Liquidity Crisis, Runs, and Security Design: Lessons from the Collapse of the Municipal Auction Rate Bond Market*

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Abstract

In this paper, we use the recent collapse of the ARS market as a case study on important issues regarding fragility of financial innovations and systemic risks. We find strong evidence of investor runs for liquidity, partly caused by a self-fulfilling panic. In addition, coordination failures triggered by an unexpected first mover led all major broker-dealers to simultaneously withdraw their liquidity support. We also find that the likelihood of auction failures and ARS reset rates depend significantly on both the rule and the level of maximum auction rates, that, as predicted by auction theories, there is also strong evidence for underpricing after dealers withdrew their liquidity supports, and that inter-auction secondary market liquidity may encourage aggressive bidding that increases the reset rates.

JEL Classifications:
Key words: Auction, auction rate securities, municipal bond pricing, liquidity

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1 Introduction

In the summer of 2007, concerns over losses on the subprime mortgages caused an overall reassessment of valuation on complex structured securities as well as of general corporate credit risk. Risk spreads on both corporate debt and asset-backed securities soared, and liquidity dried up in the world financial markets. Markets of short-term credit products that had flourished in a liquidity rich environment experienced substantial disruptions. Amid the liquidity crisis, Northern Rock, one of the largest mortgage lenders in the UK, experienced a classic bank run, which was eventually bailed out by its central bank; markets for the asset-backed commercial paper (ABCP) market, where conduits and structured investment vehicles (SIVs) rely on, shrank considerably; and the auction rate securities (ARS) market collapsed.

The liquidity crisis raised important issues on fragility of financial innovations and systemic risks. In this paper, we try to shed light on these issues by studying the collapse of the ARS market. In a nutshell, ARS are debt instruments whose interest rates are reset periodically through auctions. A majority of such auctions have failed since mid-February of 2008, drawing significant attentions from both regulators and practitioners. Widespread auction failures may lead to serious consequences. First, ARS interest costs skyrocketed, putting considerable strains on the financial conditions of a broad range of issuers. Second, investors who currently hold ARS or used to rely on ARS as cash equivalent investment vehicles faced significant liquidity squeeze. Existing ARS holders who had difficulties unloading their positions in regular auctions may face possible covenant violations, forced selling at discount in the secondary market, or high costs of using alternative funding sources. Potential holders have to consider increased likelihood of future auction failures. As a result of high interest costs and strong concerns about future auction failures, issuers scrambled to find a way to retire existing ARS, and conventional investors shied away from the market. Evidently, as shown in Figure 1, issuance of municipal auction rate bonds ("MARS", hereafter)–which accounted for about half of the overall ARS market–has come to a complete stop since February.

Using data on auction results obtained from three major auction agents, we examine the behavior of market participants, including both broker-dealers and bond investors, around mid-February when major broker-dealers stopped providing bidding support as they routinely did. We also study how the likelihood of auction failure and the reset interest rate on the bonds with successful auctions are related to the following three sets of factors: one, contractual auction rules, such as maximum auction rate and auction frequency; two, measures for secondary market liquidity, such as number of inter-auction trades and proxies for dealer's inventory capacity; and three, variables related to bonds' fundamental values, such as bond characteristics, credit risk, and interest rate term structure and volatility.

Our main findings are the following. First, after the transition period in the mid-February, all else equal, auctions of bonds with floating maximum rates are 80 percentage more likely to fail than those with fixed maximum rates. Among bonds with floating maximum rates, the failure probability falls 32 percentage when maximum rate increases by one standard deviation. Second, during the transition period, there exist a "bank-run" type behavior as an unusually large number of current holders rushed to place sell orders in a short period of time. In addition, a significant portion of the failures cannot be explained by fundamentals and thus may be caused by a self-fulfilling panic run. Third, during the transition, coordination failures triggered by an unexpected first mover led all major broker-dealers to simultaneously withdraw their liquidity support. Finally, as predicted by theories on uniform-price auctions, we find strong evidence for underpricing after dealers stopped supporting the auctions. In addition, reset rates on bonds with successful auctions are higher for bonds with fixed maximum rates, and positively related to maximum auction rate and bonds' fundamental values. Also, counterintuitively, reset rates are positively related to inter-auction secondary market liquidity, possibly because investors bid more aggressively if it is less costly to trade outside auctions.

This paper contributes to three strands of literature. First, we present new evidence on the existence and the origin of coordination failure and runs for liquidity during a financial crisis. Previous works have focused on runs in depositary institutions and in currency crises (Diamond and Dybvig (1983), Calomiris and Gorton (1991), De Bandt and Hartmann (2002), among others). The collapse of the ARS market provides a new angle to this important issue. Our study finds the important role of inherent vulnerability to systemic liquidity shocks of untested financial innovations in the short-term credit markets.

Second, we provide new empirical evidence to the literature on uniform-price auctions (Wilson (1979), Back and Zender (1993), Goldreich (20070601), McAdams (20070401), among others). Most existing empirical studies on uniform-price auctions examine either the Treasury auctions or auctions on initial public offering of equities. The ARS market presents a new venue to test and extend existing theories. Importantly, the ARS auctions differ from other uniform-price auctions in a number of ways. For example, in the ARS auctions, selling orders are submitted by strategic investors simultaneously with bidding orders, while there is generally no strategic selling in the existing studies. In addition, ARS auctions are repeated, and there exists an active inter-auction secondary market facilitating the exchanges of ownership of the securities, thus complicating the auction strategy.

Third, this paper provides a comprehensive study on the rarely-analyzed ARS auctions. While the ARS market has existed for over two decades and is sizable, only until recently did it draw significant attentions from both regulators and researchers. The scope of the few existing studies is limited, mostly using restrictive data on ARPS (Alderson, Brown and Lummer, 1987; Winkler and Flanigan, 1991; Alderson and Fraser, 1993).[1] Our analysis covers a significant portion of the market with detailed information on the auction results, allowing us to shed lights on the role of security designs, the secondary market, and economic factors in the auction outcomes.

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; Sections 4, 5, and 6 analyze, respectively, auction failures, the role of broker-dealers in the ARS crisis, and ARS pricing. Section 7 concludes.

2 ARS and The Recent Collapse of the ARS Market

Auction Rate Securities (ARS) are debt-type instruments whose interest or dividend rates are reset periodically through auctions. The frequency of the periodic auctions varies, with reset periods most commonly being 7, 28, and 35 days. ARS may be issued by municipalities or their authorities in the form of tax-exempt or taxable bonds (muni ARS) or by corporations or closed-end mutual funds in the form of preferred stocks (ARPS). Despite their usual long-term maturities, ARS are generally considered short-term investments products due to their frequent resales in auctions. Interest rates for ARS are typically only slightly above their benchmark rates, such as the Libor rates.

The ARS market emerged over two decades ago to provide a venue where corporations, mutual funds, and municipalities could sell long-term debt but pay short-term rates. Buyers, predominantly corporate treasurers and high-net-worth investors, in turn found a safe place to park their cash for brief periods and earn interest higher than short-term treasuries or bank rates. The first ARS was an ARPS offered in 1984 as an improvement upon adjustable rate preferred stocks (Newswires, 1984; Alderson et al., 1987), and the tax-exempt muni ARS debut in 1988 (Times, 1988). As shown in Figure 1, issuance of munis ARS have soared since 2002 and only slowed to a complete stop in recent months.[2] The total size of the ARS market reached to about $330 billion at the end of 2007, roughly half of which is accounted for by Muni ARS (MARS) and the bulk of the rest by ARPS issued by closed-end funds and SLARS issued by student loan authorities. Until recently, the ARS market has been considered as stable, safe, liquid, and lucrative.

[1] Alderson et al. (1987) examined 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; Alderson and Fraser (1993) study the growth and contract of the ARPS market in the late 1980's.

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

2.1 Auction Procedure

The auction process serves two purposes—setting the interest rate and facilitating the transfer of ownership. The interest rate is reset periodically through Dutch Auction. In the auction, existing bond owners are the sellers. They can place the following three different 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 order, the par amount of securities they will hold or buy as long as the clearing rate is no lower 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 limit buy 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. Importantly, all orders are submitted to the auction agent through broker-dealers, or often called "auction dealers" or "auction managers", who are usually the investment banks that underwrite the ARS when they were issued. Auction dealers can also submit bids on their own accounts.

After receiving all orders, the auction agent ranks them by rate. Bids with successively higher rates are accepted until all of 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 of the securities for sale in the auction. Multiple bids at the clearing rate are filled according to the pro rata rule.

If the auction agent does not receive sufficient bid orders to purchase all the ARS being auctioned, the auction is said to have failed, and the rate on the ARS is set at the maximum rate specified in the prospectus at the time of issuance. The maximum rate is usually either a floating rate depending on a reference index, such as Libor, or a fixed rate that may be as high as 20 percent.[3] Sale orders in a failed auction are filled pro rata, and the sellers have to hold on to their unfilled orders until the next auction, though their loss of liquidity may be somewhat compensated by a higher interest rate set by the maximum rate. [4]

To illustrate the auction mechanism, Figure 2 and Figure **??** presents two hypothetical auctions. The aggregate bid or demand curve is the solid step function. The total supply is the vertical line A. The supply can be considered as fixed, because we can consider a "hold" order by existing owner as both a "sell" order and a "buy at rate" order. This way, the total supply is equal to the total amount of bond outstanding.

Figure 2 is an example of successful auction, where total demand from existing and potential

[3]For example, ARS issued by Port Authority of New York were reset to 20 percent after auctions failed in mid-February (Braun, 2008).

[4]While maximum rates are generally designed as a penalty on failed auctions, those on some ARPS and SLARS whose auctions have failed recently are reportedly lower than market benchmark rates due mostly to complex rules capping total debt payments within a period, originally designed to protect issuers.

investors is greater than total supply. The auction is considered "cleared" and the clearing rate is the lowest rate at which the demand is equal or greater than supply. The auction set the interest rate for the inter-auction period at 6 percent in the example. If, however, the scenario is as shown in Figure **??** (left), where the total "organic" demand is less than total supply, the auction will fail. The demand schedule is visible to auction dealer. Seeing this possibility of an auction failure, the auction dealer can, but is not obligated to, submit his own bids to prevent auction failure. The total demand including dealer's bids (the red dotted line) is shown to the right in Figure **??**. Dealer's bids enable the auction to clear, and in this case, at 5 percent that the dealer bids at. As we can see from the example, since auction dealer submits his bids after seeing investors' bids, he can not only prevent the auction from failure but also dictate the clearing rate. If, however, auction dealer lets the auction fail, the rate will be reset at the maximum rate specified in the contract, which is 10 percent in the example. In reality, we have seen maximum rate as high as 20 percent.

2.2 The Recent Collapse of the ARS Market

Auction failures have been rare until the recent financial turmoil. Auction dealers had acted as the bidder of the last resort for their sponsored auctions to absorb any excess supply. Since they were able to bid after seeing the bids from the others, their support ensures market clearing. The breakout of the suprime mortgage crisis, however, raised serious concerns about the credit quality of some ARS, especially those insured or issued by troubled bond insurers such as Ambac, MBIA, and FGIC. In late 2007, failures started to occur for ARPS auctions including those issued by troubled bond insurers (Quint, 2007).

More importantly, exposures to the credit crisis have put significant strains on auction dealers' balance sheets, and liquidity provision becomes increasingly expensive. On January 22, the first day when bond investors could react to Fitch's downgrade of a major bond insurer, Ambac Inc., Lehman Brothers Holdings Inc. decided not to bid on two auctions they ran, resulting in the first ever failures to muni ARS auctions. Then, over the week of February 11, major investment banks including Goldman Sachs, Lehman Brothers, Citigroup, Merrill Lynch, and UBS, reportedly all stopped supporting their auctions (Braun and Selway, 2008; Williams and Weiss, 2008). As words of dealers' withdrawal and auction failures spread in major news outlets, auctions began to fail en masse. On February 13, auction failure rate peaked to over 80 percent. Since then, failure rates have declined somewhat but remained frequently over 60 percent. For example, on February 20, 62 percent failed (395 out of 641 auctions). As a comparison, according to a Moody's report, from 1984 until the end of 2007, there were a total of 44 failed auctions, and none of them was on muni ARS (Shilling and Stesney, 2008).

ARS investors, including big corporations like Bristol Meyers, Jet Blue, and Palm Inc. suddenly found their “cash equivalent” investments virtually inaccessible. Bond issuers struggled to pay interest rates as high as 20%. Auction dealers, whose withdraw of liquidity support ultimately brought down the market, are battling with endless lawsuits. In a crisis like this, the “loss” is mutual.

So far, the press coverage of this market has been focusing on the lack, or the misrepresentation, of information provided by investment banks to their clients regarding the liquidity risk of the ARS product. We will instead, look at the economic forces behind the sudden collapse of a 20 year old market, and argue that the design of the market is flawed in its vulnerability to coordination failure among investors, and perhaps more importantly, among auction dealers. Moreover, the price setting mechanism –uniform price auction–itself is subject to high level of underpricing, which imposes additional cost to bond issuers.

3 Data and Sampling

Our overall sample consists of all MARS whose auctions are run by three major auction agents. We combine data on auction results with data on intraday transactions in the municipal bond secondary markets and with data on bond characteristics. These various data are described below.

3.1 Data on Auction Results

We obtained proprietary reports of daily auction results from three major auction agents, including Wilmington Trust (WT), Bank of New York Mellon (BNYM), and Deutsche Bank (DB). For each auction, the reports contain the following information: auction date, bond CUSIP, lead manager, auction frequencies, auction status (fail, succeed, or all hold), auction clearing rate, benchmark rate (e.g., 30-day LIBOR or 7-day commercial paper rate), and bond insurer. The reports we used in this paper started on July 1, 2007 for WT and BNYM and January 1, 2007 for DB, but all ended on April 21, 2008. Part of our statistical analysis will only focus on sub-periods of the data.

Auction agents report results of their auctions on MARS, SLARS and ARPS. Given that only municipal securities are subject to transaction report requirement by the Municipal Securities Rule Making Board (MSRB), to fully take advantage of the information in these transaction report, we limit our analysis to ARS that has appeared in the MSRB transaction data. Thus, our data is mostly MARS. Since some student loan ARS that are issued by local education authorities also report to the MSRB, our sample will contain some student loan ARS too.

3.2 Intraday Transactions Data on Municipal Bonds

Municipal securities dealers are required by MSRB to report to RTRS the information about each purchase and sale transaction effected in municipal securities. In particular, transactions of MARS, either in or outside auctions, are subjected to the same reporting requirements as those of other types of municipal securities. Since auctions occur frequently, restricting our sample to those that appeared in RTRS is unlikely to omit bonds due to lack of trade.

