidize their on-balance sheet assets where the capital conditions became strained.

Aggregate ARS inventory rose sharply in late 2007 and early 2008 when the concerns over monoline insurers intensified. However, it is remarkable that as of February 11, 2008, aggregate inventory returned to almost the same level as the beginning of 2007. Thus, the increases in dealers' inventory are unlikely the only reason for the widespread withdrawal of liquidity support. The sharp rise in aggregate inventory in the few weeks before February 12 did point to further jumps in inventory if they had continued to support the auctions. Therefore, with stresses on other parts of their balance sheets, dealers' continued support of the market likely threatens their very survivals.

Dealers' funding costs, approximated by average CDS spreads for the top 10 dealers (the dash line, Figure 10), had also risen sharply especially in early 2008. Dealers' CDS spreads had been below 20 basis points through July 2007, but they rose to nearly 130 basis points on February 11. Overall, the data show that as the amount of inventory that dealers expected to support the auctions rose sharply and the costs of funding skyrocketed, the threat to dealers' survival dominated the concerns over the loss of reputations. Thus, dealers stopped supporting the auctions to preserve themselves.

4.2.4 Coordination Failures in the Reputation Game

While the theory of Gorton and Souleles (2006) is useful for understanding the average behavior of major dealers, it cannot explain why Goldman Sachs became the first mover withdrawing liquidity support and other dealers followed suit almost simultaneously. It is puzzling because, as discussed below, some other dealers had taken on much more inventory or experienced much larger increases in their costs of funds than Goldman Sachs. We now argue that it is coordination failures in a reputation game among the major dealers that may have driven the market into a self-fulfilling all-withdrawal equilibrium.

The value of one dealer's reputation also depends on the actions of other dealers. Reputation creates externality in the dealers' decisions on whether to support the auctions. The damage to a dealer's reputation from withdrawing its auction support may depend on whether other dealers have done the same. In particular, being the first one to stop the liquidity support without others immediately following may be detrimental in the long run. However, if many dealers act similarly, then the damage may be smaller.

Indeed, the unwillingness to become the first-mover among dealers had kept the market going for a period of time. This reluctance is vividly depicted in an UBS internal e-mail in January 2008, in which its managing director David Schulman described a worst case scenario as

> "contagion and reputational risk of UBS becoming first to fail and breaking the moral obligation to support these markets in an orderly fashion." Moreover, he further proposed to "continue to support all auctions" and stated that "if we do fail—be the 2^{nd} to fail" (January 13, 2008, Exhibit 1, Massachusetts Attorney General Investigation).

The strategic complementarity leads to multiple equilibria in the reputation game among dealers. Under certain market conditions, dealers will choose to continue to support the auctions if others also support their auctions, and they will withdraw if other dealers do the same. An all-support equilibrium, even if optimal globally, may not be stable. Small disturbances in some players' behavior will cause the whole game to move from the all-support equilibrium to the all-withdrawal equilibrium.

4.2.5 Unexpected First-Mover

A key characteristic of the unraveling of the all-support equilibrium in the above reputation game is the unpredictability of the first mover. We now show that the first overall withdrawal of liquidity support by Goldman Sachs is indeed unexpected.

Among major dealers, Goldman Sachs was unlikely to have the most difficulties supporting their auctions. First, their overall implicit commitments are not the most onerous among all dealers. As shown in Table 6, Goldman's market share was significantly lower than those of Citigroup, UBS, and Morgan Stanley and only modestly higher than those of other major dealers. Second, Goldman's remarketing effort had been more successful compared with some other dealers. In fact, Goldman was able to pare down its inventory significantly over the course of 2007. On the eve of its withdrawal, Goldman's inventory was actually below its level at the beginning of 2007. Two other banks, UBS and the Royal Bank of Canada (RBC), had experienced more significant inventory increases since 2007. Third, Goldman did not have the highest costs of funds. We can use the prices of credit default swaps (CDS) written on broker-dealers as a measure of their costs of funds. CDS spreads on all major broker-dealers had increased significantly since July 2007, but spreads on Goldman were noticeably lower than those on Morgan Stanley and comparable to those on Citigroup. Both Morgan Stanley and Citigroup ranked higher in market share and experienced more inventory pressures, but neither withdrew their liquidity support before Goldman did.

In short, Goldman's move as the first one to withdraw its auction support appeared to be unexpected. The unpredictable nature of the move and the visibility of Goldman triggered self-fulfilling responses by other dealers. In response to dealers' actions, investors rushed to sell their holdings, further validating dealers' choices.

4.3 Amplifications of the Two Dynamic Forces

Our analysis has shown that the two dynamic forces—investor runs and coordination failures among major auction dealers—amplified each other during late 2007 and early 2008. Driven by both panic and concern that auction dealers may stop acting as the bidder of last resort, an unusually large number of bondholders rushed to the auctions to sell their holdings. As a result, auction dealers' inventory accelerated sharply, putting increasing pressure on their overall liquidity positions at a time when the short-term funding markets for major investment banks experienced substantial disruptions. Moreover, if the dealers continued to support the auctions, the amount of inventory that they would have had to take on had appeared to be so large that it might threaten their survivals. Meanwhile, coordination failures in a reputational game, triggered by the liquidity withdrawal of an unexpected first-mover, led to simultaneous withdrawal of liquidity support by other major auction dealers. While investor runs made it increasingly difficult for auction dealers to coordinate their behaviors, the liquidity withdrawal by auction dealers fulfilled the investors' beliefs. The amplifications of these two forces led to the collapse of the ARS market.

5 Uniform-Price Auction Inefficiencies

In this section, we examine the pricing of ARS in both pre- and post-crisis periods. As discussed, the main difference between the two periods is that dealers actively bid in the pre-crisis period to absorb surplus sell orders, but they stop doing so in the post-crisis period. Based on both existing auction theories and key features of the ARS auctions, we first develop hypotheses on the reset rates for both periods. These hypotheses are tested using data on successful auctions.

5.1 Hypotheses on Reset Rates

5.1.1 Pre-Crisis Auctions

We hypothesize that in the pre-crisis auctions, reset rates may be related strongly to bonds' fundamental values. First, with broker-dealers' active participation, the ARS auctions may be more competitive than the standard uniform-price auctions. As discussed in Section 4, the ARS auctions with dealers' liquidity provision resemble the modified uniform-price auctions in which the seller can adjust the supply *after* observing all bids. Theories on the endogenous supply auctions suggest that such auctions are more competitive (see, for example, Back and Zender, 2001). We thus predict that reset rates in the pre-crisis period better reflect the fundamental values of the bonds.

Second, to maintain their creditability, broker-dealers have incentives to influence the auction clearing rate toward the range in the pre-auction price talk. Because price talks supposedly reflect dealers' views on bonds' fair values, auction reset rates should relate strongly to factors relevant to the dealers' valuation.

In sum, we hypothesize the following:

Hypothesis 1 In the pre-crisis period, when broker-dealers act as the bidder of last resort, (a) reset rates are strongly related to the fundamental value of bond yields; (b) auction design characteristics, such as maximum rate, are not important; and (c) reset rates may be weakly positively related to dealer's inventory.

5.1.2 Post-Crisis Auctions

As discussed in Section 4, ARS auctions in the post-crisis period closely resemble the standard uniform-price auctions. The existence of a continuum of equilibria implies that these auctions may be associated with underpricing. Indeed, among all equilibria, the one with the highest clearing rate (or the lowest price) is always the most preferable to bidders, and that equilibrium—when reset rate equals maximum rate—is achievable when all bidders collude tacitly (for example, Wilson, 1979, Back and Zender, 1993). In other words, auction theories suggest that in the post-crisis period, the reset rates may be only weakly related to the fundamentals. In addition, underpricing is likely to occur, and the reset rates should be *positively* related to maximum rate.[22]

A couple of other features of ARS auctions may also affect reset rates. First, because there exists a non-auction secondary market, reset rates may depend on the liquidity condition

[22] The prediction of underpricing is in sharp contrast to competitive pricing. In a competitive environment, reset rates should be *negatively* related to maximum rate due to lower liquidity risk, because, as we have shown, the auctions of bonds with higher maximum rates are less likely to fail.

post auctions. Importantly, not only can a potential holder buy ARS in the non-auction secondary market, the prices of trades in that market are always par.[23] The ability to buy at par outside auctions will possibly make an already non-competitive auction even less competitive, because the cost of losing a bid is low. So when liquidity in the non-auction secondary market is high, bids are likely to be more collusive, resulting in higher reset rates in auctions.[24]

Second, reset rates may be positively related to dealers' inventory. All else equal, dealers face higher liquidity risk for taking on more inventories, requiring higher rates as a compensation. Also, for profit making, dealers may have incentives to bid on their own accounts to achieve higher reset rates, and such incentives are stronger when dealers hold larger inventories.

In sum, we hypothesize the following:

Hypothesis 2 In the post-crisis period, (a) reset rates are weakly related to bonds' fundamental values due to the existence of multiple equilibria; (b) there exists underpricing; (c) reset rates are positively related to maximum rate, as the equilibrium with the highest rate is preferable to bidders; (d) reset rates increase with the liquidity of the non-auction secondary market as investors may bid more collusively due to the greater ability to buy post auctions; and (e) reset rates increase with broker-dealer's inventory.