The RTRS data also allow us to estimate the amount and the direction of transactions in auctions, a piece of information which is not available in the original auction reports. 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." Therefore, while the RTRS data don't have an indicator for whether the trades happened in or outside an auction, we can generally classify trades on auction dates as "auction trades" and those on non-auction dates as "non-auction trades". 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.

In addition to trade quantity, the RTRS data also identify the direction of each trade. As described early, selling by existing bondholders has to go through the broke-dealer of the auction, which is reported in RTRS as dealer "purchases from customer"; similarly, buying by potential bondholders also has to go through the broker-dealer, which is reported as dealer "sales to customer". Prior to the recent crisis, broker-dealers also frequently participated in auctions by bidding on surplus supply and selling the bonds later in the "non-auction secondary market". Such transactions are reported in RTRS accordingly as dealer " purchases from customer" and dealer "sales to customer".

Unlike fixed rate bonds, ARS almost always trade at par value. We do not use the price information reported for each trade.

The transaction data provide us a wealth of information that is not available in the auction result reports. First, auction agents do not report the order placement in each auctions. Trades that happened as a result of the auction can provide us a rare glimpse to the supply and demand in each auction.[5] We show that some of the hidden facts about the market, which were later un-covered in legal investigation, were in fact, possible to find out through the free post-trade transaction report. Secondly, the transaction data enabled us to reconstruct the dynamics of dealer's inventory, given that we know the lead-manager of the auction and most, if not all, of the auction and non-auction secondary trades happened with the lead-manager acting as a counter-party. This is critical because, as we argue that auction managers are in fact, market-makers in the auction and post-auction market. They actively manage their inventory while providing liquidity. Finally, transaction data make it possible for us to examine the post-auction secondary market and

[5] In auctions that failed, there will be truncation in the supply of bonds.

look at the interaction of non-auction secondary market and the auctions.

3.3 Data on Bond Characteristics

Both the auction reports and the RTRS data have only limited information on bond characteristics, such as auction dealer, auction frequency, and benchmark rate. We obtain from Bloomberg additional bond description data, including bond type (general obligation (GO) or revenue bond), taxability (tax-exempt or taxable), credit enhancement (insurer), underlying credit rating (i.e., credit rating in absence of credit enhancement), dates of issuance and maturity, and size of the issuance. Still, the information on the maximum interest rate—the penalty rate applied upon a failed auction—is not readily available in any data sources.

Specified in bond prospectuses, the rules to determine the maxim interest rates generally belong to one of the following four types:

- Type A: fixed maximum rate, usually a rounded percentage that can be as high as 20 percent.
- Type B: maximum rate is a multiple of a benchmark rate up to a fixed cap. Examples of benchmark rates are 30-day Libor rate and 7-day nonfinancial commercial paper rate at of the date of the auction, and the multiples often depend on the bond's overall credit rating (e.g., the multiples are 150, 150, 175, 200, and 265 percent if the bond is rated, respectively, AAA, AA, A, BBB, and below BBB).
- Type C: maximum rate equals to a markup plus a benchmark rate up a fixed cap, with the markup often depending on the bond's overall credit rating.
- Type D: complex rule, usually a combination of the above types, possibly with look-back features. For example, the maximum rate may be a multiple of a benchmark rate but such that the total interest payments over the previous year are below a ceiling determined by the average rate of an index rate.[6]

Instead of reading through all bond prospectuses, we first develop a statistical method to estimate the rules used in calculating the maximum rate. First, because maximum rate is a linear function of the benchmark rate in Type A, B, and C rules, the rules can be estimated accurately using data from two failed auctions. Thus, for bonds that failed twice or more, we can determine if the rule is Type A, B, or C. Second, for bonds that have failed only once over the entire period, we use the following criterion to determine if the rule is Type A, B, or C: If the maximum rate in the failed auction, accurate to the 1/1000 of a percent, is rounded to a full percentage, the rule

[6] The look-back feature is usually seen in student loan ARS. As witnessed in the current crisis, these ceiling restrictions have resulted in zero maximum rate. This happens when the cap on 90-day rolling average interest rate is relatively low, and the rates were set high for consecutively several auction periods.

is considered as Type A; if the ratio of the maximum rate to the benchmark rate, rounded to 1 percent, is a multiple of 25 percent, the rule is considered to be of Type B; if the difference between the maximum rate and the benchmark rate, rounded to 1/1000 of a percent, is a multiple of a half percent, it is Type C.

The potential issues with the above statistical method are the following: (i) we cannot identify the rule if it is Type D or if auctions had never failed; (ii) for bonds with only one failed auction, we identify the rules with some tolerance of error; and (iii) errors may also occur if the rules have changed in issuer's discretion according to the pre-specified terms in the bond contract. In particular, leaving out bonds in (i) may potentially induce selection bias to our analysis.

To address the selection bias issues, we manually collect information on bonds whose maximum rate rules are not identifiable using the above statistical method. We also check bond prospectus for a random-selected sample of bonds whose maximum rate rules are determined using the above statistical method, and find fairly low errors.

3.4 Sample Construction

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 MSRB's RTRS data (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 3,526 bonds, which we label as our "overall sample" (Line 4). The overall sample consists of 2,725 bonds issued by non-student loan municipalities with total par outstanding of \$151 billions, or 90 percent of the entire non-student loan MARS market, and 801 bonds issued by student loan authorities with total par outstanding of \$38 billions, or 45 percent of the entire student loan ARS market.[7]

As shown on Line 5, for 2,755 bonds in the overall sample, we are able to identify the types of their maximum rate rules and compute their maximum rates using both statistical and manual identification method. In particular, as shown in Table 2, the identification rates are 90 percent for bonds with no or only one failed auction during our sampling period (976 of 1,094 and 329 or 364, respectively) and 70 percent for those with two or more failed auctions (1,450 of 2,068). We label the sample with non-missing maximum rates as "restricted sample."

Among the 2,755 bonds with known maximum rate rules, 42 percent (1,159) have fixed maximum rates (Type A), 48 percent have fixed multiple rules (Type B), and the rest split about equally in fixed markup or complex rules (Types C and D). Bonds whose auctions never failed

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

almost always have fixed maximum rates(888 of 976, or 97 percent), and bonds with at least one failed auctions most likely have fixed multiple rules (1,284 of 1,779, or 72 percent). While this may suggest that fixed maximum rate may be associated with lower likelihood of auction failure, we also note that maximum rates on bonds with fixed maximum rates, 14.0 percent, are significantly higher than those on bonds with floating maximum rates, from 6.2 to 7.5 percent (memo line). We will examine in-depth the relationship between auction failure, pricing and maximum rate.

3.5 Summary Statistics

Table 3 shows summary statistics. In our overall sample, only about 1.5 percent of the bonds are general obligation bonds, 17 percent are taxable, and 22 percent are issued by student loan authorities. Most of the bonds have reset periods at 7, 28, and 35 days (45, 18, and 37 percent, respectively). About 41 percent of the bonds are not rated, and among those rated, over half have a underlying rating of A. About 41 percent of the bonds are insured by weak insurers–those under review for downgrades and in headlight news during the sampling periods, including Ambac, MBIA, FGIC, CFIC, and XLCA, 11 percent are insured by strong insurers, including FSA and Assured Guaranty, and the rest are either insured by other insurers (20 percent) or not insured (28 percent).

About 28 percent of the bonds in the overall sample have multiple broker-dealers running their auctions. As a lead manager, Citigroup, UBS, and Morgan Stanley account for about half of the bonds (22, 18, and 10 percent, respectively), and the top 10 broker-dealers account for about 91 percent of the bonds. On average, the bonds have $54 millions of par outstanding, $40 thousand 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 information available on their maximum rates. The average maximum rate on all auction dates for this restricted sample is about 11 percent with a standard deviation of 4 percent.

4 Auction Failures and Runs

This section first examines the dynamics of auction failures, showing that the ARS market switched to a completely different state after the week of February 11. We then study the determinants of auction failures when the markets are stable. Finally, we present evidence of runs for liquidity in the transition period and show that a significant portion of the runs is not driven by fundamentals.

4.1 A Tale of Two Equilibria

We consider two measures of auction outcomes. The first measure is auction failure rate, which equals to the fraction of auctions that failed to clear among all auctions running on each day. The second measure is pseduo-failure rate, which equals to the fraction of auctions in which broker-dealer's net buy from customer is positive among all auctions running on each day. Thus, unless broker-dealers bid in the auction for investment purposes, pseduo-failure rate indicates the fraction of auctions that would have failed if broker-dealers had not bid on its own account.

Figure 4 plots the two measures for the overall sample over our sample period. Remarkably, auction outcomes are completely different after the week of February 11. Auction failure has been rare until the week of February 11 when it shot up to 60 percent, but it fell to about 55 percent for the rest of the sample period. On the other hand, pseduo-failure rates have hovered around 55 percent until late Janurary when they started to climb up to nearly 80 percent on February 11. This suggests that the market has been relatively stable with broker-dealers providing constant bidding supports to the auctions but increasingly more auctions experienced insufficient bids in early February, as crisis in the short-term funding markets spread to the municipal markets.

In the week of February, major broker-dealers also simultaneously withdrew heir liquidity supports on a large set of auctions. As evident, pseduo-failure rates fell sharply to about 20 percent at the end of our sample period. Interpreting the pseduo-failure rates post the week of February 11, however, is complicated by reports that after the crisis broke off, broker-dealers had bid actively for investment purposes on selected auctions.

The dynamics of the series of auction failure rates and pseudo-failure rates suggest that the ARS market switched in the week of February 11 from a state where broker-dealers, as investors expected, provide the bidder of the last resort to prevent auctions from failing to clear to a state where such supports disappeared.

4.2 Determinants of Equilibrium Failure Rate

We now examine what factors affect the equilibrium failure rate when the market stabilized after the week of February 11, as well as pseudo-failure rate before the crisis. While existing auction theories almost always focus on equilibrium with successful auctions, they nonetheless provide guidance on our empirical analysis on auction failure.

Without broker-dealer acting as the bidder of the last resort, the auctions used in the ARS market resembles closely to uniform-price auctions that are extensively studied in the literature (e.g., Wilson (1979), Back and Zender (1993)). A major theoretical result of these studies is that there generally exists a continuum equilibria in such auctions as long as the maximum auction rate is higher than the upper support of the uncertain fundamental value (e.g., Theorem 1, page 741, Back and Zender (1993)). A corollary of this result is that all else equal, auctions on bonds with low maximum rate would be more likely to fail (see, Proposition 1, page 748, Back and Zender (1993)). In addition, conditional on current maximum rate, for bonds with floating rules, their future maximum rates are uncertain and may become too low compared to their fundamental values. Concerns about future auction failure would depress demand in current auctions thus increase the current likelihood of failure.

The importance of maximum rate and rule type to auction outcomes can be seen in Figure 5. In the top panel, we plot failure rates of bonds with high maximum rate—higher than median maximum rate—and of bonds low maximum rate—lower than median maximum rate. Failure rates of bonds with low maximum rate, dash line, shot up to about 95 percent in the week of February 11 and stayed very much at that level since. Failure rates of bonds with high maximum rate, solid line, also jumped in the week of February 11 but to only about 35 percent; moreover, they fell back to about 5 percent since February 20. As shown in the middle panel, we plot failure rates by maximum rate rules. As we can see, failure rates on bonds with floating rule, dash line, and those with fixed rule, solid line, follow fairly closely with those with low and high maximum rates, respectively. This may not be surprising given that, as discussed in Section **??**, maximum rate and the rule are highly positively correlated. In the bottom panel, we plot failure rates by maximum rate for bonds with fixed and floating rule separately. Among bonds with fixed rule, failure rates don't vary with the level of maximum rates, which partly may be due to the low variation in maximum rates among these bonds (see Section **??**). Among bonds with floating rule, failure rates for bonds with high maximum rates are generally lower than those with low maximum rates. Therefore, while having fixed maximum rate rules clearly lowers the likelihood of failure, higher levels of maximum rates reduce the likelihood of failures for only bonds with floating rules.

These results are confirmed in our econometric analysis, where we estimate logit models of failure rate on a set of variables besides maximum rate levels and rules. These additional variables include bond characteristics (bond size, remaining maturity, bond age, tax status, student loan dummy, general obligation bond dummy, refunding status), auction characteristics (maximum rate, type of maximum rate rule, reset period, minimum bid size, dummy for multiple dealer), proxies for credit risk (bond insurance status, underlying credit rating, 1-month Libor, Treasury term spread), proxies for market liquidity (2-year Treasury on-the-premium, implied Treasury rate volatility), and inter-auction secondary market liquidity (dealer's inventory accumulated since January 1, 2007, inter-auction trading frequency).

To contrast, we also estimate logit models of pseudo-failure on the same set of independent variables. With broker-dealer acting as the bidder of last resort, the auctions the ARS market resembles closely to uniform-price auctions with sellers endogenously adjusting supply after observing all bid orders. Auction theories with such a endogenous supply, however, focus squarely on equilibria in which sellers never need to exercise such an option (Back and Zender, 2001; Wang and Zender, 2002; Damianov, 20051001; LiCalzi and Pavan, 2005; McAdams, 20070401). Nonetheless, we hypothesize that the insufficient demand in these auctions are driven mainly by liquidity shocks.

The data used for the pseudo-failure analysis include auctions up to December 31, 2007, and the data for the actual failure analysis include auctions between February 20, 2008 to March 19, 2008. The period in between is excluded because, as discussed above, the ARS market was in the transition from a state with highly expected dealer support to a state with no dealer support. The results on pseudo-failure are presented in Columns 1-4 of Table **??**, and those on actual failure are in Columns 5-8. The first striking finding is that whether including maximum rate, the pseudo-R^2s for the pseudo-failure regressions are just below 3 percent, suggesting that the occurrence of insufficient bids prior to the crisis was highly unpredictable. The low predictability of supply-demand imbalance in auctions suggests that during normal period of the market, dealers are playing a positive role in providing liquidity to facilitate market functioning.

For the logit regressions of actual auction failures, the pseudo-R^2 for those regressions without maximum rate is 27 percent, but it jumps to over 75 percent when maximum rate level and rule are included as an independent variables. This suggests that auction failures in the post-crisis period are not pure liquidity events but may be related strongly to fundamental risk factors and auction design.

The regressions for the post-crisis period also confirm the findings in Figure 5. As shown in Column (10), having taken into account the interactive term between the fixed rule dummy and maximum rate level and evaluated at the overall sample mean of maximum rate 10.4 percent , the coefficient of fixed rule dummy is -2.06 with a standard error 0.39. This implies that, all else equal, failure rates on bonds with fixed rules are 80 percentage lower than those with floating rules. On the other hand, the impact of maximum rate level on failure rates depends on maximum rate rules. For bonds with floating rules, the coefficient of maximum rate is statistically significant at the 99 percent of confidence level, implying that the failure probability falls 32 percentage when maximum rate increases by one standard deviation (3.8 percent for bonds with floating rules). For bonds with fixed rules, however, the coefficient of maximum rate is statistically insignificant.

4.3 Runs for Liquidity in Transition

We now turn our attention to the investor behavior during the transition period. The sharp rise in failure rates during the week of February 11, as shown in Figure 4 is the first indication that a "bank run"-type behavior may have occurred. Analog to the bank run literature, we define a run as either an unusually large number of current holders rushed to place sell orders in a short period of time or the number of bidders fell substantially below their usually levels. In this section, we first show concrete evidence that current holders ran for liquidity during the transition period. Our further analysis suggests that a part of the runs is of sunspot type as a significant portion of the failures during the transition period cannot be explained by fundamentals.

4.3.1 Evidence of Runs

Ideally, to test the existence of runs, we need data on bid and sell orders by both current and potential ARS holders. Such information is not available in the data we obtained from auction agents, which as discussed, contain information only on *realized* auction outcomes. However, The MSRB's requirements that broker-dealers report all executed transactions to RTRS and the ARS allocation rules permit us to use the MSRB's RTRS data to estimate reasonably the number of sell orders placed in auctions, though not the number of buy orders nor the amount of sell or buy orders.

We illustrate our estimation approach in Table 7. First, for successful auctions, by definition, both the number and amount of sell orders should equal to those of customer sell trades reported in MSRB's RTRS data on the corresponding auction days (upper-left); and for failed auctions, the number and amount of buy orders should equal to those of customer buy trades in the RTRS data (lower-middle).[8] Second, in failed auctions, the amount of executed customer sell trades is, by definition, smaller than the amount of sell orders in auctions (upper-middle, right). But, as discussed early, when an auction fails, hold-at-rate orders are filled fully, and (unconditional) sell orders are filled in pro rata. Thus, unless there is no bid at all, the number of customer sell orders reported in the RTRS data should equal to the number of sell orders placed in auctions that failed (upper-middle, left). Finally, both the number and amount of executed customer buy trades are smaller than those of buy orders in successful auctions because bid orders with rates higher than or equal to the clearing rates are not or partially filled (lower-left). In short, we summarize the above discussions in the following:

Result 1 (i) The number of customer sell trades on auction dates reported in the RTRS data estimates unbiasedly the number of sell orders, including both unconditional sell and hold-at-rate orders, as long as there exists at least one bid in the auction; (ii) The amount of customer sell trades estimates unbiasedly the amount of sell orders for successful auctions but underestimates for failed auctions; (iii) The number and amount of customer buy trades underestimates those of bid orders, including both bid by potential holders and hold-at-rate orders, for successful auctions but estimate unbiasedly for failed auctions.

We plot the average number of customer sell trades on auction dates in the upper-left panel of Figure 6, and, for the sake of completeness, also the average amount of customer sell trades (upper-right panel) and the average number and amount of customer buy trades (lower panels).

[8]This holds up to the assumption that there are no trades outside auctions on auction dates.

The average number of customer sell trades, thus the number of all sell orders, has been steady at about 4 trades per bonds, but it started to creep up in late January to about 10 trades per bonds and surged to nearly 40 trades per bond on February 12 and 13. The average amount of customer sell trades, an underestimate for the amount of sell orders placed in auctions, also shot up in the week of February 11. Result 1 (ii) suggests that the rate of increases in the amount of sell orders may be even higher. The surges in both the number and amount of sell orders during the week of February 11 are clear evidence for investor runs for liquidity.

4.3.2 Abnormal Failure Rate: Information-Based or Sunspot Runs

Investor runs for liquidity may be caused by two fundamentally different reasons, either information-based or by self-fulfilling panic triggered by perhaps "sunspots" (e.g., Cass and Shell (1983)). The information-based run is driven by sharp changes in a short period of time in the key risk factors that affect the ARS valuations. These key risk factors include expected likelihood that broker-dealers withdraw their liquidity supports as well as the credit risk on the bonds. While investors may have gradually placed higher odds on the withdraw of liquidity support as major dealers faced more liquidity issues. However, the odds are unlikely higher than what investors have realized after the week of February 11 when major dealers reportedly had indeed withdrawn. Thus, the probability of auction failures predicted by the model that is estimated using the period immediately after the transition period should be the upper bound of failure rates if the runs are completely information-based. Following the terminology used in the standard event studies, we call the portion of the observed failure rates that is above this predicted upper bound as "abnormal failure rate."

Our approach to estimating the abnormal failure rate resembles to the standard event studies (see, e.g., Campbell, Lo and MacKinlay (1997)). The notable exception is that our estimation window is after the event window (the week of February 11) instead of prior to the event window in the standard event studies. Calomiris and Mason (2003) use a similar approach to examine the impact of contagion on bank failures.

To fix idea, denote auction status for bond i at t by the indicator $\mathbf{I}_{it}$ with $\mathbf{I}_{it} = 1$ if an auction fails, 0 otherwise. Let N_t be the number of bonds in auctions at t. Then, at t, the observed failure rate is

$$\overline{p}_t = \frac{\sum_i \mathbf{I}_{it}}{N_t}.$$

We compute the predicted probability of failure using the estimated probit model of auction failure using the post-transition equilibrium according to

$$\hat{p}_{it} = E(\mathbf{I}_{it}|X_{it}) = 1 - \Phi(\hat{\beta}X_{it}),$$

where $\hat{\beta}$ is the estimated coefficient vector in Column (10) of Table **??**. Then, the abnormal failure rate is

$$p^{\star}_{it} = \mathbf{I}_{it} - \hat{p}_{it}.$$

Thus, the average predicted failure rate is

$$\bar{\hat{p}}_t = \frac{\sum_i \hat{p}_{it}}{N_t},$$

and the average abnormal failure rate is

$$\overline{p^{\star}}_t = \frac{\sum_i p^{\star}_{it}}{N_t}.$$

Table 6 shows our event study results. The average abnormal failure rates on February 11 and 12 are both negative and statistically significant, mainly reflecting that investors may have placed just a small odd, though still higher on the 12th, on the withdraw of liquidity supports by dealers. On the 13th, major news sources reported that major dealers have indeed withdrawn their liquidity supports. For the next three days since then, the average abnormal failure rates turn to positive, at about 11 percent, and are statistically significant. But the market set into a new equilibrium on the 19th when the average abnormal failure rate falls to just about 1 percent and is statistically insignificant. Overall, from the 13th to the 15th, the abnormal failure rates account for about 18 percent of overall failure rates. Note that this is only the lower bound of the portion of failure rates that cannot be explained by information-based runs. Therefore, we conclude that a significant portion of auction failures in the week of February 11 is due to a self-fulfilling panic or sunspot runs.

5 The Role of Broker-Dealers: Coordination Failure

In this section, we examine the role of broker-dealers in the collapse of the ARS market. We show that broker-dealers acted as market-makers in the pre-crisis periods as they stayed ready to buy under-subscribed sell orders at auctions and then sold them in the inter-auction secondary markets. All major dealers, however, stopped to support their auctions almost simultaneously after one major dealer withdrew its support, leading to widespread auction failures. We find that these simultaneous decisions may have been the result of coordination failure instead of economic fundamental risks of supporting the auctions.

5.1 Broker-Dealer as Market Maker

We first present evidence that broker-dealers effectively play the role of market maker during the normal times of the auction market. In Figure 7, we average dealer net buy, that is, customer sell minus customer buy trades, on auction dates and after auction dates in the inter-auction secondary market. During the pre-crisis period, dealers had been net buyers in auctions and net sellers post-auctions. That is, like a market maker, they absorbed surplus supply into their inventories by acting as the bidder of last resort during auctions but unloaded them after auctions in the inter-auction secondary market.

Dealer's directional liquidity provision may be closely related to the way bonds are sold and bought in the ARS market. Since it is a secondary market, all sellers are existing owners. They bought the products knowing that liquidity is limited to the day of the auction. Therefore, they almost always sell their bonds in the auctions by simply submitting sell orders. Buyers of the ARS bonds, especially the unsophisticated investors, are talked into the investment by their investment advisors, who can directly tap the corporate inventories at any day of the month. Thus, sell orders come in bunches, while buy orders come continuously. This makes it necessary that dealers provide temporary liquidity during auctions. Such practice is sustainable if total supply and demand in and out of the auction can be balanced.

As shown in the figure, the dynamics of the ARS market appeared to have changed significantly in late 2007 and early 2008. While broker-dealers had to buy increasing larger amount of bonds in auctions, it was getting hard for them to unload them in the inter-auction markets.[9] In a few days since February 12, dealers net buys fell dramatically to zero as all major dealers were reportedly stopped to support their auctions. On the other hand, dealers appeared to continue to unload their inventories, though at a notably slower pace, in the inter-auction market.

The interesting question then is why dealers suddenly and almost simultaneously changed their strategies. There are several possible reasons for withdrawing the liquidity supports. First, the amount of capital needed for making the market may become too large to maintain. Second, the price of raising additional capitals for the increased liquidity demand may be too high. Third, the value of reputation of making the auction market may have dropped significantly under the current market conditions. Lastly, coordination failures among the dealers may have driven the market into a self-fulfilling equilibrium. We look into these possibilities below.

5.2 Is There A Coordination Failure?

5.2.1 Accumulative Aggregate Inventory

First, we examine how aggregate inventory maintained by dealers has changed prior to the ARS crisis. In Figure 8, we plot aggregate inventory accumulated by all dealers since January 1, 2007. Consistent with the role of market maker, aggregate inventory stayed largely unchanged in the

[9] On December 15, 2007 David Shulman (Muni director) emailed Joseph Scoby (UBS Chief Risk Officer) and indicated that he "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...."

first quarter of 2007. However, dealers started to aggressively pare down their inventory in the second quarter. Aggregate inventory picked up temporarily in the summer of 2007 when the financial market turmoil started to unravel. After having reached its low in October, 2007, aggregate inventory rose sharply in late 2007 and early 2008. However, it is remarkable that as of February 11, 2008, aggregate inventory returned almost the same level at the beginning of 2007. This suggests that the amount of total ARS inventory that dealers had to maintain is unlikely the driving force to the widespread withdraw of liquidity supports. Still, given the rising rates on ARS, the amount of capital required to support the same amount of inventory may have still increased.

5.2.2 A Perfect Storm: Reputation, Contagion, and Coordination Failure

Reputation matters on dealer's decision on providing liquidity support. Dealers value their reputations as the market maker for their auctions largely because they are also underwriters for the bonds and want to maintain continued business relationship with the issuers. However, there is externality on the reputation cost. The damage to a dealer's reputation from withdrawing the auction support may depend on whether other dealers have done the same. In particular, being the first one to stop the liquidity support may make the dealer look really bad. On the other hand, as an old Chinese saying, "the law cannot impose on the mass," if many dealers have done the same, then the potential damage may be much smaller. To avoid being the first mover is a realistic concern among the dealer. For example, David Shulman of UBS, in an email in January 2008, described a "worse 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 "if we do fail—be the 2^{nd} to fail" (January 13, 2008, Exhibit 1, Massachusetts Attorney General Investigation).

The effects of the two contagion and reputational risk on dealer's decision create possibilities of multiple equilibria in the game among dealers. Under certain parameter value, dealers will choose to continue support the auctions if most others also support their auctions, and they will withdraw if small amount of other dealers do the same. An all-support equilibrium, even if optimal globally, may not be very stable. Small disturbances in one or two opponents' behavior will cause the whole game to move from the all-support equilibrium to the all-withdraw equilibrium.

We now show that a withdraw by a seemly unlikely dealer triggered such a coordination failure, which in turn drove the market into the equilibrium with all dealers withdrawing liquidity supports and investors running for liquidity. Figure 10 shows that while there have sporadic failures since September, 2007, it is only in the week of February 11 when all major dealers almost simultaneously stopped to bid in the auctions. Figure 11 zooms into the week. The first dealer that allowed all of auctions with insufficient bids to fail is Goldman Sachs on February 12. In the next three days, all other dealers followed suit.

We argue that among major dealers, Goldman Sachs appeared to be at least not the first one that would have the most difficulties supporting their auctions. First, as shown in Figure 12, Goldman had pared significantly down its inventory over the course of 2007, and its inventory on the eve of its withdraw was actually below its level at the beginning of 2007. The two banks that experienced significant inventory increases were UBS and Citigoup. Second, Goldman was not the one with the highest costs of funds. We use spreads on credit default swaps (CDS) written on broker-dealers as a measure for their costs of funds. As shown in Figure 9, CDS spreads on all major broker-dealers have increased significantly since July 2007. But spreads on Goldman CDS were notably lower than those on Lehman Brothers and Morgan Stanley. Third, Goldman did not appear to be the one with the lowest reputation value. As shown in Table 3, while Goldman has a significantly lower market share than Citigroup, UBS, and Morgan Stanley, its share was nonetheless modestly higher than those of other dealers such as Lehman Brothers, Merrill Lynch, JP Morgan, and Bank of America.

In short, Goldman's move as the first one to withdraw its auction support appeared to be unexpected. The unpredictable move triggered a self-fulfilling strategy among other dealers as each expected others would withdraw and reputation costs would be significantly reduced. Anticipating, correctly, these strategical moves, investors rushed to sell their holdings, further strengthening the validity of dealers' strategies.

6 Pricing of MARS: Security Design

In this section, we examine the pricing of MARS in two different equilibria before and after the mid-February transition period. The main difference between the two market regimes is that before the market fall-out, dealers actively step in the auctions to absorb surplus supply; after the market turmoil, dealers stopped providing liquidity supports. Existing literature in auction theory has analyzed auctions that resemble the setting under each of the two regimes. We can thus use our unique auction data to test the predictions of these auction theories.

6.1 Theoretical Predictions for Two Equilibria

6.1.1 Auction Theory

The setting of our post-February auctions without dealers' support resembles closely a standard uniform-price auction with fixed supply. One can consider existing owners' "hold at rate" orders to be a hybrid of "sell" and "buy at rate" order. The supply in the auction is the total number of bonds outstanding. Fixed-supply uniform-price auctions are widely used in financial and commodity markets to sell identical securities or goods to multiple buyers. Both UK and US treasury auctions and electricity auctions are conducted this way. An important result of the extensive theoretical studies is that that standard uniform-price auctions are susceptible to arbitrarily large underpricing (e.g., Wilson (1979), Back and Zender (1993)).