5.2 Empirical Results on Auction Pricing

To test our hypotheses, we run OLS regressions of reset rates of successful auctions using the same specifications as in the failure rate models. The results are reported in Table 8. Note that standard errors of all estimated coefficients are adjusted for clustering at issuer levels.

[23] MARS almost always trade at par even after February 2008, when auctions started to fail. Trades at discounted prices did exist on some alternative market platforms, notably the SecondMarket trading platform. Anecdotal accounts from the SecondMarket indicate that most of these discounted trades are on SLARS or ARPS. These sub-par trades, however, account for only a negligible amount of the secondary market trades.

[24] Existing theories generally suggest lower clearing rates for bonds with higher secondary market liquidity. For example, the liquidity premium theory suggests that more liquid bonds should command liquidity premium and thus have lower yields. This theory assumes competitive pricing in the auction market, which is likely not true according to, for example, Back and Zender (1993). Also, the "signalling" theory suggests that buyers in auctions may intentionally bid higher prices (lower yields) to signal higher values so that they can sell at even higher prices in the resale market (for example, Nyborg and Strebulaev, 2003). This theory assumes that only a limited number of buyers can participate in the auctions and that they would sell securities in the non-auction secondary market for a profit. Thus, the auction and non-auction secondary markets are complementary in the signalling theory. For ARS, the auction and non-auction markets are instead substitutable because bidders in the ARS auctions are the ultimate bondholders. In addition, because the prices of all trades in both auction and non-auction secondary markets are always par, flipping bonds is not profitable.

5.2.1 Pre-Crisis Auctions

Results on the pre-crisis auctions are shown in the left panel. As we can see, reset rates are strongly related to the fundamental values of the bonds. The R^2 in the specification with only fundamental variables, Column (1), is 62 percent. All variables that have statistically significant coefficients have signs consistent with common views on bond valuations. Specifically, taxable bonds have higher reset rates than tax-exempt bonds to compensate for the tax liability; bonds backed by student loans have higher rates, but those backed by general tax powers have lower rates; bonds that are wrapped by both strong and weak insurers have lower rates, as those insurers were all big players in the industry before the crisis; bonds with underlying ratings equal to or better than AA also have lower rates by about 13 basis points; and reset rates are positively related to both the SIFMA Swap Index and interest rate volatility.

Also as we hypothesized, auction design characteristics matter only marginally for reset rates in the pre-crisis period. Specifications with or without auction variables, such as maximum rates, have similar R^2. The coefficient on the maximum rate, albeit statistically significant, is quantitatively tiny and thus, economically insignificant. Based on the full model, Column (4), for a one-percentage increase in maximum rate, reset rates are only around 1 basis point higher.

Finally, reset rates are positively but weakly related to dealer inventory and not related to the liquidity in the non-auction secondary market pre-crisis. The coefficient on lagged cumulative dealer inventory is positively and statistically significant. The point estimate implies that for every additional $1 billion in inventory, reset rates increase 5 basis points. This result suggests that dealers may have tried to influence reset rates either to compensate for inventory risks or to induce more successful bids to reduce their inventory.

5.2.2 Post-Crisis Auctions

As shown in the right panel, for the post-crisis period, reset rates are weakly related to the fundamental values of the bonds. The R^2 in the simplest specification, where only bond fundamentals are included, is only 26 percent. The signs of some coefficients on bond fundamentals deviate from the conventional predictions of bond valuation. Specifically, reset rates on insured bonds, even those with strong insurers, are significantly higher, both statistically and economically, than those on uninsured bonds. This suggests that investors indiscriminately shunned away from all insured bonds during the period when investors were concerned about the strength of some monoline insurers. Also, the coefficients on student loan indicators are not statistically significant any more. The coefficients on both SIFMA

Swap Index and interest rate volatility are negative and statistically significant. This is unusual because as shown in Figure 6, the SIFMA ARS Index and Swap Index were fairly close to each other in the pre-crisis period.

The regression results also suggest that the key factors for ARS valuations changed dramatically after the crisis. Notably, underlying ratings become much more important. The difference between AA- and A-rated bonds widened after the crisis. Reset rates on AA or better rated bonds and A-rated bonds are, respectively, about 185 and 58 basis points lower than those on unrated bonds. These findings are consistent with reports that as investors increasingly became concerned about insurers' financial strength, they started to value underlying ratings much more.

Perhaps the most notable finding in regression is that the reset rates are significantly positively related to maximum rates. Notice that the R^2 increases when maximum rate is included in the model. The magnitude of the coefficient on maximum rate also increase significantly from the pre-crisis period. Based on the full model, Column (8), for a one-percentage increase in maximum rate, reset rates are 16 basis point higher. The finding that reset rates are strongly positively related to maximum rates supports the predictions of auction theories for tacitly collusive bidding.

Finally, reset rates are positively related to both the liquidity in the non-auction secondary market and dealer's inventory. The coefficient on the average daily number of non-auction trades is positive and statistically significant, and the point estimate implies that reset rates increase 60 basis points for one additional trade per day in the inter-auction period prior to the auctions. This supports our hypothesis that the existence of a more liquid non-auction secondary market may induce more aggressive bidding in non-competitive auctions. This result casts doubt on the naive notion that higher secondary market liquidity is universally good. Liquidity, combined with an ill-designed auction (uniform-price auction market), may have the unexpected negative effect of altering the strategic behavior of bidders toward less competitive bidding.

Reset rates are also significantly higher if lagged dealer cumulative inventory is higher. Reset rates increase 28 basis points when dealers accumulate $1 billion of additional inventory, a much larger magnitude than in the pre-crisis period. The higher reset rates may be a compensation for higher inventory risk; alternatively, it may be because broker-dealers bid on their accounts to influence the clearing rates to make a profit or to induce more successful bids so that they can more easily pair down their inventories.

5.2.3 Underpricing in the Post-Crisis Auctions

To assess underpricing in the post-crisis auctions, we need a model to estimate the fundamental bond values. The natural choice for such a model is the one we have estimated for the pre-crisis auctions, because as we have shown above, in the pre-crisis period, reset rates are highly related to the set of variables used in conventional bond valuations.

Our estimation has two steps. First, we use the estimated model in Column (5) to predict the would-be fair values of the reset rates for the post-crisis auctions. We then compute the difference between the observed reset rates and the predicted fair rates. This difference is our estimate of underpricing.

Table 6 shows the estimated underpricing. The average reset rate for the post-crisis auctions is 7.4 percent, but the average predicted fair rate is just 4.5 percent. The difference, 2.9 percent, is statistically significant. The magnitude is large as the observed reset rates are, on average, 60 percent higher than their estimated fundamental values. Therefore, there exists substantial underpricing in the post-crisis auctions.

One may argue that the model estimated from the pre-crisis sample does not fully account for the increased risk of auction failure after the crisis. However, the fact that maximum interest rates, which are negatively related to fail probability, are positively related to auction reset rates convinced us that underpricing does exist. The underpricing is larger for bonds with higher maximum rates.

The underpricing found here is in sharp contrast to the results in the existing studies on Treasury auctions. Many countries conduct Treasury auctions using uniform-price auctions. However, even in studies that do find underpricing, the magnitudes are typically very modest (for example, Simon, 1994 and Umlauf, 1993).[25] This may be due to the following special features of Treasury auctions. First, the participants of Treasury auctions are usually a limited number of well-known dealers, making it easier and costly to be caught in engaging in collusive bidding. Second, all bidders bid simultaneously with no one having the kind of advantage that broker-dealers have in the ARS auctions. Third, the seller and the issuer are the same in Treasury auctions, thus their interests are properly aligned.

[25] The existence of underpricing in Treasury auctions is still debatable. For example, Simon (1994) finds uniform-price auctions to be revenue inferior to discriminatory auctions based on the United States' experience with the Treasury auction, while Umlauf (1993) finds the opposite for Mexican Treasury auctions. The difference may be because Mexican Treasury retains the right to restrict supply of bonds ex post. As Back and Zender (2001) shows, uniform-price auctions with endogenous supply may generate more revenue for the seller. In any case, the underpricing in Treasury auctions, even if it exists, is believed to be small.

6 Conclusions

In this paper, we use the recent collapse of the ARS market to study financial innovations and systemic risks. There is strong evidence of investor runs during the crisis, partly caused by a self-fulfilling panic. In addition, coordination failures among major broker-dealers, triggered by the decision of an unexpected first-mover, resulted in a simultaneous withdrawal of liquidity support for auctions. The two runs amplified each other and led to the market's collapse.

In the pre-crisis period, the auctions were a managed bidding process. Broker-dealers acted as the bidder of last resort in the auctions by absorbing positive net liquidity demand. As a result, the incidences of positive net liquidity demand were mostly driven by exogenous liquidity shocks, and the reset rates were strongly related to their fundamental values and weakly related to auction design factors and dealers' inventory.

In the post-crisis period, broker-dealers withdrew their liquidity supports. The likelihood of any-failures depended not only on bond fundamentals, but also heavily on auction design factors. In particular, consistent with the predictions of auction theories, auctions of bonds with high maximum rates were less likely to fail. Reset interest rates were significantly higher than their fundamental values and increasing in dealer's inventory. Dealers may have tried to push up the reset rates to compensate for higher inventory risks, or simply try to profit from higher rates. Also, we find that, counter-intuitively, reset rates were increasing with the liquidity of the non-auction secondary market, as investors may have bid less competitively when the opportunity cost of losing a bid was low.