In the case of a yield-based auction, theory predicts that the equilibrium clearing rate (price) is generally higher (lower) than the security's fundamental value. In particular, the results of Back and Zender (1993) suggest that if the maximum auction rate is higher than the upper support of the uncertain fundamental value, there exists a continuum equilibria with the clearing rate being in between the two values (Theorem 1, page 741). In these equilibria, bidders ignore their information concerning the fundamental value of the security. Among the continuum of equilibria, the highest rate (lowest price) is preferred by bidders.

The result of multiple equilibria has spurred many attempts to reduce the number of equilibria by modifying auction design. One of such attempt is introducing endogenous supply (Back and Zender, 2001; Wang and Zender, 2002; Damianov, 20051001; LiCalzi and Pavan, 2005; McAdams, 20070401). In this setting, the seller has the option to adjust the quantity sold after observing the bids. Back and Zender (2001) find that with endogenous supply, the auction generates equilibrium result that is highly competitive. This new result reconciles the contradictory empirical findings of Simon (1994) and Umlauf (1993). Simon (1994) finds uniform price auction to be revenue inferior to discriminatory auctions based on the US experience with 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.

We observe that the ARS auctions before the turmoil are effectively auctions with endogenous supply. This is because dealers observe the demand schedule and place their own bids ex post to absorb any surplus supply. Dealers are paid by bond issuers to act in their interests to interfere the auctions. Dealers' bids effectively create endogeneity in the residual supply for all the other investors. Assuming that investors are aware of dealers' support, their bidding strategy will resemble what is predicted in the modified auction theory. We can thus use auction results before January 2008 to test the predictions from auction theory under endogenous supply. More specifically, we expect prices to be more competitive in the pre-crisis regime, and prices to reflect fundamental value too.

We summarize the above theoretical predictions in the following hypotheses:

Hypothesis 1 In the post-crisis equilibrium, where auction supply is fixed, (a) auction results deviate from bonds' fundamentals value; (b) auction reset rates are positively related to maximum rate; and (c) there exists underpricing

Hypothesis 2 In the pre-crisis equilibrium, where auction supply is endogenously determined by the auction dealers, (a) auction results reflect fundamental value; (b) auction variable such as the maximum rate is not as relevant; and (c) dealers play an active role in pricing, they can use prices to manage their inventories

6.1.2 Non-Auction Secondary Market

The theoretical models that we above refer to do not assume the existence of a secondary market. A secondary market, however, does exist in the ARS market.[10] ARS underwriters, who also manage auctions, typically use the secondary market to unload their inventories and provide timely liquidity to their clients who want to trade outside of auction dates. Almost all of the trades between auctions are executed at par value. This is true even after February 2008, when auctions started to fail, indicating that the dealers continued to provide limited intermediation in the secondary market.

Secondary market adds an extra level of complexity to the bidding behavior of potential buyers. The setting is particularly relevant in an environment where a resale market almost always exists. Literature on auctions with secondary market is abound. Jegadeesh (1993) shows that in May 1991, when Solomon Brothers admitted to having violated auction regulations, prices of two year notes in the auctions were reliably higher than the estimated secondary market prices after issuance. Their finding supports the market's concern that Solomon bid low in the primary market in exchange for an option to potentially squeeze the secondary market. Nyborg and Strebulaev (2003) developed a model of multiple unit auction with short-squeezes in the post auction market. They show different valuations of the auctioned asset between short and long bidders.

Short-squeeze is less likely to happen in the ARS market, given that hundreds of similar auctions happen every day. The institutional setting of the ARS market and its secondary market are unique. We cannot use any existing models to predict the strategic behaviors of bidders in our auctions. At this stage, we do not attempt to develop our own model to describe the complex market, but try to make qualitative predictions through reasoning.

A main feature of the secondary MARS market is that trades almost always happen at par value.[11] The ability to buy at par value in the secondary market after the auction clearly reduces the competitiveness in the primary market. For the bidder, being able to acquire the securities between auctions at par reduces the cost of losing the bid if he bids too aggressively (too high rates, too low prices). Therefore, when secondary liquidity is high, bids will be more aggressive, and we will see higher reset rates in auctions. On the other hand, a liquid secondary market means smaller risk associated with failed auctions. The required rate of return for bidders should be lower when

[10] Strictly speaking, all auctions happen in the secondary market, our intended "secondary market" should referred to "non-auction secondary market". We use "secondary market" to refer to the non-auction market loosely.

[11] Discounted prices did appear in trades through some alternative market platforms, notably the Restricted Securities Trading Network(RSTN). Anecdotal accounts from RSTN indicate that majority of the discounts happened on student loan ARS or ARPS. Muni ARS were able to trade at par.

liquidity risk is low.

The contradicting predictions boils down to the price setting mechanism of the auction. If the auction is designed to reflect fundamental value, then we expect the rates in auctions with more liquid secondary market to be lower; if the auction encourages speculative bidding, then we expect the rates in auctions with more liquid secondary market to be higher. Given that uniform auction with fixed-supply encourages collusive bids (e.g., Back and Zender (1993)), we expect higher reset rates associated more secondary trading in auctions post-crisis. We empirically test the following hypothesis:

Hypothesis 3 Reset rates on successful auctions in the post-crisis equilibrium are increasing in the secondary market liquidity.

6.2 Empirical Results for Auction Pricing

We use an OLS regression model to test our hypothesis. Table 7 shows results from regressions of auction reset rates from successful auctions on various factors that may affect the pricing. Each column represents a model specification. All standard errors are clustered at the issuer level. Each issuer can have multiple ARS bonds. We use the first six digits of bonds' CUSIPs to identify them. Columns 1 to 5 uses the sample between July 1 2007 and December 31 2007. Columns 6-10 uses all successful auctions between Feb 20 2008 to Mar 19 2007. One can see that using the simplest model specification (columns 1 and 5), where only fundamental variables are included, the R^2 dropped from 71% (column 1) before crisis to 20% (column 6) after the crisis. These support H1 (a) and H2 (a).

More specific evidence for the lack of relevance of fundamental variables in the pricing of post-crisis equilibrium is that the dummy variable for "student loan" , which is significant in the pre-crisis sample, becomes insignificant in the sample after Feb 20th 2008. Student loan bonds are asset-back securities that should be priced differently from regular municipal bonds. Similarly, macro-economic variables "on-the-run premium for 2-year T-Bill" and "volatility of 10-year Treasury", which measure liquidity premium and market risk, both change from being significant in the pre-crisis sample to being insignificant in the post-crisis sample.

Another peculiar evidence of the deviation from fundamental value in the post-crisis equilibrium prices is that the coefficient for Libor rate turns negative after the crisis. Since there is no obvious reason to believe that bond values should be negatively related to the Libor rates, we consider this as further evidence for H1(a) that post equilibrium prices reflect little fundamental values compared with pre-crisis equilibrium.

One may argue that the lack of predictability in post-crisis auction prices using fundamental factors specified in column (6) is due to its omission of important pricing factors that were not as important before the crisis. One possible factor is liquidity risk– the risk of auction failure, which was hidden before the crisis. From early analysis (see Table 4), we found that auction failure is largely determined by the the level of maximum rates. We can thus use maximum rate as a proxy for the risk of auction failure and add it into our basic pricing model. If prices in the post-crisis equilibrium reflect a premium for liquidity risk, we would expect the auction reset rate to be negatively related to maximum rate.

Column 7 shows that the R^2 significantly increased after adding "maximum rate" as regressor, a sign of relevance. However, the coefficient for "maximum rate" is significantly positive, instead of negative. This is evidence for both H1(a) and (b). On the one hand, prices do not reflect "liquidity risk", which should be an important part of bond's fundamental value; on the other, auction reset rates can be arbitrarily high, as high as the maximum rates, causing positive relationship between maximum rate and auction reset rate. The coefficients for "maximum rate" in the "before" sample is also statistically significant, but not economically, given its small magnitude. We consider this evidence for H2(b). Column 9 adds interaction terms of the maximum rate types (fixed or floating) and the maximum rate into the model. Result shows that for both fixed maximum rate or floating maximum rate bonds, maximum rate is significantly positively related to auction reset rates. For floating maximum rate bonds, 100 basis points increase in the maximum rate corresponds to 60 basis points increase in the auction reset rates.

We verify the existence of underpricing in the post-crisis equilibrium (H1 (c)) by comparing the rates before and after the crisis using the pricing model estimated from the before-crisis sample. This is justified given its higher R^2 and our discussion about H2(a), that the before-crisis equilibrium reflects bonds' fundamental value better. We predict the post-crisis equilibrium prices using estimated model in Column (5), and compare the abnormal rates with zero. Abnormal rates are calculated as the difference between actual rates and predicted rates. Table **??** shows the summary statistics of the actual rates and predicted rates. The mean rate of post-crisis auctions is 3.7% higher than model predictions. The difference is highly statistically significant, and positive.

We show in earlier section that dealers actively participate in auctions before the crisis, and play a crucial role in both liquidity and pricing. Thus, we expect that they can bias prices in a way that reduces their inventory (H2 (c)). This is verified in Column (5) where dealer's cumulative inventory, as of the day before the auction date, is included in the regression. One can see that it is significantly positive at 99% level. Therefore, when dealers' inventories are high, they seem to be propping up the auction rates to reduce inventories. This relationship is also significant in the post-crisis sample. Although we didn't expect dealers to remain relevant in auction pricing after the crisis, our analysis point to the possibility that dealers continue to participate in selected auctions.

To test H3, we turn to models in column (5) and (10), which include a measure of secondary liquidity. The secondary liquidity is measured by trading volume– average daily number of secondary market trades during the last inter-auction period. Column 10 of Table 7 shows that reset rates of successful auctions are positively related to secondary trading volume. The result confirms our predictions in H3 and indirectly provides further evidence of H1 (a), that the post-crisis prices reflect little fundamental value. Speculative bidding drives auction reset rates higher for bonds more liquid in the secondary market. Our finding provides a connection between the auction market and the non-auction secondary market. It casts doubt on the naive notion that higher secondary liquidity is universally good. We show that liquidity, combined with an ill-designed auction market (uniform price auction market), may have the unexpected negative effect of altering the strategic behavior of bidders towards more aggressive bidding.

6.3 Discussion About Securities Design

Our analysis about ARS pricing in two equilibria confirms predictions in auction theory that there exists underpricing in standard uniform-price auction with fixed supply, not so when supply is endogenous. More importantly our results reveal interesting facts that have not been raised despite the market's heavy press coverage, that the design of auction process is flawed, especially without the watch of the auction dealers.

We show strong evidence, predicted by Back and Zender (1993), that auction results can be arbitrarily bad in fixed supply uniform price auctions. More often than not, reset rates are just below the maximum allowed rates. Bond issuers, who are not designed to play a role in the auctions, being the payer of the interest rates set through the auction, are ultimately paying a high price for such security design. We do not see such rampant underpricing in treasury auctions because the sellers can monitor the auctions and adjust the parameters from one to the next. Auctions of ARS, however, are theoretically auctions in the secondary market, where all parameters of the auctions are set at issuance. Issuers, who are designed to be outsiders in auctions, are the most vulnerable to collusive bids.

One potential solution to the underpricing is re-introducing endogenous supply by allowing issuers to bid on their own bonds. In fact, issuers have been trying to do exactly this, but were deterred by a lack of regulatory framework that allow them to do so. The SEC cleared the hurdle for such bids in late March. Our analysis shows that the SEC's decision is supported by auction theory.

7 Conclusions

In this paper, we use the recent collapse of the ARS market as a case study on important issues regarding fragility of financial innovations and systemic risks. We find strong evidence of investor runs for liquidity which are partly caused by a self-fulfilling panic. We also find that coordination failures triggered by an unexpected first mover caused all major broker-dealers to simultaneously withdraw their liquidity support. In addition, the likelihood of auction failures and ARS reset rates depend significantly on both the rule and the level of maximum auction rates. Moreover, there is strong evidence for underpricing, as predicted by auction theories.

Our analysis of the collapse of the ARS market offers two lessons. First, liquidity is fragile. ARS were invented partly because auction was thought to be able to provide greater liquidity for existing holders to temporarily park their cash. This assumption has never been seriously tested until recently. Loss of dealers' liquidity support exposed the vulnerability of the liquidity assumption. Moreover, like in some other short-term financial products, such as SIVs, that recently experienced extraordinary difficulties, the liquidity support provided by auction dealers is not written in the contract and thus not binding. Auction dealers almost always acted as the bidder of the last resort in usual times, perhaps for the sake of reputation or maintaining a good relationship with the issuers. But the support can disappear on a very short notice when reputation or relationship suddenly becomes too cheap relative to survival. The dealers' decisions of withdrawing their liquidity supports in the MARS auctions are indeed extraordinary, because underlying securities, whether insured by troubled financial guarantors or not, are very safe.

Recognizing the fragility of liquidity is important. The ARS experience suggests the current regulatory framework and risk management models fail to fully take into account it. Fragility has two aspects: first, liquidity crisis tends to come very quickly; second, it can be contagious. The current crisis has been in formation for quite a while. Helped by rosy market conditions, confidence became overconfidence or complacency. As we have seen, this overconfidence can disappear very quickly, giving no time for risk management models or regulators to react.

The second lesson is that market turmoil is the ultimate test on innovations. Financial innovations produce securities that may be inherently vulnerable to liquidity shocks. Our analysis suggests that there is strong evidence, both theoretically and empirically, that the design of the ARS is flawed. As a result of these design flaws, the price discovery failed and reset rates deviated from their fundamental values. Going forward, ARS may disappear or have to be significantly modified to address these design issues. Likewise, other innovations such as CDO^2 and structured investment vehicles (SIVs) will have similar fates. However, as a result of this evolutionary process, hopefully the markets will become more resilient, and perhaps get ready for the next excitement.

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Table 1: **Sampling Construction**

To construct our sample, we start with all ARS contained in auction reports received from Wilmington Trust, Bank of New York Mellon, and Deutsche Bank 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	N. of bonds
1. All ARS from WT, BNYM, and DB	4945
2. Identifying municipal securities using MSRB's RTRS data	3709
3. Merge Bloomberg bond description data	3567
4. Reset frequencies are no less than 7 days and no longer than 35 days	3526
5. Maximum rate rules are identifiable statistically or collected manually	2755

Table 2: **Distribution of the Types of Maximum Rate Rules**

This table shows the number of bonds by the types of maximum rate rules. Possible types include

- Type A: maximum rate is fixed, say 15 percent;
- Type B: maximum rate is a multiple of a benchmark rate up to a cap;
- Type C: maximum rate equals to a markup plus a benchmark rate up to cap;
- Type D: complex rule, usually combining Types B and C with possibe looking-back features.

We first use a statistical method to estimate and identify the maximum rate rules. For bonds whose rules are not identifiable using the statistical method, we manually collect the rule data from their bond prospectuses.

	Types of Maximum Rate Rules						
	Identified					Unidentified	Total
Sample	A	B	C	D	Subtotal		
Auctions never failed	888	34	2	52	976	118	1094
Auctions failed only once	191	134	3	1	329	35	364
Auctions failed twice or more	80	1149	126	95	1450	618	2068
Total	1159	1317	131	148	2755	771	3526
Memo:							
Average maximum rate	14.0	7.5	6.4	6.2	10.6		

Table 3: **Summary Statistics**

	Whole sample, $N = 3526$		Restricted sample, $N = 2755$	
	Panel A: Categorical Variables			
	N	Percent	N	Percent
Is a GO bond	51	1.45	49	1.81
Is taxable	605	17.17	391	14.19
Is student loan	801	21.57	502	18.22
Reset period				
7	1595	45.2	1385	50.3
14	3	0.1	3	0.1
21	3	0.1	2	0.1
28	625	17.7	445	16.3
35	1300	36.8	920	33.4
Underlying rating				
AAA	4	0.1	3	0.1
AA	576	16.3	514	18.7
A	1181	33.5	1011	36.7
BBB	302	8.6	252	9.2
Unrated	1463	41.5	975	35.4
Strength of bond insurers[a]				
Strong	387	11.0	360	13.0
Weak	1465	41.4	1138	41.3
Other insurers	688	19.5	587	21.3
Not insured	943	27.9	639	23.1
Multiple broker-dealer	994	28.0	814	29.6
Lead manager				
Citigroup	762	21.6	619	22.4
UBS	648	18.4	467	16.9
Morgan Stanley	356	10.1	282	10.2
RBC	278	7.9	180	6.5
Goldman Sachs	241	6.8	223	8.1
Bear Stearm	205	5.8	177	6.4
Lehman Brothers	192	5.5	128	4.6
Merrill Lynch	179	5.1	159	5.7
JP Morgan	178	5.1	158	5.7
Bank of America	174	4.9	121	4.3
Others	313	8.9	241	8.7
	Panel B: Continuous Variables[b]			
	Mean	Std. Dev.	Mean	Std. Dev.
Bond size($ MM)	53.6	39.7	53.4	29.3
Min. bid size ($ K)	39.8	26.3	38.1	26.3
Remaining Term-to-mat.	23.7	8.1	23.5	8.1
Maximum rate			10.6	4.1

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

[b]The numbers of bonds for minimum bid size are 3488 and 2720, respectively, for whole sample and restricted sample. Summary statistics for maxrimum rate are computed for all dates.

Table 4: Determinants of Auciton Failure

The table shows logistic regression of pseudo failure for the period from 7/1/2007 to 12/31/2007 and of actual auction failure for the period from 2/20/2008 to 3/20/2008. Standard error are clustered on issuer level with *, **, and *** for p-values less than 0.10, 0.05, 0.01, respectively.

	Jul 1, 2007-Dec 31, 2007					Feb 20, 2008-Mar 19, 2008				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.
Log(size)	0.403***	0.419***	0.419***	0.422***	0.405***	-0.002	0.460***	0.477***	0.471***	0.441***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.12)	(0.14)	(0.15)	(0.15)	(0.15)
Log(maturity)	-0.004	0.006	0.008	0.009	0.020	0.090	-0.084	-0.209	-0.195	-0.192
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.20)	(0.19)	(0.24)	(0.24)	(0.24)
Log(age)	-0.062***	-0.042*	-0.036	-0.041*	-0.040*	1.345***	0.407***	0.250*	0.224	0.226
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)
Log(reset freq)	0.033	0.032	0.035	0.034	0.015	0.356***	0.537***	0.488***	0.502***	0.509***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.11)	(0.17)	(0.17)	(0.17)	(0.17)
Student Loan	0.256**	0.267*	0.262*	0.239*	0.266*	4.010***	5.707***	4.795***	4.541***	4.683***
	(0.12)	(0.14)	(0.14)	(0.14)	(0.14)	(0.63)	(1.23)	(1.00)	(0.92)	(0.99)
Taxable	-0.587***	-0.455***	-0.446***	-0.459***	-0.417***	-0.236	0.946**	0.534	0.432	0.462
	(0.13)	(0.11)	(0.12)	(0.11)	(0.10)	(0.41)	(0.47)	(0.53)	(0.50)	(0.51)
GO Bond	-0.312**	-0.267*	-0.278*	-0.280*	-0.266*	0.093	-0.363	0.059	-0.006	0.020
	(0.13)	(0.15)	(0.15)	(0.15)	(0.15)	(0.42)	(0.40)	(0.40)	(0.42)	(0.41)
Refunding Bond	-0.049	-0.063	-0.064	-0.060	-0.066	0.035	0.251	0.252	0.294	0.308
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.17)	(0.17)	(0.21)	(0.19)	(0.19)
No Credit Enhancement	-	-	-	-	-	-	-	-	-	-
enhancetype==Strong	0.150	0.078	0.071	0.056	0.007	-0.413	-0.256	0.245	0.194	0.246
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.45)	(0.49)	(0.51)	(0.52)	(0.54)
enhancetype==Weak1	0.135	0.096	0.091	0.075	0.032	-0.114	0.321	0.652	0.618	0.704
	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.42)	(0.41)	(0.43)	(0.42)	(0.44)
enhancetype==Weak2	0.163	0.114	0.111	0.110	0.073	-0.364	0.219	0.296	0.362	0.454
	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.42)	(0.45)	(0.47)	(0.47)	(0.50)
No Underlying Rating	-	-	-	-	-	-	-	-	-	-
udlyCredit==0	0.005	0.017	0.013	0.017	0.027	-0.342	-0.127	-0.035	-0.069	-0.130
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.31)	(0.44)	(0.50)	(0.49)	(0.48)
udlyCredit==1	-0.138**	-0.100	-0.103	-0.098	-0.095	-0.221	0.192	0.237	0.232	0.208
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.25)	(0.34)	(0.37)	(0.37)	(0.36)
udlyCredit==2	-0.203***	-0.142*	-0.147*	-0.140*	-0.139*	-0.156	-0.003	0.258	0.211	0.140
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.29)	(0.37)	(0.40)	(0.41)	(0.40)
30-Day Libor	-0.026	0.013	0.021	0.033	0.024	-0.403**	-0.767*	-1.264**	-1.192**	-1.195**
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.19)	(0.46)	(0.51)	(0.52)	(0.52)
Term Spread	0.431***	0.491***	0.490***	0.492***	0.469***	0.561	1.217	1.275	1.278	1.491
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.44)	(1.14)	(1.21)	(1.21)	(1.25)
On-the-Run Premium 2Y	0.027***	0.029***	0.029***	0.029***	0.030***	0.009	0.014	0.018	0.015	0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.05)	(0.05)	(0.05)
Vol of 10Y Trsy	0.059***	0.043**	0.042**	0.041**	0.048**	-0.017	0.202	0.232	0.241	0.220
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.14)	(0.33)	(0.34)	(0.34)	(0.34)
Min Piece (K)	-0.001	-0.000	-0.000	-0.000	0.001	-0.006	-0.008*	-0.006	-0.006	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multiple Dealer	0.037	-0.029	-0.028	-0.023	-0.024	-0.235	-0.815***	-0.898***	-0.901***	-0.902***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.19)	(0.20)	(0.22)	(0.21)	(0.21)
Max Rate		0.031***	0.018				-0.691***	-0.230***		
		(0.01)	(0.01)				(0.03)	(0.09)		
Fixed Max Rate			0.104	-0.365	-0.371			-4.011***	-6.361***	-6.525***
			(0.09)	(0.30)	(0.30)			(0.74)	(1.47)	(1.49)
Fixed Max * Max Rate				0.039*	0.036*				-0.124	-0.120
				(0.02)	(0.02)				(0.09)	(0.09)
Float Max * Max Rate				-0.004	-0.009				-0.399***	-0.414***
				(0.02)	(0.02)				(0.15)	(0.15)
Lag Dealer Inv.					-0.000					-0.000*
					(0.00)					(0.00)
Secondary Mkt. Trade Freq.					0.069*					0.122
					(0.04)					(0.22)
Cons.	-7.312***	-8.079***	-8.045***	-7.964***	-7.668***	-1.593	-5.499	-6.711*	-6.053	-5.883
	(0.59)	(0.67)	(0.67)	(0.66)	(0.67)	(2.38)	(3.69)	(3.99)	(4.22)	(4.16)
R2	0.023	0.025	0.025	0.025	0.025	0.273	0.741	0.754	0.755	0.755
N	44933.000	35021.000	35021.000	35021.000	33793.000	7921.000	6189.000	6189.000	6189.000	6152.000

Table 5: **Estimating the Number and the Amount of Sell and Buy Orders in Auctions**

Definitions:

- $\hat{N}_s$: number of customer sell in RTRS; N_s: number of sell order in auction;
- $\hat{Y}_s$: amount of customer sell in RTRS; Y_s: amount of sell order in auction;
- $\hat{N}_b$: number of customer buy in RTRS; N_b: number of bid order in auction;
- $\hat{Y}_b$: amount of customer buy in RTRS; Y_b: amount of bid order in auction.

All statistics are computed on auction days.

	Successful aucitons		Failed auctions		All auctions	
	Number	Amount	Number	Amount	Number	Amount
Sell	$\hat{N}_s = N_s$	$\hat{Y}_s = Y_s$	$\hat{N}_s = N_s$	$\hat{Y}_s < Y_s$	$\hat{N}_s = N_s$	$\hat{Y}_s < Y_s$
Buy	$\hat{N}_b \leq N_b$	$\hat{Y}_b \leq Y_b$	$\hat{N}_b = N_b$	$\hat{Y}_b = Y_b$	$\hat{N}_b \leq N_b$	$\hat{Y}_b \leq Y_b$

Table 6: **Abnormal Failure Rates in Early February**

To estimate the abnormal failure, we first compute the predicted probability of failure using the estimated probit model for auction failure 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 an auction failed, 0 otherwise. Then, the abnormal 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 failure rate is $\overline{p}_t = \frac{\sum_i \mathbf{I}_{it}}{N_t}$, the average predicted failure rate is $\overline{\hat{p}}_t = \frac{\sum_i \hat{p}_{it}}{N_t}$, and the average abnormal failure rate is $\overline{p^{\star}}_t = \frac{\sum_i p^{\star}_{it}}{N_t}$.

Date	$\overline{p}_t$	$\overline{\hat{p}}_t$	$\overline{p^{\star}}_t$	Std. Dev. of $p^{\star}_{it}$	N_t	t-Statistics of $\overline{p^{\star}}_t$
2/11/2008	0.04	0.42	-0.40	0.44	225	-13.64
2/12/2008	0.13	0.39	-0.28	0.51	358	-10.45
2/13/2008	0.60	0.43	0.11	0.48	385	4.49
2/14/2008	0.57	0.43	0.09	0.37	309	4.04
2/15/2008	0.57	0.38	0.11	0.32	359	6.79
2/19/2008	0.53	0.45	0.01	0.32	403	0.83

Table 7: Determinants of Reset Rates on Successful Auctions

The table shows OLS regression of auction reset rates for the period from 7/1/2007 to 12/31/2007 and of actual auction failure for the period from 2/20/2008 to 3/20/2008. Standard error are clustered on issuer level with *, **, and *** for p-values less than 0.10, 0.05, 0.01, respectively.