When ARS were first created, auctions were thought to facilitate better price discovery and enhance liquidity. This assumption was never tested seriously until recently. The financial turmoil exposed serious flaws in the ARS design. First, the implicit guarantee of liquidity provision by broker-dealers is fragile. Consistent with the theory of Gorton and Souleles (2006), dealers withdrew implicit liquidity supports when supporting the auctions threatened their own survivals, because other parts of their balance sheets were also under stress. More importantly, the reputation game played among major dealers can switch easily from an all-support to all-withdraw outcome in a liquidity stressed environment. Second, the ARS design failed to address the well-documented underpricing issue in the uniform-price auctions. Third, there is strong misalignment of interest among issuers, broker-dealers, and bondholders. Finally, the ARS design failed to fully take into account the existence of the non-auction secondary market.

The lessons we learn from the ARS market have broader implications. Trading complex financial products based on simple trust is fragile. The lack of market transparency also creates a false sense of safety. Moreover, dealers' role in the collapse of the ARS market suggests that dealers can be a channel of cross-market contagion. This is due to the fact that the same balance sheet is used to support the market making activities across multiple markets.

Importantly, our analysis draws attention to how regulations should treat implicit liquidity support for non-derivative products. Although the existing regulatory framework, BASEL II, has guidelines on capital requirements for derivative securities to move away from implicit liquidity supports, no such guidance exists for cash securities such as ARS. Recent settlements of major broker-dealers with regulators require banks to buy back substantial amount of ARS sold before the crisis, suggesting that the non-contractual support should be treated as contractual. Therefore, there seems to be two alternatives going forward for the ARS market: either banks commit to not supporting auctions or commit to supporting auctions and do so. These principles are applicable to other financial innovations.

The ARS market may disappear as we have witnessed in other innovations such as CDO^2 and SIVs. But for it to survive in the long run, the debt contract and the auctions have to be significantly modified to address the flaws mentioned above. The SEC decision that allowed issuers to bid on their own bonds resulted in a somewhat improved alignment of interests; however, more work needs be done to improve the design of the securities.

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Table 1: **Sample Construction**

To construct our sample, we start with all ARS contained in auction reports received from Wilmington Trust (WT), Bank of New York Mellon (BNYM), and Deutsche Bank (DB) and impose a set of restrictions to filter out bonds that are not municipal securities or have missing values for key variables. This table shows how the sample changes after each filtering.

Sampling	Number of bonds
1. All ARS from WT, BNYM, and DB	4,945
2. Municipal securities appearing in MSRB's RTRS data	3,709
3. Having Bloomberg bond description data	3,567
4. 7 Days $\leq$ reset frequencies $\leq$ 35 days	3,526 ("overall sample")
5. Maximum rate rules are identified	2,845 ("restricted sample")

Table 2: **Summary Statistics**

	Whole sample, $N = 3,526$		Restricted sample,[a] $N = 2,845$	
	Panel A: Categorical Variables			
	N	Percent	N	Percent
Is student loan	1,063	30.2	688	24.2
Is a GO bond	51	1.5	50	1.8
Is taxable	605	17.2	406	14.3
Reset period				
7	1,600	45.4	1,418	49.8
14	3	0.1	3	0.1
21	1	0.0	0	0.0
28	631	17.9	458	16.1
35	1,291	36.6	966	34.0
Underlying rating				
AAA	4	0.1	3	0.1
AA	576	16.3	522	18.3
A	1,181	33.5	1,034	36.3
BBB	302	8.6	255	8.9
Unrated	1,463	41.5	1,031	36.2
Strength of bond insurers[b]				
Strong	388	11.0	363	12.7
Weak	1,468	41.4	1,174	41.2
Other insurers	690	19.5	606	21.1
Not insured	945	27.9	671	23.6
Multiple broker-dealer	994	28.0	814	28.5
Top 5 lead managers	2,285	64.7	1,770	64.7
Citigroup	762	21.6	639	22.4
UBS	648	18.4	487	17.6
Morgan Stanley	356	10.1	294	10.3
RBC	278	7.9	198	6.9
Goldman Sachs	241	6.8	228	8.0
	Panel B: Continuous Variables			
	Mean	Std. Dev.	Mean	Std. Dev.
Bond size($ MM)	53.6	39.7	53.5	29.2
Minimun bid size ($ K)	39.8	26.3	38.4	26.4
Remaining years-to-maturity	23.7	8.1	23.6	8.1
N. of non-auction trades per day	0.38	0.64	0.39	0.66
N. of auction trades per auction	9.62	13.4	9.99	13.9

[a]The restricted sample excludes bonds for which we are unable to determine their maximum rates.

[b]Strong insurers are FSA and Assured Guaranty; and weak insurers are those under review for downgrades and in headlight news, including Ambac, MBIA, FGIC, CFIG, and XLCA.

Table 3: **Maximum Rates**

Panel A shows the distribution of the types of maximum rate rules. Broadly speaking there are fixed and floating rules, whereas among floating rules, there are multiplicative, additive, and complex ones. Our definitions of these types are the following:

- Fixed: maximum rate is fixed at a number, say 15 percent;
- Multiplicative: maximum rate is a multiple of a benchmark rate up to a fixed cap rate;
- Additive: maximum rate equals to a markup plus a benchmark rate up to a fixed cap rate;
- Complex: complex rule, usually with a mix of multiplicative and additive formulas and often linking to interest payments made during a period of time prior to the current auction.

Panel B shows summary statistics of maximum rates for the restricted sample, which are computed for all bond-dates because, for bonds with floating maximum rate rules, maximum rates may change each date.

Panel A: Types of Maximum Rate Rules						
				Floating Rules		
Sample	Fixed	Floating	Total	Multiplicative	Additive	Complex
Auctions never failed	865	106	971	49	5	52
Auctions failed only once	191	141	332	136	4	1
Auctions failed twice or more	87	1,455	1,542	1,219	141	95
Total	1,143	1,702	2,845	1,404	150	148
Panel B: Summary Statistics of Maximum Rates						
Mean	13.9	6.85	10.4	6.94	6.37	6.06
(Std. dev.)	(1.75)	(1.98)	(3.99)	(2.05)	(1.23)	(1.14)

Data sources: Auction agents, Bloomberg, and authors' compilations.

Table 4: Determinants of Any-Failures during the Pre-Crisis Period

This table shows results from probit regressions of the likelihood of "any-failures," including actual and pseudo-failures, for the period from 7/1/2007 to 12/31/2007. Any-failures occur when net liquidity demand in an auction is positive. Standard errors, shown in the parentheses, are clustered at the issuer level. * and ** indicate that the corresponding p-values are less than 0.10 and 0.05, respectively.

	(1) Coeff/SE	(2) Coeff/SE	(3) Coeff/SE	(4) Coeff/SE	(5) Marg. Eff./SE
Log(size)	0.259**	0.262**	0.257**	0.243**	0.096**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Log(maturity)	0.011	0.010	0.009	0.013	0.005
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Log(bond age)	-0.041**	-0.042**	-0.020	-0.020	-0.008
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Is taxable	-0.241**	-0.241**	-0.265**	-0.270**	-0.107**
	(0.07)	(0.07)	(0.07)	(0.06)	(0.03)
Refunding bond	-0.047	-0.047	-0.048	-0.049*	-0.019*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Is student loan	0.154**	0.152*	0.197**	0.200**	0.077**
	(0.08)	(0.08)	(0.09)	(0.09)	(0.03)
Is GO bond	-0.189**	-0.190**	-0.152*	-0.151*	-0.060*
	(0.09)	(0.09)	(0.09)	(0.09)	(0.04)
Strong insurers	0.030	0.031	0.037	0.031	0.012
	(0.07)	(0.07)	(0.07)	(0.07)	(0.03)
Weak insurers	0.046	0.047	0.054	0.048	0.019
	(0.07)	(0.07)	(0.06)	(0.07)	(0.03)
Other insurers	0.083	0.083	0.071	0.066	0.026
	(0.07)	(0.07)	(0.07)	(0.07)	(0.03)
Underly. rat. $\geq$ AA	-0.099**	-0.098**	-0.093*	-0.093*	-0.037*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)
Underly. rat. = A	-0.059	-0.057	-0.060	-0.060	-0.024
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)
Underly. rat. $\leq$ BBB	0.028	0.029	0.019	0.028	0.011
	(0.06)	(0.06)	(0.06)	(0.06)	(0.02)
SIFMA swap index	0.149**	0.149**	0.138**	0.151**	0.060**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
Vol. of swap rate	0.022**	0.022**	0.021**	0.021**	0.008**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(reset freq)		0.001	0.009	0.009	0.004
		(0.03)	(0.03)	(0.03)	(0.01)
Min. piece (K)		0.000	0.000	0.000	0.000
		(0.00)	(0.00)	(0.00)	(0.00)
Multiple dealer		-0.013	-0.019	-0.015	-0.006
		(0.03)	(0.03)	(0.03)	(0.01)
Maximum rate			0.019**	0.018**	0.007**
			(0.01)	(0.01)	(0.00)
Lag. cum. inventory				-0.034*	-0.014*
				(0.02)	(0.01)
Lag. non-auc. trade				0.043*	0.017*
				(0.02)	(0.01)
Constant	-5.313**	-5.357**	-5.470**	-5.335**	
	(0.37)	(0.37)	(0.38)	(0.39)	
Pseudo-R^2	0.02	0.02	0.02	0.02	0.02
N	34,166	34,166	34,166	34,166	34,166

Table 5: Determinants of Any Failures during the Post-Crisis Period

This table shows results from probit regressions of the likelihood of "any-failures," including actual and pseudo-failures, for the period from 2/27/2008 to 3/19/2008. Any-failures occur when net liquidity demand in an auction is positive. Standard errors, shown in the parentheses, are clustered at the issuer level. * and ** indicate that the corresponding p-values are less than 0.10 and 0.05, respectively.