	Jul 1, 2007-Dec 31, 2007					Feb 20, 2008-Mar 19, 2008				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.	Coef./SE.
Log(size)	0.005	0.001	0.000	-0.001	0.012	0.176	0.087	0.068	0.033	0.003
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.13)	(0.11)	(0.10)	(0.10)	(0.10)
Log(maturity)	0.037*	0.033	0.032	0.032	0.030	0.398**	0.353*	0.376*	0.388**	0.340*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.20)	(0.19)	(0.19)	(0.19)	(0.18)
Log(age)	-0.028***	-0.018**	-0.023**	-0.021**	-0.020**	0.055	0.059	0.105	0.103	0.073
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Log(reset freq)	0.238***	0.234***	0.232***	0.232***	0.240***	0.282**	0.404***	0.410***	0.403***	0.422***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Student Loan	0.283***	0.307***	0.311***	0.321***	0.337***	-0.617	0.242	0.500	0.673	0.746
	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.63)	(0.61)	(0.58)	(0.57)	(0.59)
Taxable	1.360***	1.361***	1.354***	1.359***	1.359***	1.084***	0.859***	0.959***	0.969***	0.876***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.23)	(0.25)	(0.25)	(0.24)	(0.23)
GO Bond	-0.152***	-0.153***	-0.144***	-0.143***	-0.141***	-1.160***	-1.026***	-1.119***	-1.118***	-1.049***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.33)	(0.31)	(0.31)	(0.31)	(0.26)
Refunding Bond	0.031*	0.026	0.027	0.025	0.024	0.219	0.228	0.203	0.175	0.135
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
No Credit Enhancement	-	-	-	-	-	-	-	-	-	-
enhancetype==Strong	-0.127***	-0.128***	-0.123***	-0.117**	-0.108**	1.540***	1.418***	1.363***	1.436***	1.330***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.28)	(0.31)	(0.32)	(0.31)	(0.30)
enhancetype==Weak1	-0.128***	-0.137***	-0.133***	-0.126***	-0.120***	2.220***	2.177***	2.120***	2.199***	2.052***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.27)	(0.29)	(0.30)	(0.29)	(0.28)
enhancetype==Weak2	-0.051	-0.063	-0.060	-0.060	-0.052	2.550***	2.495***	2.436***	2.480***	2.348***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.25)	(0.27)	(0.28)	(0.27)	(0.27)
No Underlying Rating	-	-	-	-	-	-	-	-	-	-
udlyCredit==0	0.031	0.062	0.066	0.064	0.058	0.182	0.179	0.153	0.155	0.189
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.36)	(0.34)	(0.34)	(0.33)	(0.32)
udlyCredit==1	-0.073**	-0.058*	-0.055	-0.058*	-0.057	-0.527**	-0.494*	-0.539**	-0.577**	-0.551**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.26)	(0.26)	(0.26)	(0.26)	(0.24)
udlyCredit==2	-0.122***	-0.109***	-0.105***	-0.108***	-0.109***	-1.710***	-1.747***	-1.806***	-1.840***	-1.774***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.28)	(0.29)	(0.29)	(0.29)	(0.28)
30-Day Libor	0.478***	0.476***	0.470***	0.465***	0.442***	-0.943***	-0.945***	-0.923***	-0.945***	-1.032***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.23)	(0.23)	(0.23)	(0.22)	(0.22)
Term Spread	0.487***	0.467***	0.467***	0.467***	0.465***	-3.470***	-4.113***	-4.166***	-4.147***	-3.608***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(1.17)	(1.23)	(1.23)	(1.22)	(1.19)
On-the-Run Premium 2Y	-0.029***	-0.029***	-0.029***	-0.030***	-0.028***	0.020	0.032	0.034	0.032	0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Vol of 10Y Trsy	0.097***	0.093***	0.094***	0.094***	0.098***	0.451*	0.435*	0.413*	0.405*	0.445*
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.24)	(0.25)	(0.24)	(0.24)	(0.25)
Min Piece (K)	0.002***	0.001***	0.002***	0.002***	0.002***	0.009**	0.011***	0.010**	0.009**	0.009**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multiple Dealer	0.022	0.013	0.012	0.011	0.007	-0.193	-0.265*	-0.267*	-0.269*	-0.240*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)
Max Rate		0.010***	0.020***				0.205***	0.116***		
		(0.00)	(0.01)				(0.03)	(0.04)		
Fixed Max Rate			-0.082	0.114	0.088			1.324***	4.359***	4.236***
			(0.05)	(0.12)	(0.12)			(0.40)	(1.11)	(1.10)
Fixed Max * Max Rate				0.011	0.014*				0.091**	0.094**
				(0.01)	(0.01)				(0.04)	(0.04)
Float Max * Max Rate				0.029***	0.029***				0.599***	0.597***
				(0.01)	(0.01)				(0.14)	(0.14)
Lag Dealer Inv.					0.000***					0.000**
					(0.00)					(0.00)
Secondary Mkt. Trade Freq.					-0.012					0.608***
					(0.01)					(0.10)
Cons.	-0.061	-0.045	-0.073	-0.108	-0.171	6.519**	6.729**	7.286***	5.270**	4.858*
	(0.23)	(0.27)	(0.27)	(0.28)	(0.26)	(3.14)	(2.78)	(2.69)	(2.68)	(2.58)
R2	0.707	0.678	0.678	0.679	0.682	0.200	0.268	0.276	0.282	0.301
N	44921	35009	35009	35009	33781	3521	3279	3279	3279	3279

Figure 1: **Gross Issuance of Auction Rate Securities by Municipalities**

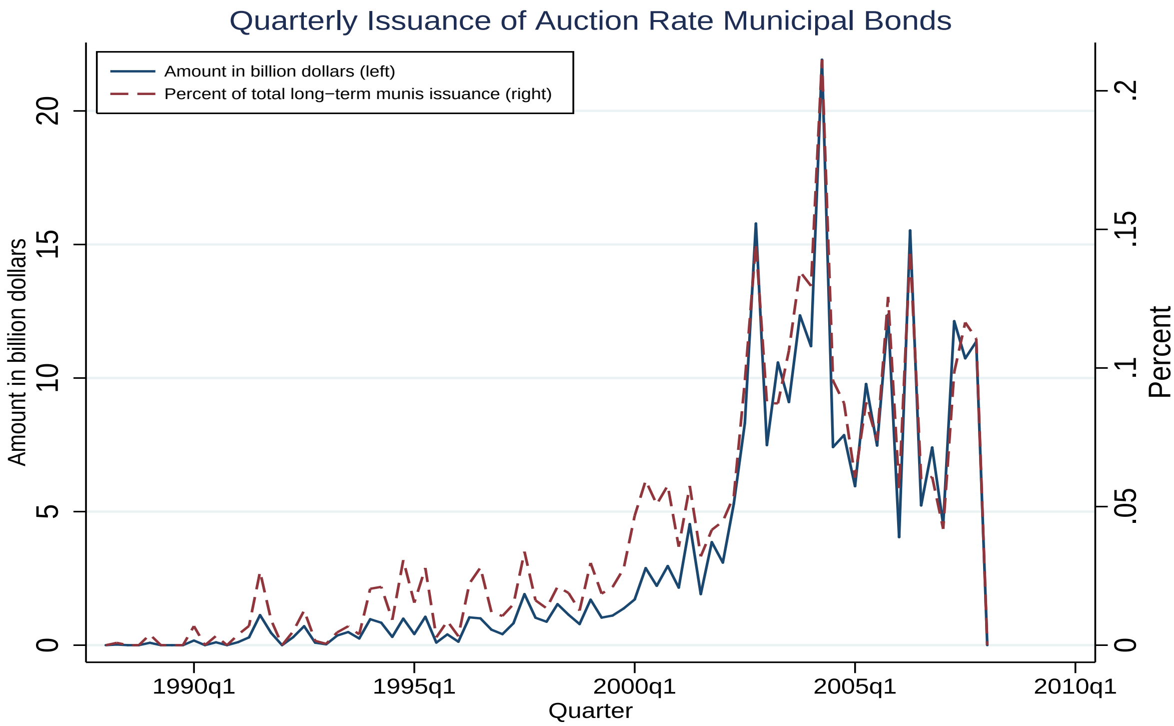


Figure 2: **The Auction Procedure**

Figure A: An Example of Cleared Auction

The blue line represents the demand curve aggregated from all bids. The red line represent the supply curve. The supply can be considered as fixed by considering "hold" orders from existing owners as both a "sell" order and a "buy at rate" order. This way, the total supply is equal to the total amount of bond outstanding.

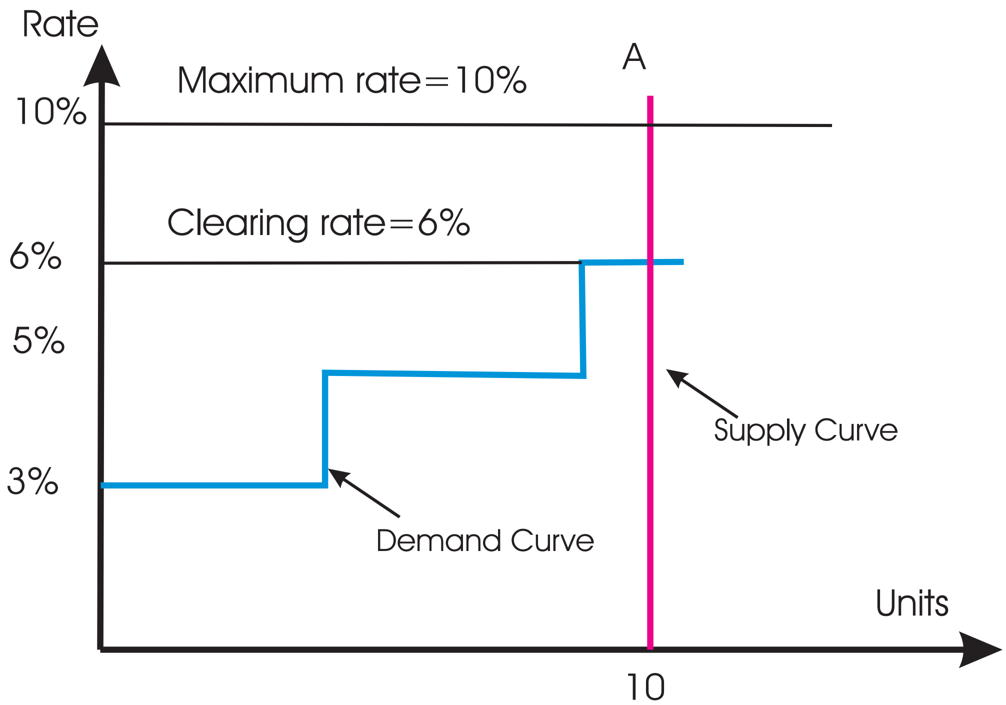


Figure B: An Example of Pseudo-Failed Auction

Graph on the left shows a scenario where "organic" demand from existing and potential investors, in blue line, is not large enough to meet supply. Auction will not clear due to lack of demand.
Graph to the right shows the effect of dealer's bid in the same auction. Bids from dealer extended the demand curve. Auction appears successful. Dealer's bid 5% is accepted as the clearing rate. We call an auction pseudo-failed auction if it appears successful, but would have failed without dealer's supporting bids.