Coeff/SE	(1)	(2)	(3)	(4)	(5)
	Coeff/SE	Coeff/SE	Coeff/SE	Coeff/SE	Marg. Eff./SE
Log(size)	0.006	0.005	0.097*	0.089	0.017
	(0.07)	(0.07)	(0.05)	(0.06)	(0.01)
Log(maturity)	0.089	0.096	0.131*	0.132*	0.026*
	(0.10)	(0.10)	(0.07)	(0.07)	(0.01)
Log(bond age)	0.541**	0.523**	0.146**	0.146**	0.029**
	(0.04)	(0.05)	(0.05)	(0.05)	(0.01)
Is taxable	-0.017	-0.079	0.428**	0.428**	0.068**
	(0.14)	(0.14)	(0.12)	(0.12)	(0.02)
Refunding bond	-0.058	-0.052	-0.049	-0.050	-0.010
	(0.08)	(0.08)	(0.06)	(0.06)	(0.01)
Is student loan	1.989**	1.952**	1.641**	1.669**	0.166**
	(0.34)	(0.35)	(0.38)	(0.38)	(0.01)
Is GO bond	0.230	0.238	-0.109	-0.108	-0.022
	(0.23)	(0.23)	(0.21)	(0.20)	(0.04)
Strong insurers	-0.076	-0.033	0.300*	0.308*	0.053*
	(0.23)	(0.23)	(0.18)	(0.18)	(0.03)
Weak insurers	0.174	0.209	0.513**	0.519**	0.100**
	(0.22)	(0.22)	(0.16)	(0.16)	(0.03)
Other insurers	0.075	0.111	0.493**	0.500**	0.085**
	(0.22)	(0.22)	(0.17)	(0.17)	(0.03)
Underly. rat. $\geq$ AA	-0.194	-0.182	-0.289**	-0.293**	-0.063**
	(0.14)	(0.14)	(0.12)	(0.12)	(0.03)
Underly. rat. = A	-0.166	-0.168	-0.196*	-0.197*	-0.039*
	(0.13)	(0.13)	(0.11)	(0.11)	(0.02)
Underly. rat. $\leq$ BBB	-0.083	-0.112	-0.023	-0.033	-0.007
	(0.16)	(0.16)	(0.15)	(0.15)	(0.03)
SIFMA swap index	0.061	0.073	0.209	0.199	0.039
	(0.14)	(0.13)	(0.18)	(0.18)	(0.03)
Vol. of swap rate	0.012	0.015	0.026	0.027	0.005
	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)
Log(reset freq)		0.262**	0.234**	0.229**	0.045**
		(0.06)	(0.06)	(0.06)	(0.01)
Min. piece (K)		-0.002	-0.003	-0.002	-0.000
		(0.00)	(0.00)	(0.00)	(0.00)
Multiple dealer		-0.008	-0.018	-0.024	-0.005
		(0.09)	(0.07)	(0.07)	(0.01)
Maximum rate			-0.225**	-0.225**	-0.044**
			(0.01)	(0.01)	(0.00)
Lag. cum. inventory				-0.029	-0.006
				(0.04)	(0.01)
Lag. non-auc. trade				0.060	0.012
				(0.06)	(0.01)
Constant	-0.870	-1.506	-1.514	-1.392	
	(1.61)	(1.66)	(1.49)	(1.49)	
Pseudo-R^2	0.17	0.18	0.43	0.43	0.43
N	5,839	5,839	5,839	5,839	5,839

Table 6: **Abnormal Rates of Any-Failures in Early February 2008**

"Any-failures" include actual and pseudo-failures, which occur when net liquidity demand (NLD) is positive. To estimate the abnormal any-failure rates, we first compute the predicted probability of any-failures using the estimated probit model for any-failures in the post-Feb equilibrium. That is, $\hat{p}_{it} = E(\mathbf{I}_{it}|X_{it}) = 1 - \Phi(\hat{\beta}X_{it})$, where the indicator for observed auction status $\mathbf{I}_{it} = 1$ if NLD¿0, 0 otherwise. Then, the abnormal any-failure rate for bond i at t is $p^{\star}_{it} = \mathbf{I}_{it} - \hat{p}_{it}$. Let N_t be the number of bonds in auctions at t. Then, at t, the observed any-failure rate is $\overline{p}_t = \frac{\sum_i \mathbf{I}_{it}}{N_t}$, the average predicted any-failure rate is $\overline{\hat{p}}_t = \frac{\sum_i \hat{p}_{it}}{N_t}$, and the average abnormal any-failure rate is $\overline{p^{\star}}_t = \frac{\sum_i p^{\star}_{it}}{N_t}$. * indicates the estimate is statistically significant at the 95 percent confidence level.

Date	$\overline{p}_t$	$\overline{\hat{p}}_t$	$\overline{p^{\star}}_t$	Std. Dev. of $p^{\star}_{it}$	N_t	t-Statistics of $\overline{p^{\star}}_t$
22-Jan-08	0.69	0.62	0.05	0.59	367	1.68
23-Jan-08	0.67	0.64	0.03	0.58	376	0.92
24-Jan-08	0.71	0.63	0.08*	0.54	210	2.15
25-Jan-08	0.61	0.61	0.00	0.58	154	0.10
28-Jan-08	0.74	0.64	0.09*	0.52	224	2.46
29-Jan-08	0.70	0.61	0.08*	0.58	352	2.54
30-Jan-08	0.65	0.62	0.03	0.57	383	0.89
31-Jan-08	0.72	0.59	0.15*	0.55	291	4.54
1-Feb-08	0.71	0.55	0.13*	0.53	154	2.99
4-Feb-08	0.74	0.60	0.15*	0.49	218	4.42
5-Feb-08	0.73	0.59	0.15*	0.55	354	5.05
6-Feb-08	0.70	0.60	0.12*	0.56	385	4.04
7-Feb-08	0.69	0.61	0.08*	0.57	307	2.49
8-Feb-08	0.66	0.55	0.11*	0.57	158	2.42
11-Feb-08	0.82	0.59	0.23*	0.52	227	6.64
12-Feb-08	0.81	0.58	0.25*	0.50	369	9.60
13-Feb-08	0.90	0.65	0.26*	0.39	470	14.31
14-Feb-08	0.78	0.64	0.14*	0.38	365	7.11
15-Feb-08	0.76	0.63	0.15*	0.39	443	8.09
19-Feb-08	0.79	0.69	0.13*	0.36	497	8.07
20-Feb-08	0.79	0.71	0.09*	0.37	475	5.12
21-Feb-08	0.78	0.69	0.10*	0.38	360	4.95
22-Feb-08	0.75	0.66	0.10*	0.38	179	3.42
25-Feb-08	0.82	0.72	0.12*	0.34	284	5.87
26-Feb-08	0.76	0.71	0.06*	0.39	436	3.00

Table 7: **Unexpected First Mover**

This table shows the changes in inventory and costs of funds for the top 10 broker-dealers. Market share is the fraction of the bonds in the amount of face values in the whole sample for which the firm acts as the lead manager. See Table 2 for description of the whole sample. Change in inventory is the accumulative net buy (both on auction dates and non-auctions) from December 31, 2006 to February 11, 2008. CDS spreads are quotes in basis points from Markit.

Dealers	Market shares		Inventory ($Bill)		CDS spreads (bps)		
			Change from		Level on	Change from	
	$Bill	Percent	7/2/07	1/2/07	2/11/08	7/2/07	1/2/07
1. Citigroup	43.6	23.2	2.09	-0.10	106	91	98
2. UBS	32.7	17.4	4.85	3.42	84	73	79
3. Morgan Stanley	19.0	10.1	-0.76	-1.88	152	115	130
4. RBC	13.6	7.2	1.14	1.02	45	36	35
5. Goldman Sachs	13.5	7.2	-0.04	-0.82	107	69	85
6. Lehman Brothers	12.7	6.7	0.56	-0.04	180	140	159
7. Bear Stearns	12.6	6.7	-0.98	-1.63	275	222	253
8. Merrill Lynch	10.1	5.4	0.11	-1.02	179	141	163
9. JP Morgan	10.1	5.3	-0.35	-1.39	80	60	65
10. Bank of America	9.4	5.0	-0.94	-1.65	82	67	73
11. Top 10	112.9	94.1	5.90	-3.89	128	101	114

Table 8: Determinants of Auction Reset Rates

This table shows results from OLS regressions of auction reset rates for the pre-crisis period from 7/1/2007 to 12/31/2007 and the post-crisis period from 2/27/2008 to 3/19/2008. Standard errors, shown in the parentheses, are clustered at the issuer level. * and ** indicate that the corresponding p-values are less than 0.10 and 0.05, respectively.

	Pre-Crisis Period				Post-Crisis Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(size)	0.007	0.003	-0.001	0.011	0.039	0.096	0.075	0.059
	(0.02)	(0.02)	(0.02)	(0.02)	(0.13)	(0.12)	(0.12)	(0.12)
Log(maturity)	0.019	0.034	0.033	0.031	0.336	0.304	0.288	0.253
	(0.02)	(0.02)	(0.02)	(0.02)	(0.21)	(0.20)	(0.19)	(0.18)
Log(bond age)	-0.007	-0.028**	-0.015	-0.014	0.151	0.064	0.065	0.044
	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.10)	(0.10)	(0.09)
Is taxable	1.407**	1.377**	1.363**	1.362**	1.710**	1.537**	1.328**	1.225**
	(0.07)	(0.05)	(0.05)	(0.05)	(0.24)	(0.23)	(0.23)	(0.23)
Refunding bond	0.019	0.021	0.020	0.021	0.141	0.175	0.186	0.149
	(0.02)	(0.02)	(0.02)	(0.02)	(0.18)	(0.17)	(0.17)	(0.17)
Is student loan	0.558**	0.316**	0.343**	0.347**	-0.575	-0.825	-0.444	-0.221
	(0.07)	(0.06)	(0.06)	(0.05)	(1.19)	(1.38)	(0.99)	(1.05)
Is GO bond	-0.192**	-0.171**	-0.149**	-0.148**	-1.332**	-1.257**	-1.006**	-0.907**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.33)	(0.36)	(0.37)	(0.32)
Strong insurers	-0.137**	-0.099**	-0.096**	-0.085*	1.845**	1.908**	1.724**	1.631**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.31)	(0.29)	(0.30)	(0.30)
Weak insurers	-0.153**	-0.107**	-0.103**	-0.094**	2.588**	2.713**	2.549**	2.411**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.30)	(0.28)	(0.29)	(0.29)
Other insurers	-0.071	-0.023	-0.030	-0.021	2.969**	3.066**	2.910**	2.793**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.29)	(0.27)	(0.27)	(0.27)
Underly. rat. $\geq$ AA	-0.132**	-0.116**	-0.112**	-0.112**	-1.954**	-1.986**	-1.939**	-1.844**
	(0.04)	(0.03)	(0.03)	(0.03)	(0.32)	(0.32)	(0.31)	(0.30)
Underly. rat. = A	-0.065	-0.056	-0.057*	-0.058*	-0.668**	-0.680**	-0.621**	-0.575**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.30)	(0.30)	(0.30)	(0.28)
Underly. rat. $\leq$ BBB	0.101*	0.084	0.078	0.067	-0.008	0.005	0.038	0.073
	(0.05)	(0.05)	(0.05)	(0.05)	(0.40)	(0.39)	(0.37)	(0.36)
SIFMA swap index	0.444**	0.437**	0.430**	0.412**	-0.354	-0.337	-0.343	-0.418**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.22)	(0.22)	(0.21)	(0.20)
Vol. of swap rate	0.059**	0.059**	0.059**	0.059**	-0.009	-0.004	-0.012	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)	(0.03)
Log(reset freq)		0.226**	0.231**	0.234**		0.577**	0.555**	0.532**
		(0.02)	(0.02)	(0.02)		(0.15)	(0.15)	(0.15)
Min. piece (K)		0.001**	0.001**	0.001**		0.006*	0.008**	0.008**
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Multiple dealer		0.023	0.019	0.013		-0.327**	-0.294*	-0.263*
		(0.02)	(0.02)	(0.02)		(0.17)	(0.16)	(0.15)
Maximum rate			0.011**	0.013**			0.155**	0.156**
			(0.00)	(0.00)			(0.03)	(0.03)
Lag. cum. inventory (B)				0.050**				0.278**
				(0.01)				(0.12)
Lag. non-auc. trade				-0.011				0.604**
				(0.01)				(0.14)
Constant	1.024**	0.522*	0.460	0.375	5.152*	2.766	1.486	1.766
	(0.33)	(0.28)	(0.28)	(0.27)	(2.96)	(2.97)	(2.89)	(2.77)
R^2	0.62	0.65	0.65	0.65	0.26	0.27	0.30	0.32
N	34,152	34,152	34,152	34,152	2,420	2,420	2,420	2,420

Table 9: **Evidence of Underpricing**

We first compute the predicted auction rate for all successful auctions between February 20, 2008 and March 19, 2008 using the estimated pricing model for auctions before January 1 2008. We then compare the mean between the actual reset rate and predicted reset rate. The difference between actual reset rate and predicted reset rate—our measure for underpricing—is significantly positive.

	N	Mean	Std. Dev	Min	Max	t-Statistic
Reset Rate	2,420	7.409	2.181	1.429	17.000	168.3
Predicted Rate	2,420	4.540	0.394	3.923	6.372	567.5
Difference	2,420	2.869	2.093	-3.562	10.742	66.7

Figure 1: **Gross Issuance of Municipal Auction Rate Securities**
The figure plots quarterly gross issuance of MARS, both in dollar amount and as a fraction of total gross issuance of long-term municipal bonds, from the first quarter of 1988 to the first quarter of 2008.

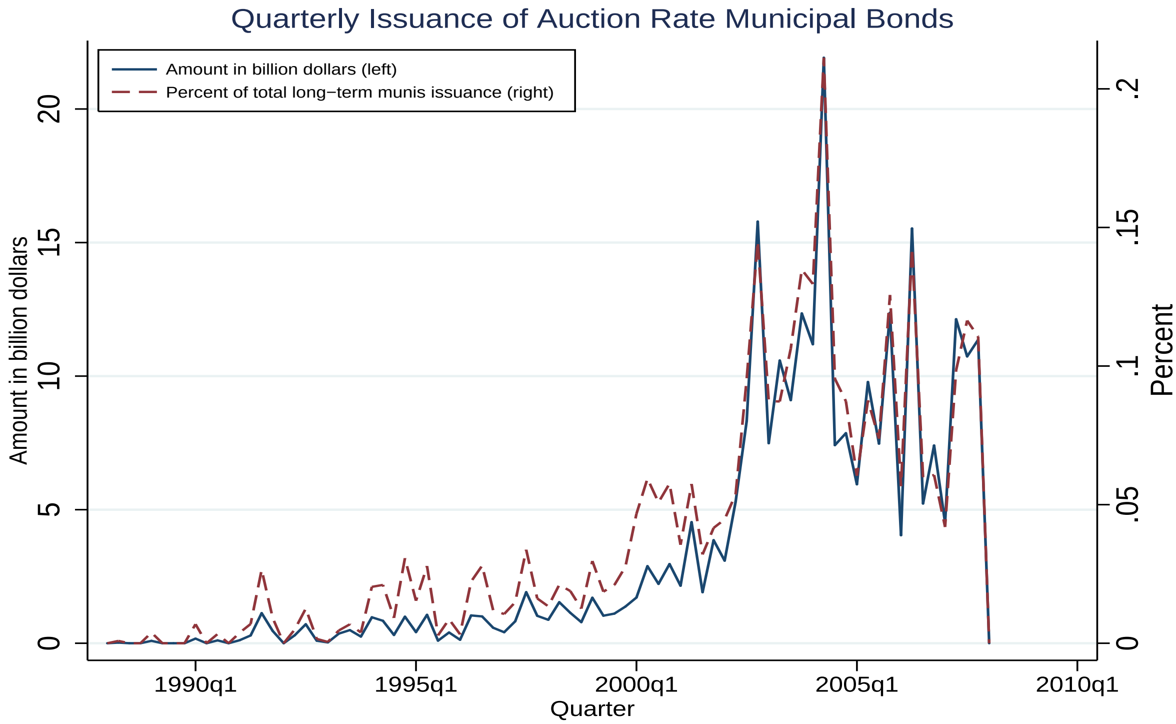


Figure 2: **The Auction Procedure**

This figure illustrates the auction mechanism using an example. In the hypothetical auction, the aggregate bid or demand curve is the solid step function. If the total sell or supply curve is the vertical line A, which crosses the bid curve, the auction is said to have "cleared", and the clearing rate is the lowest rate at which total bids are greater than total supply, which is 6 percent in the example.

If the total supply is instead the vertical line B, which does not cross the total bid curve, auction dealer can, but is not obligated to, submit its own bids to move the demand curve to the left. Importantly, auction dealer submits its bids after seeing all customer orders; thus, not only can it prevent the auction failure but also dictate the clearing rate. In the example, the bid curve is extended by auction dealer to clear the auction at 5 percent, a rate lower than the highest rate among all customer bids. If, however, auction dealer lets the auction fail, the rate will be reset at the maximum rate, 10 percent.