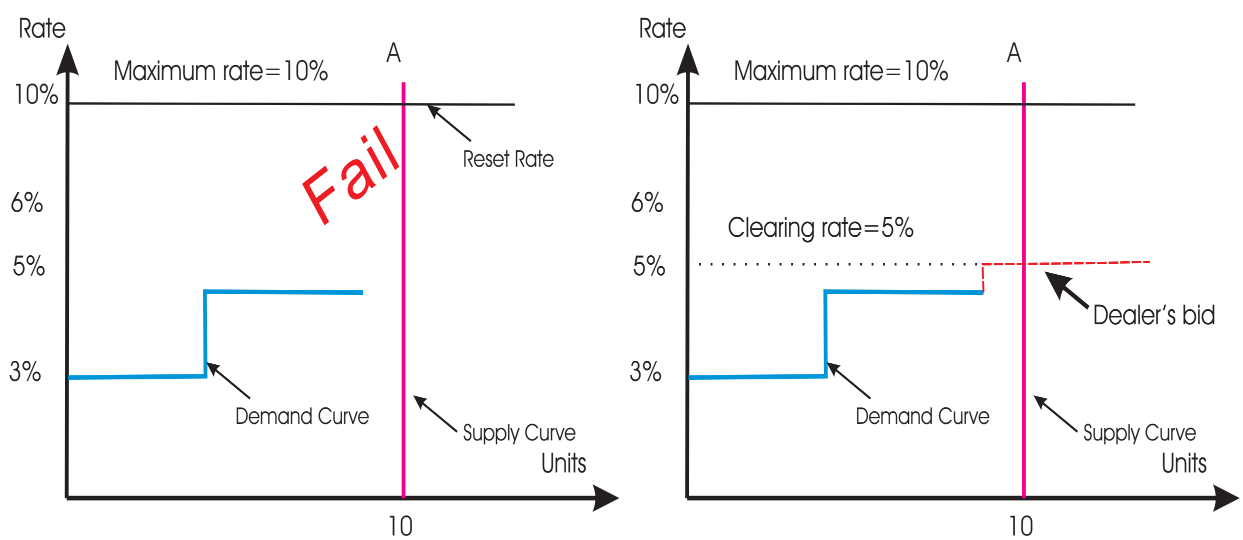


Figure 3: **Distribution of Maximum Rate**

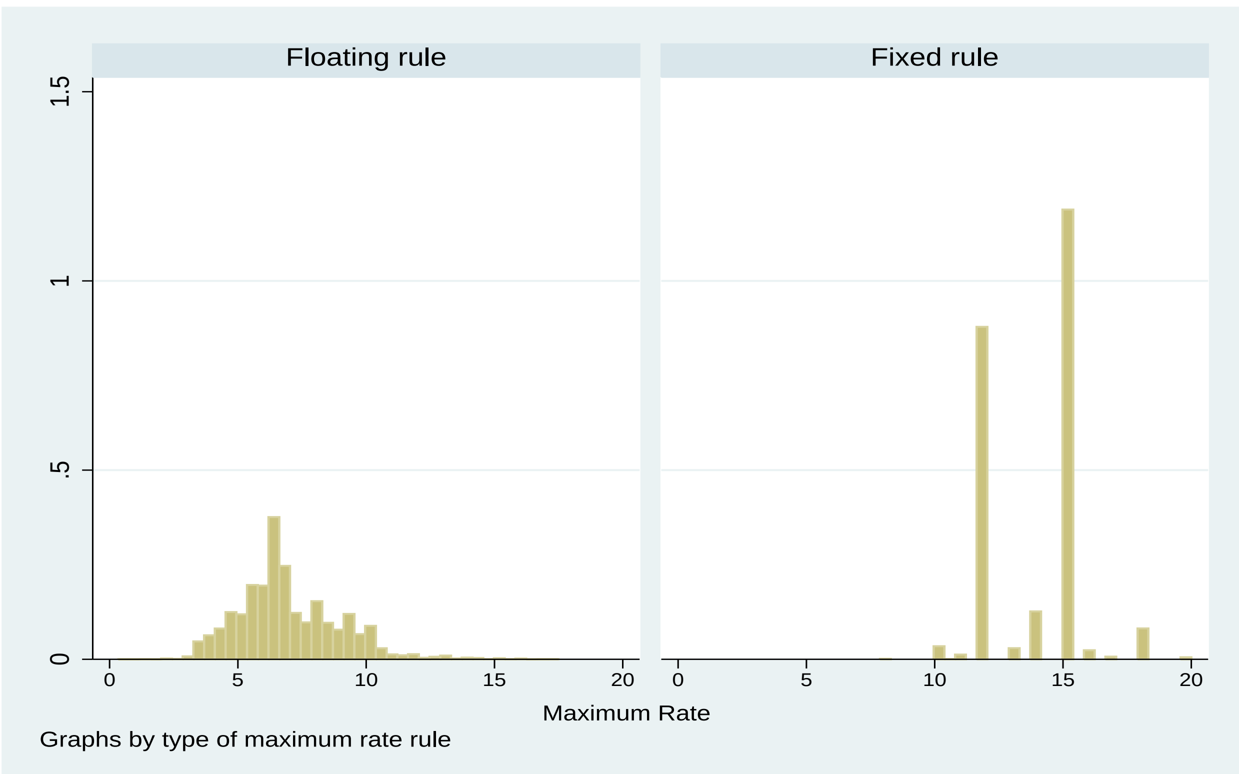


Figure 4: **Auction Failure Rates and Pseudo-Failure Rates**

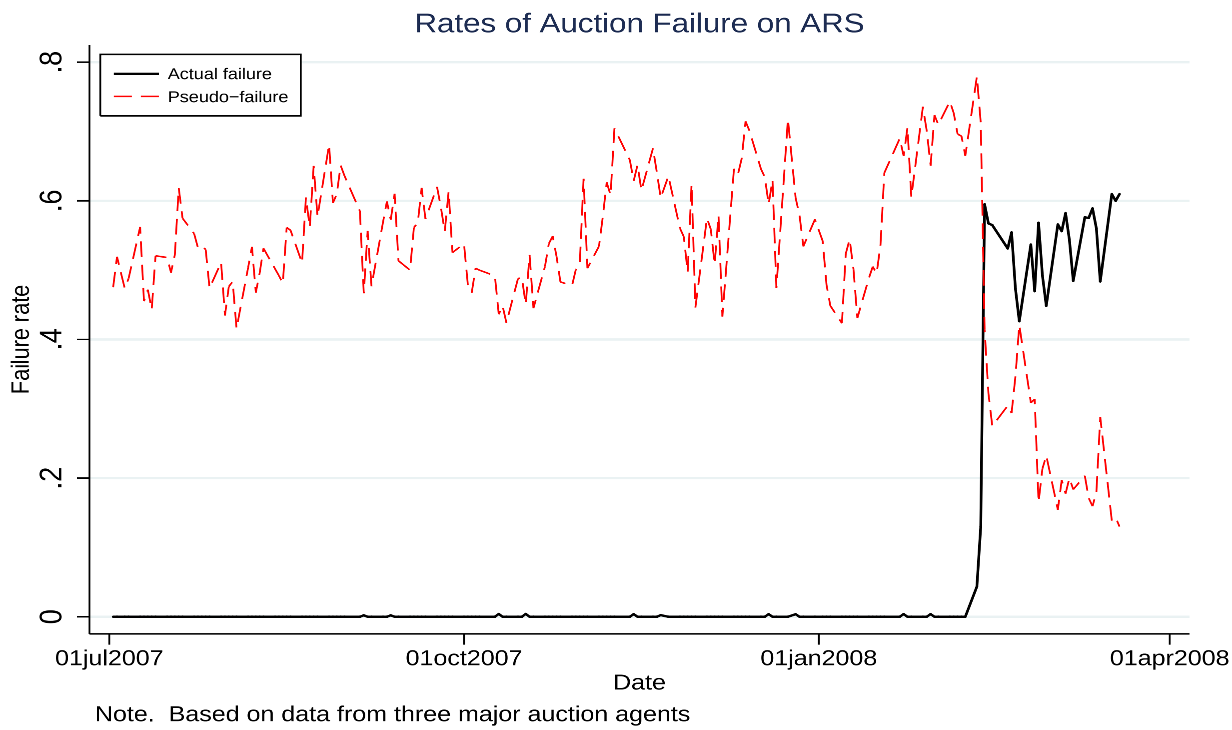
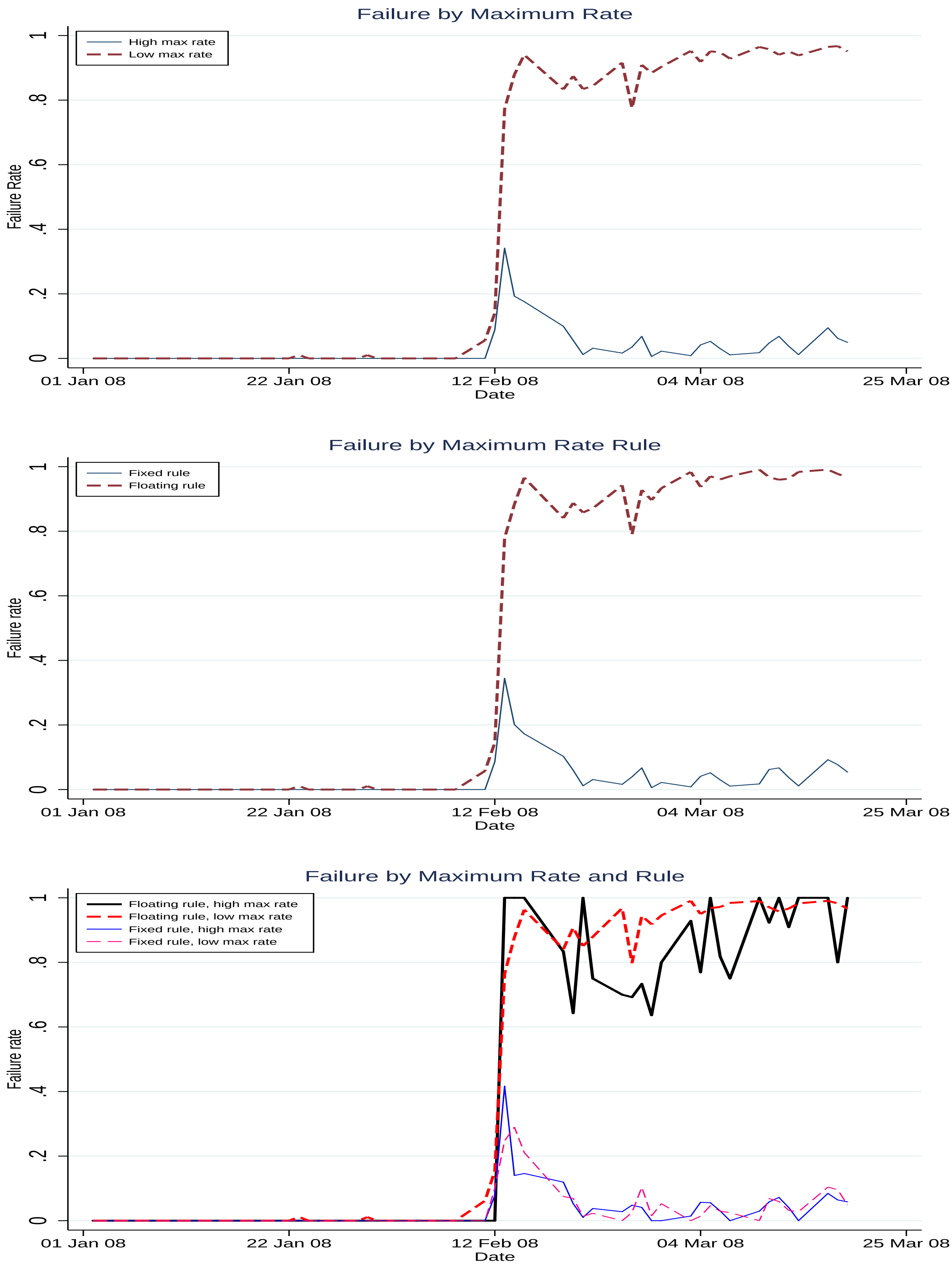


Figure 5: **Auction Failure Rates by Maximum Rate and by Maximum Rate Rule**



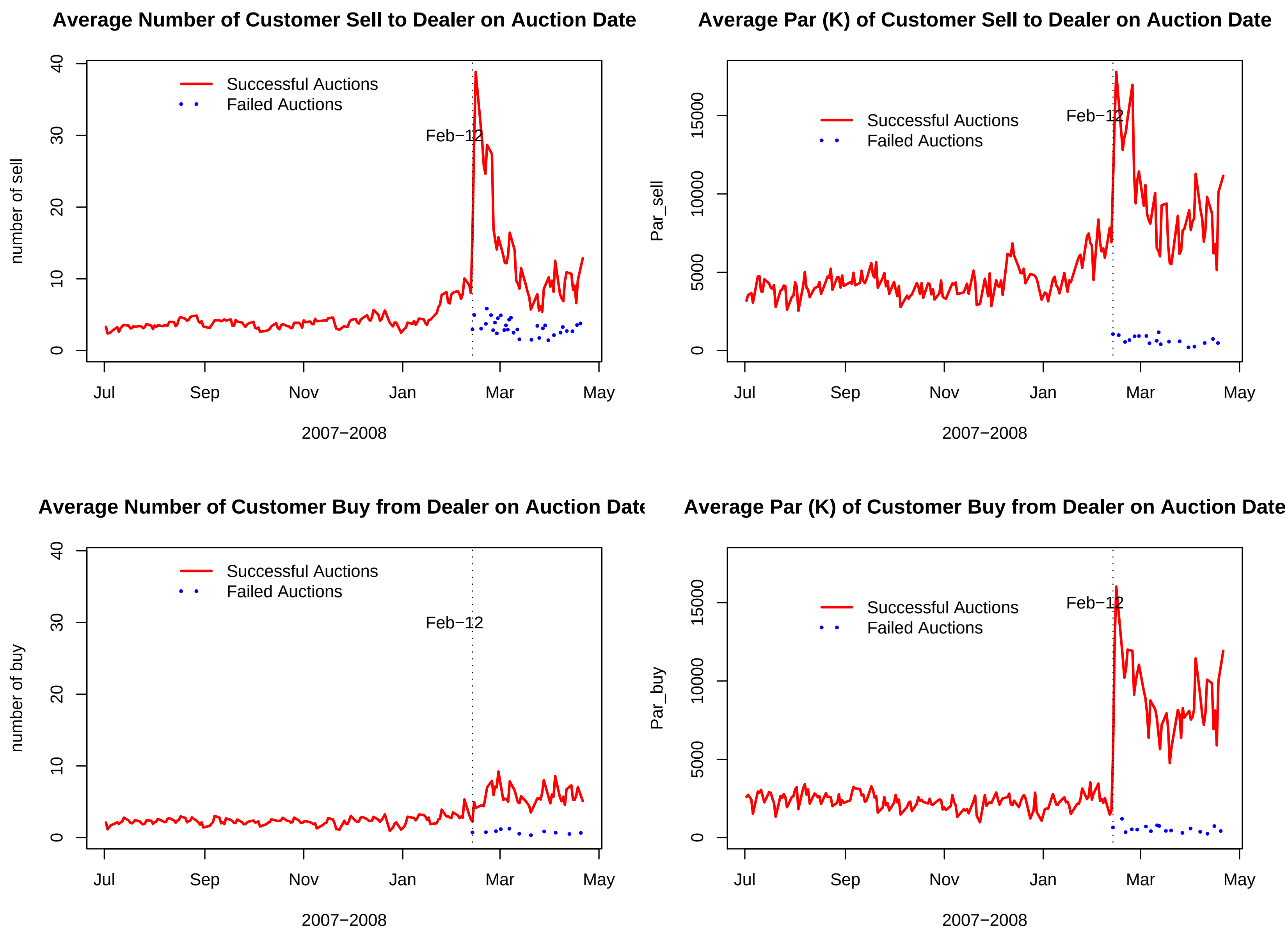


Figure 6: **Executed Trades on Auction Dates Reported in the MSRM's RTRS Data**

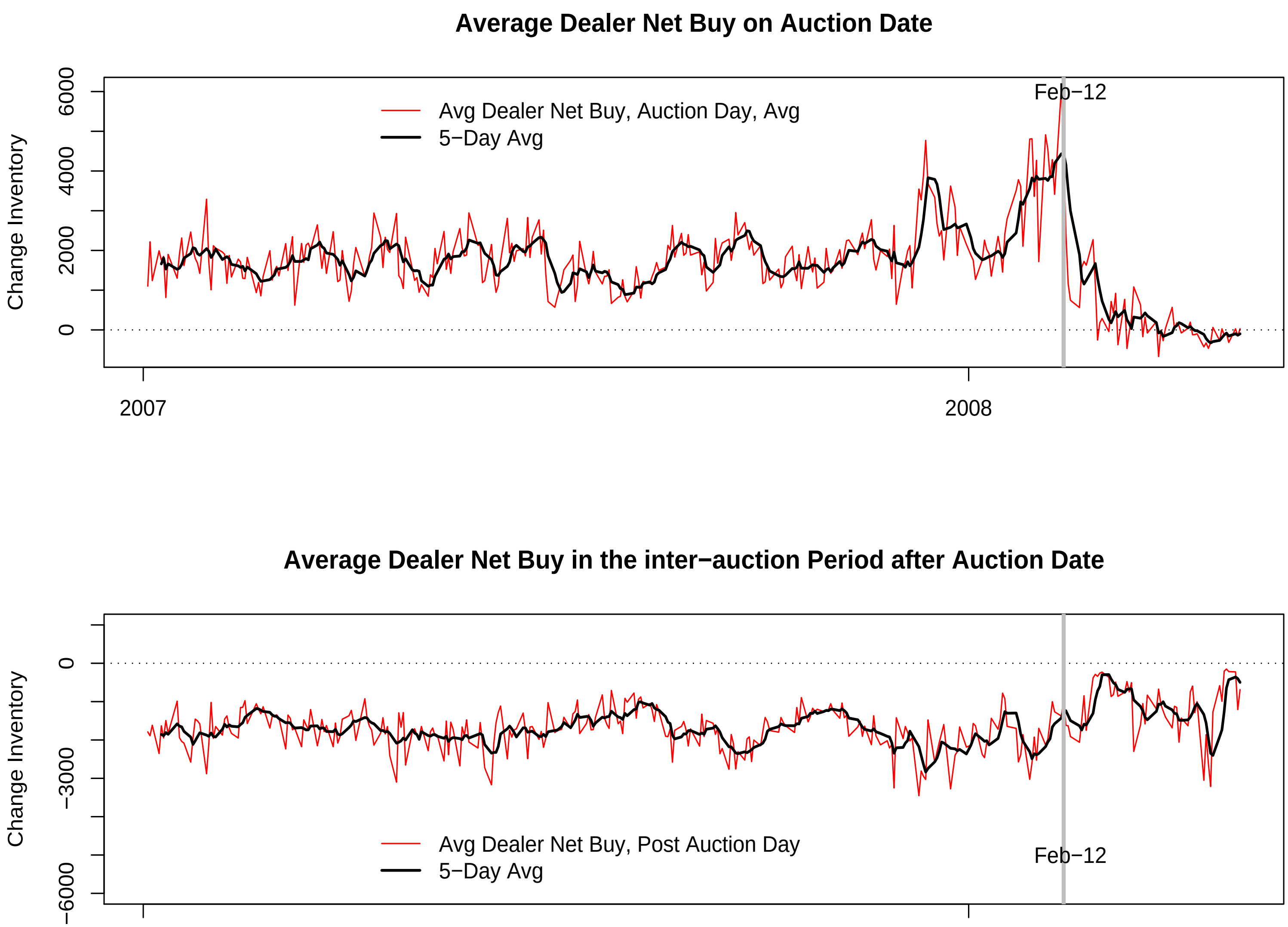


Figure 7: **Broker-Dealers as Market Makers**
Upper panel shows average dealer net buy (in thousand dollars) on auction dates; lower panel shows dealer net buy in the inter-auction period immediately following auction days.