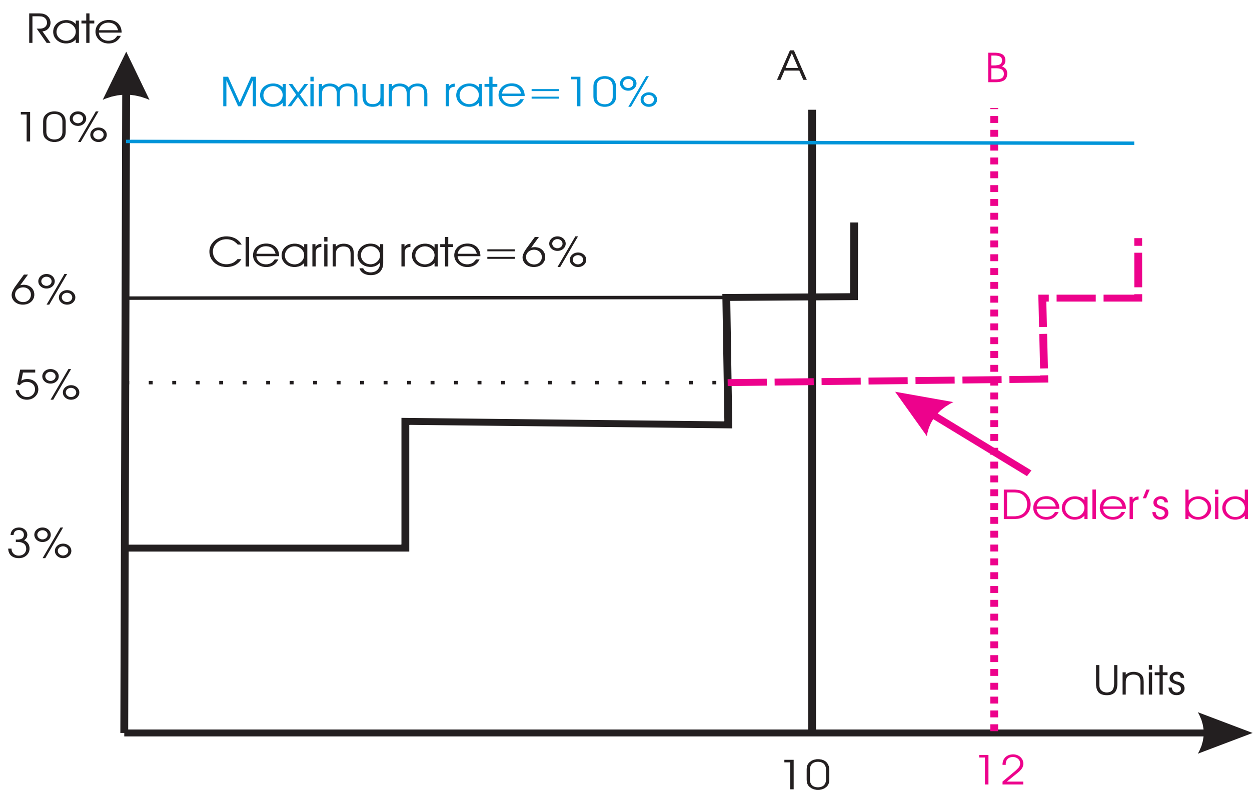


Figure 3: **Distribution of Maximum Rate by the Maximum Rate Rules**
This figure plots the histograms of maximum rate for MARS with floating maximum rate rules (left panel) and with fixed maximum rate rules (right panel).

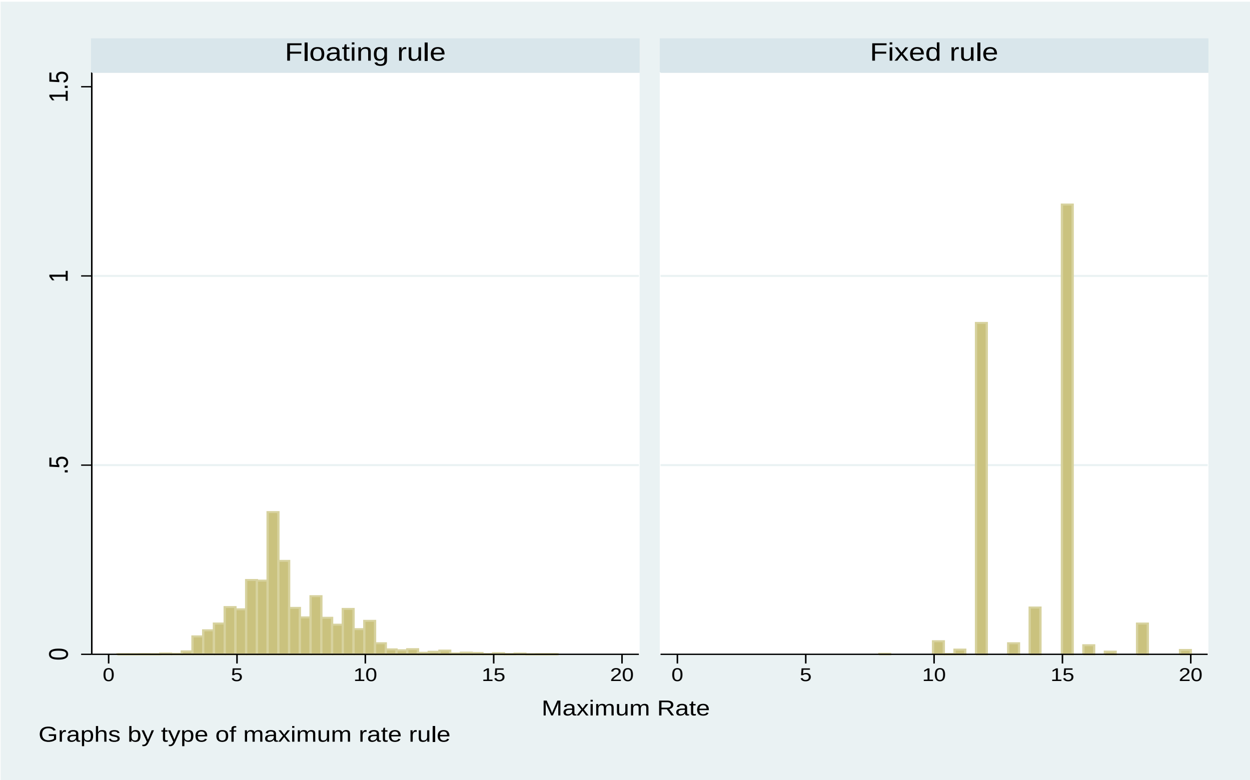
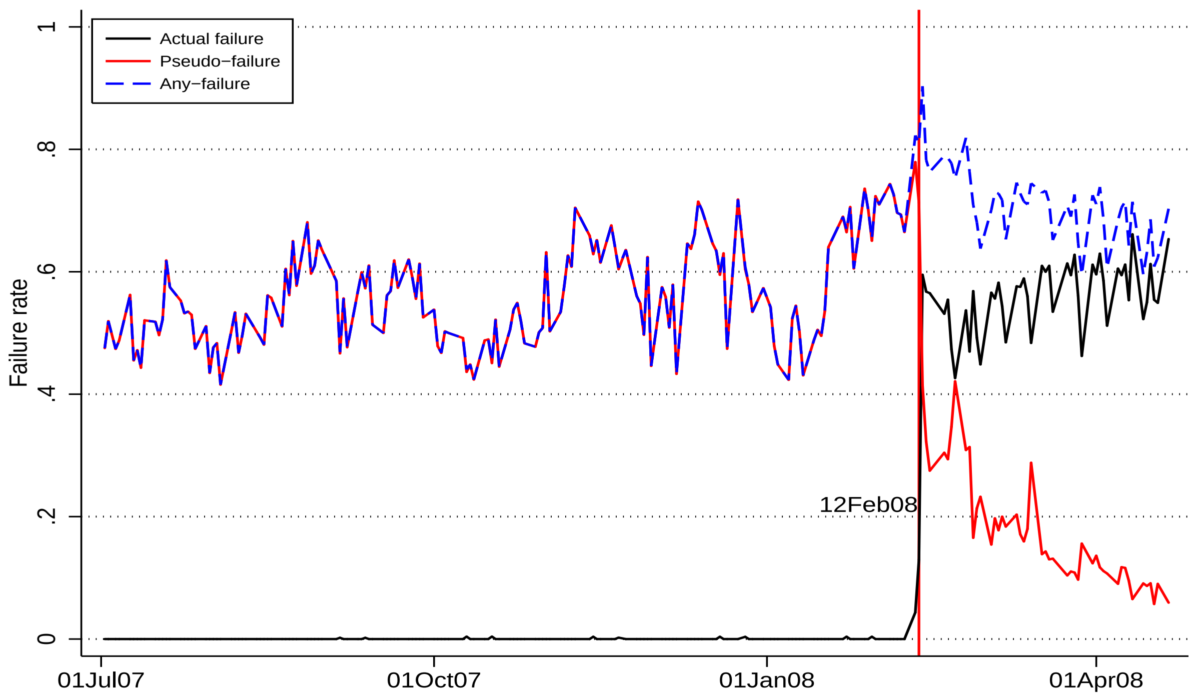


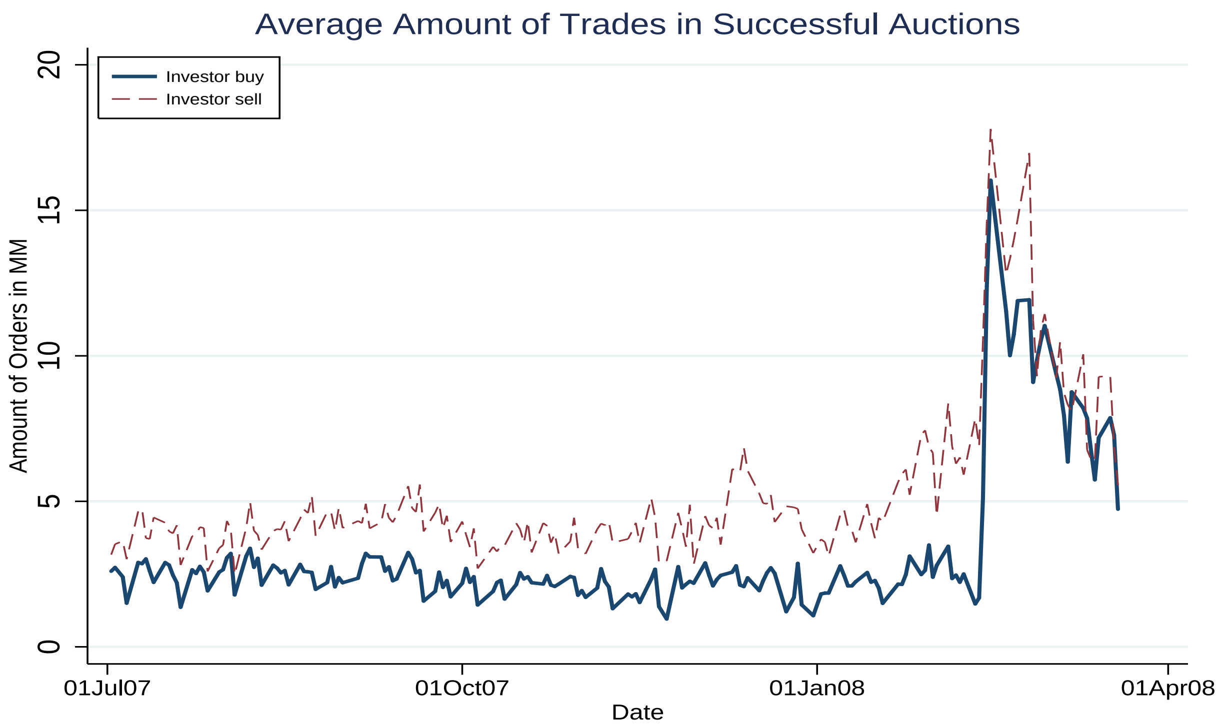
Figure 4: **The Rate of Any-Failures**

This figure shows the time series of the fraction of auctions with positive net liquidity demand (NLD). NLD is defined as $NLD = \sum Sell - \sum_{r_j \geq r_{min}}^{r_{max}} Buy@r_j$, where $Sell$ and $Buy@r_j$ are the amount of sell and buy orders, respectively, submitted by investors in auctions. The occurrence of positive NLD is observationally equivalent to either "actual failure"—when the auction dealer does not intervene and let the auction fail—or "pseudo-failure"—when the auction dealer intervenes by submitting its own bid so that the auction clears. We call the occurrence of positive NLD "any-failure."



Note. Based on data from three major auction agents

Figure 5: **Demand and Supply of Liquidity during the Auction Run**
This graph illustrates changes in the demand and supply of liquidity in the week of February 11, 2008. Sell and buy orders in auctions are proxied using "customer sell" and "customer buy" trades reported to MSRB on auction dates.



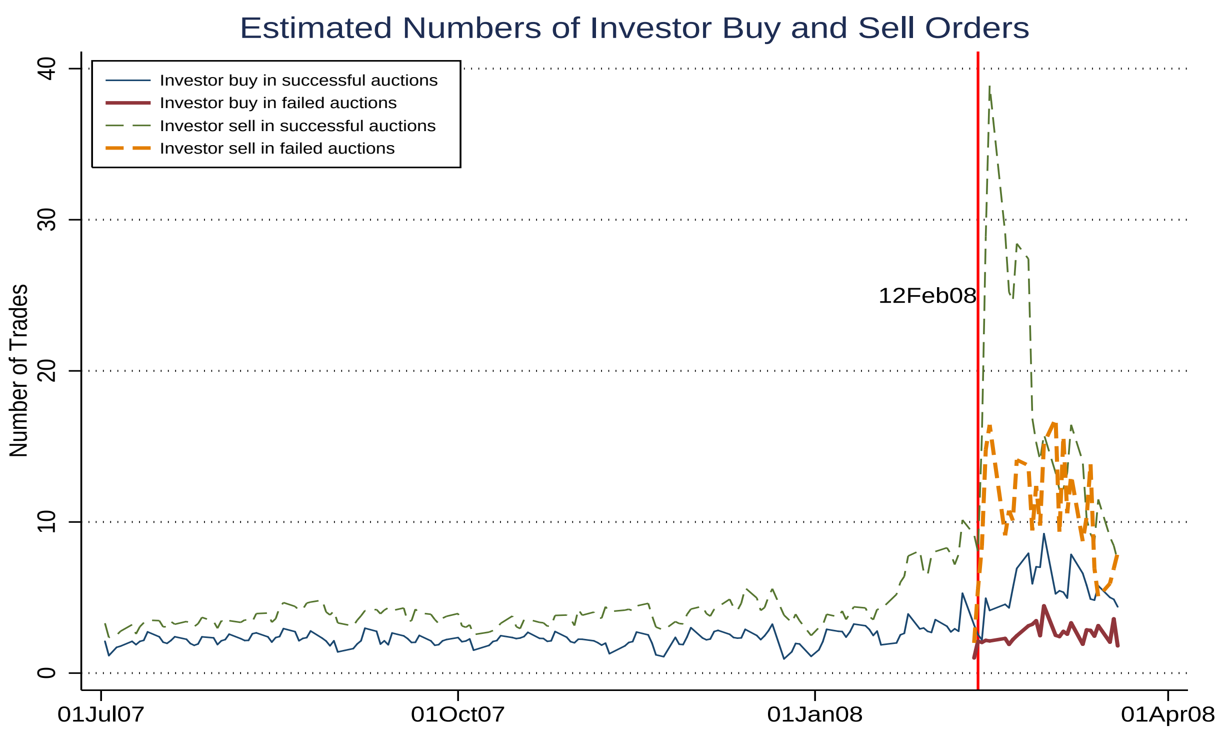


Figure 6: **Interest Rates on ARS and Variable Rate Demand Obligations**
This figure plots the SIFMA Swap index and the SIFMA 7-Day ARS Index. The SIFMA Swap Index is a 7-day index comprised of high-grade tax-exempt VRDOs. The SIFMA 7-Day ARS Indices are based on reset rates from actual ARS auctions for a sample of high-grade ARS that meet a minimum size requirement and reset every 7 days. See http://www.sifma.org for more details on these indexes.

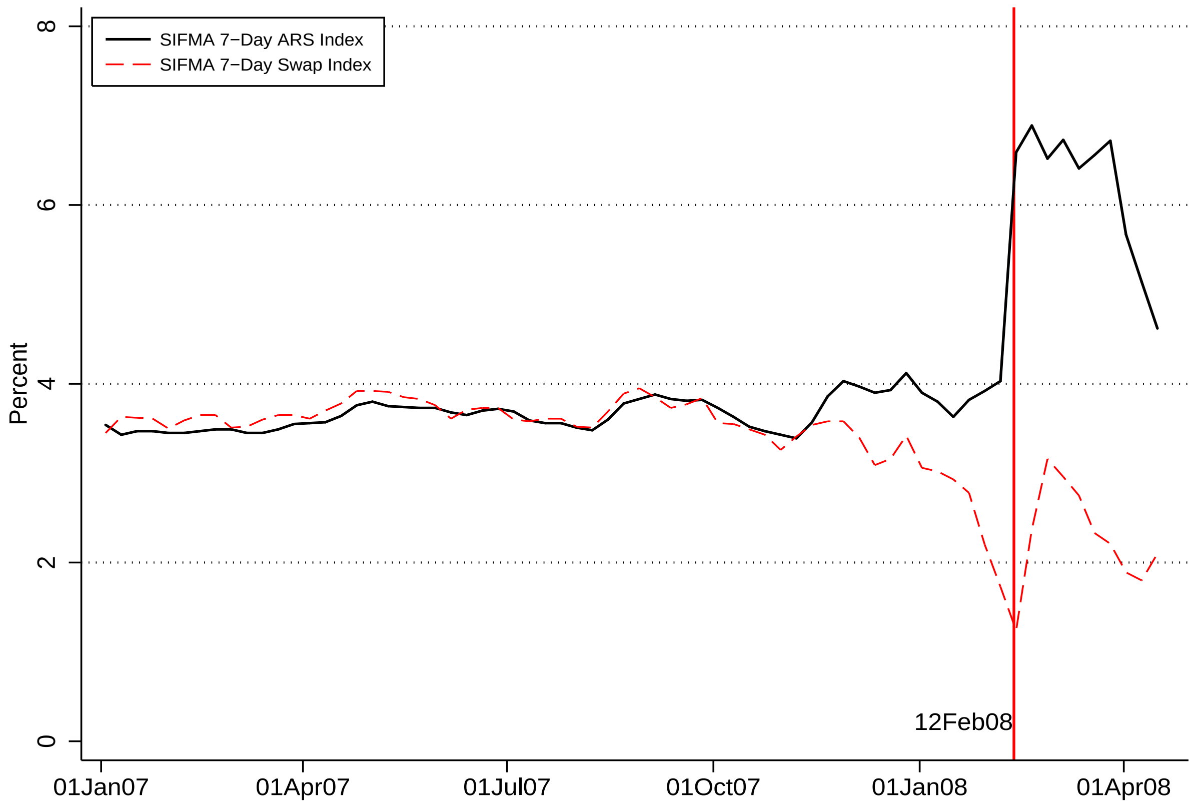


Figure 7: **Evidence of Investors Runs**

This figure shows the time series of the any-failure rate and the predicted likelihood of any-failures based on the empirical models using the pre-crisis auction data.

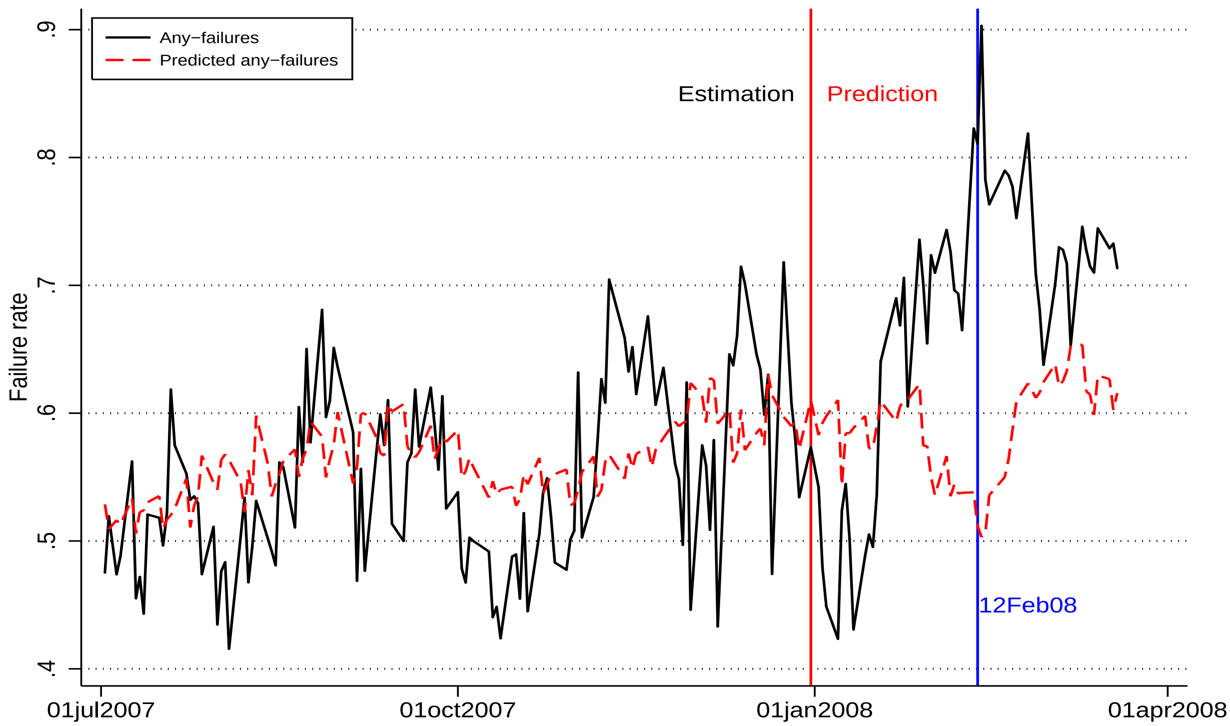


Figure 8: **Broker-Dealers as Market Makers**
This figure shows average values of dealer net buy (in million dollars) on auction dates and in the inter-auction period immediately following auction days.

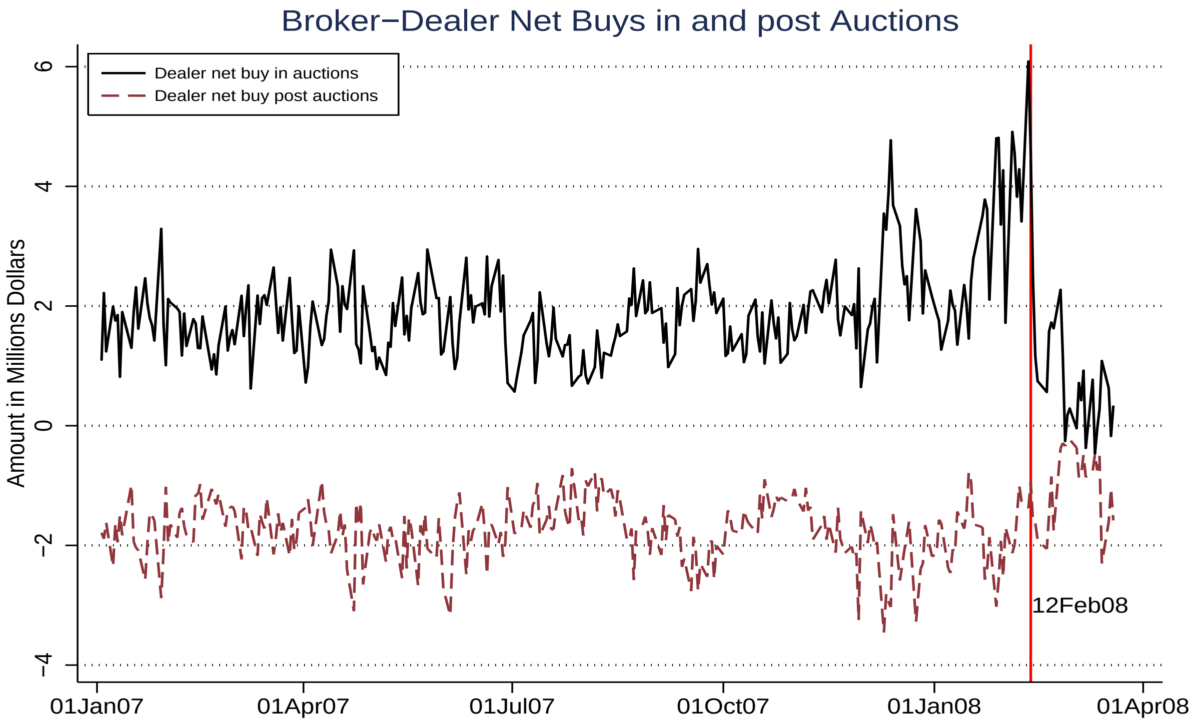


Figure 9: **The Rate of Actual Auction Failures by Major Broker-Dealers**
This chart plots the rates of actual auction failures for MARS auctions managed by each of major broker-dealers in the week of February 11, 2008.

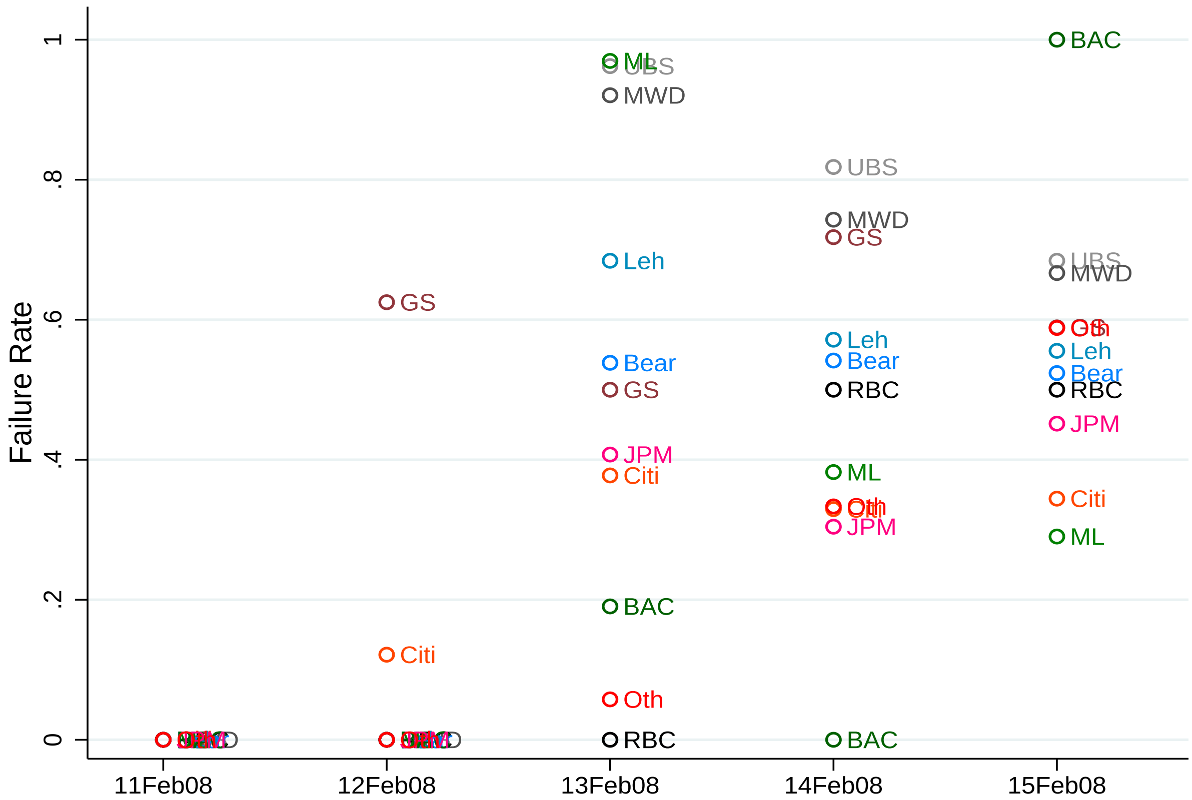


Figure 10: **Cumulative Inventory of All Broker-Dealers**
This figure shows the total cumulative changes in all dealers' inventory since the beginning of 2007. Daily changes in dealers' inventories are calculated by subtracting the total values of "customer buy" from dealers from the total values of "customer sell" to dealers.