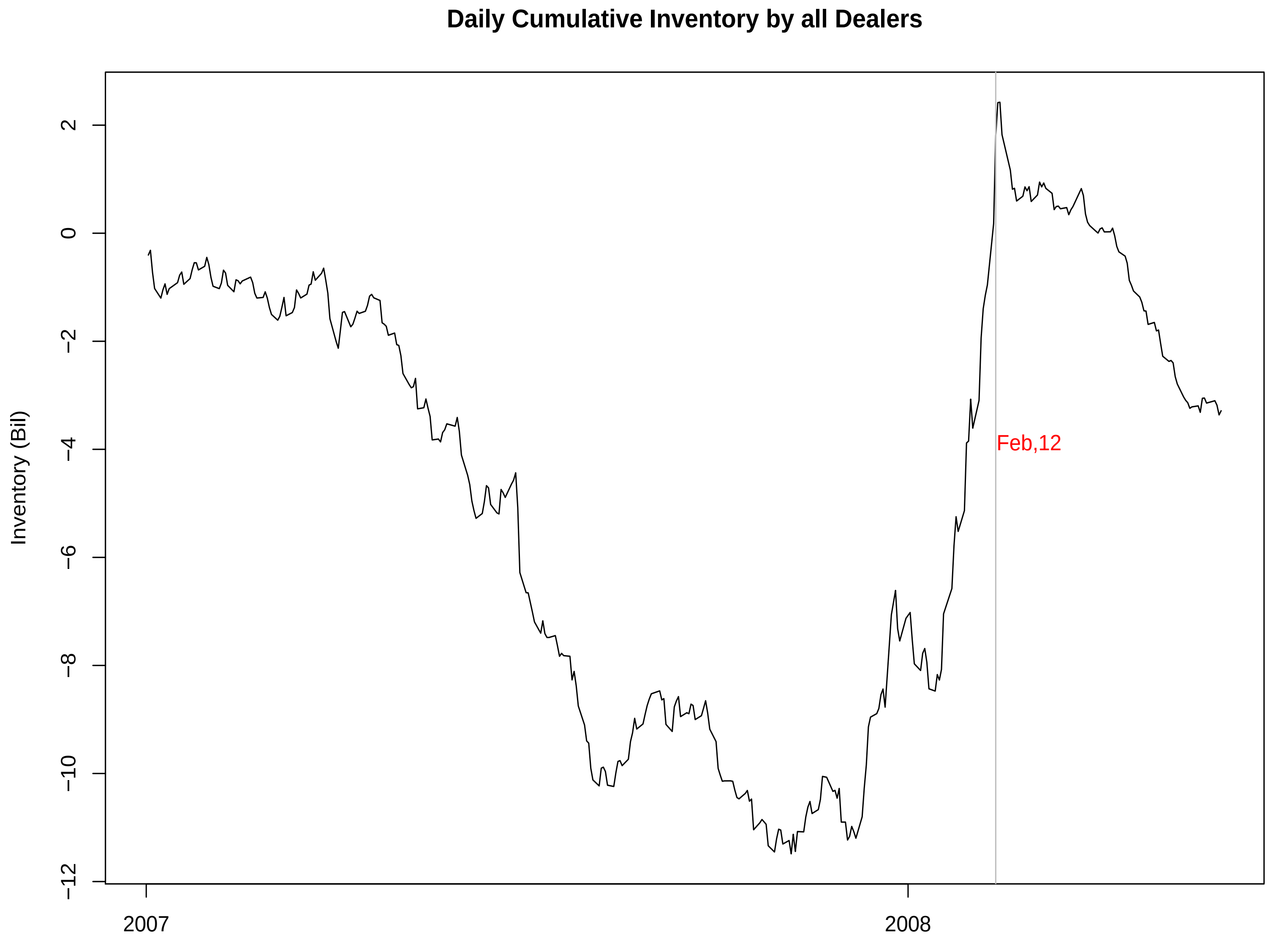
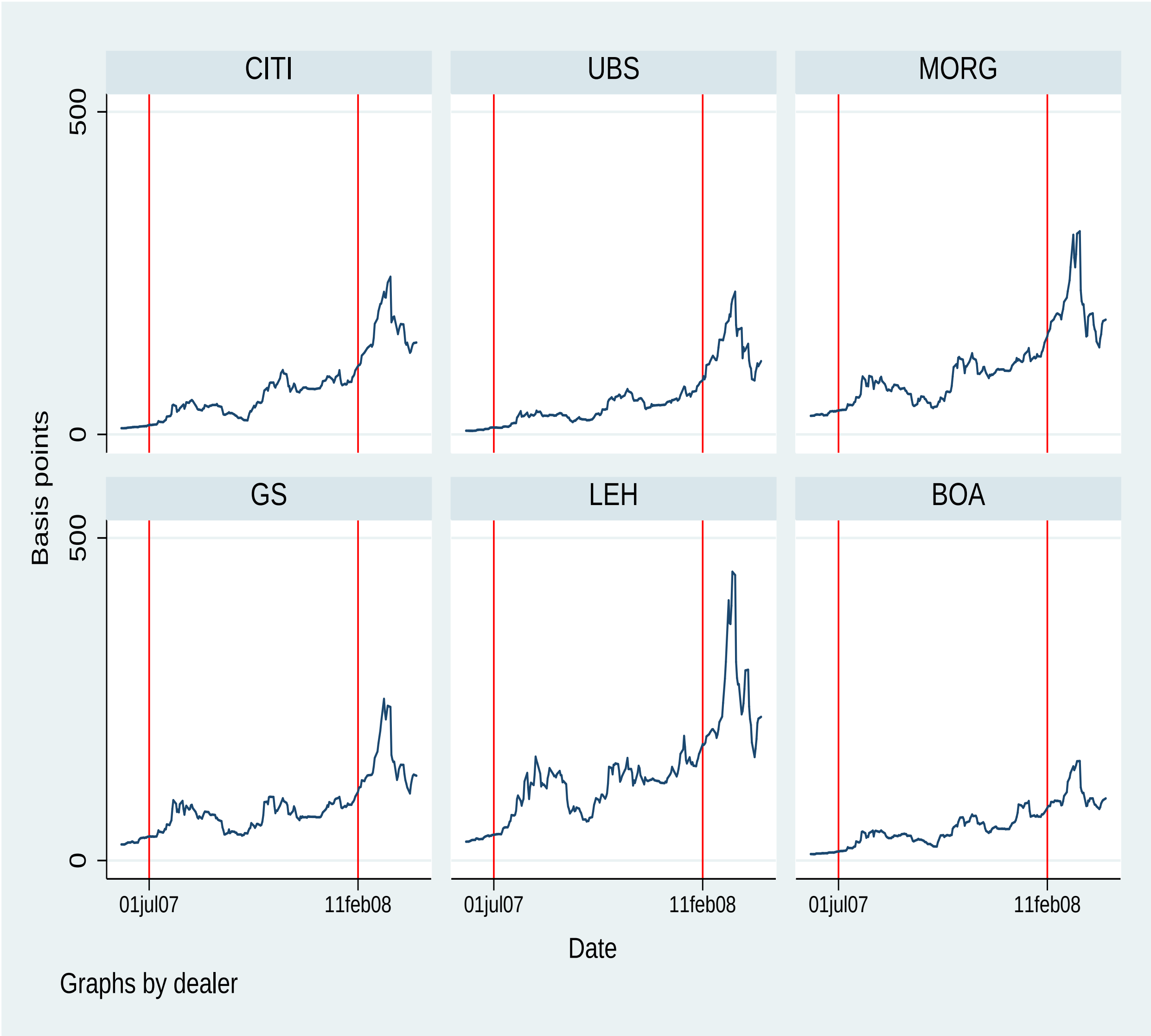


Figure 8: **Aggregate Inventories Accumulated by All Broker-Dealers Since Janurary 2007**

Figure 9: **Costs of Funds of Major Broker-Dealers as Measured by CDS Spreads**



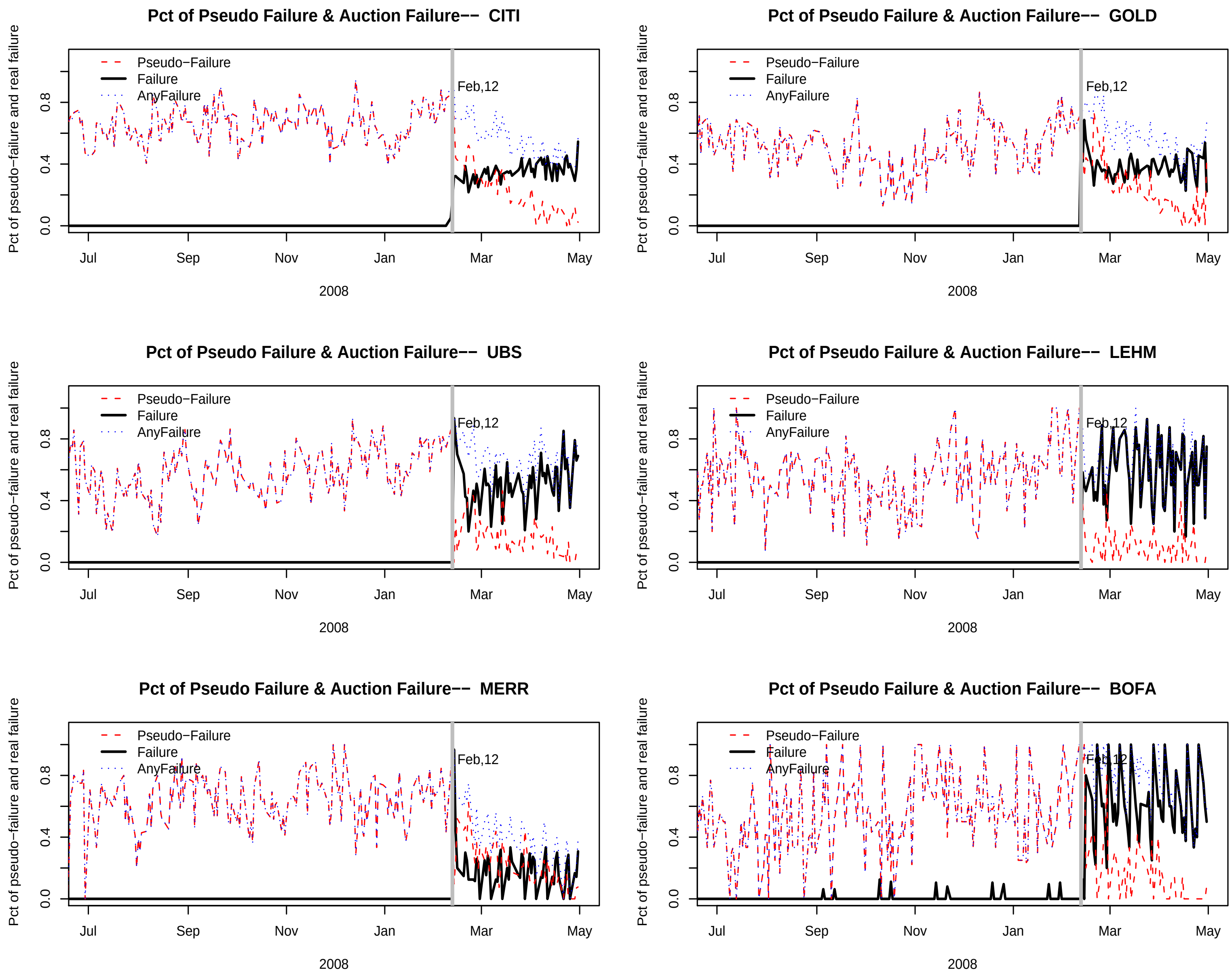
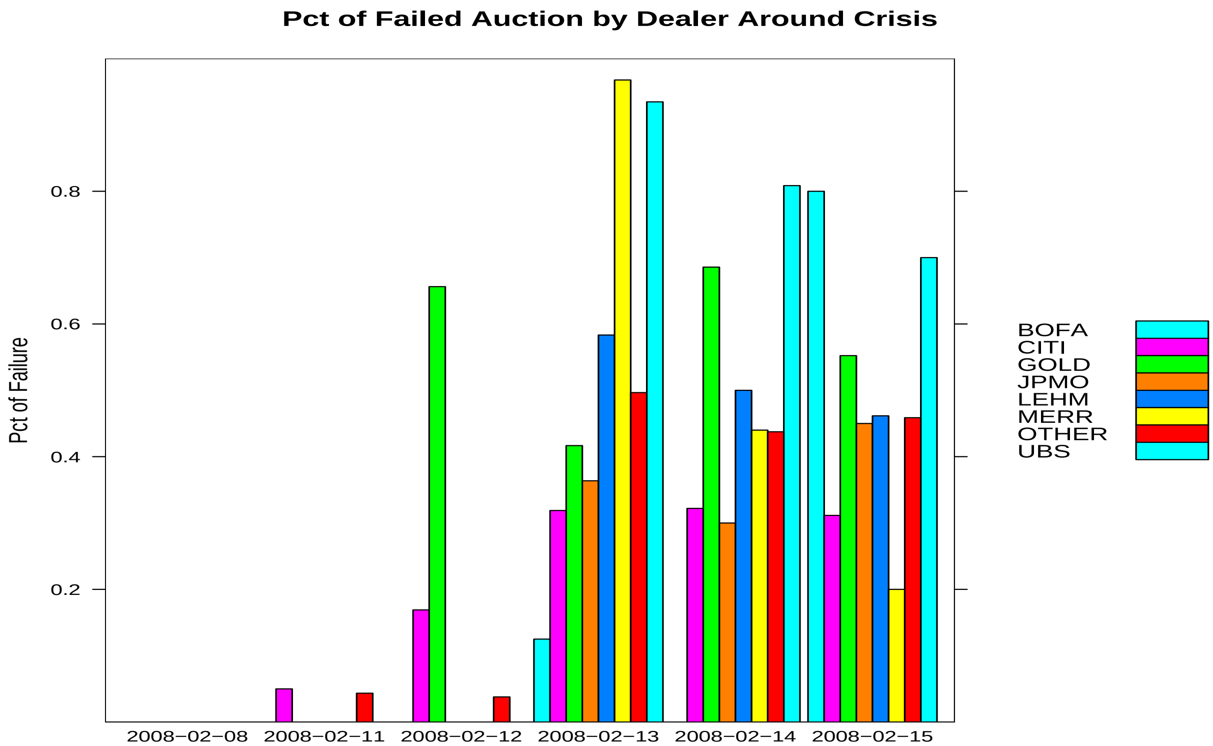


Figure 10: **Failure Rates on Auctions Run by Major Broker-Dealers**

Figure 11: **Major Broker-Dealers Withdrew Liquidity Supports after Goldman Sachs Took the First Move**



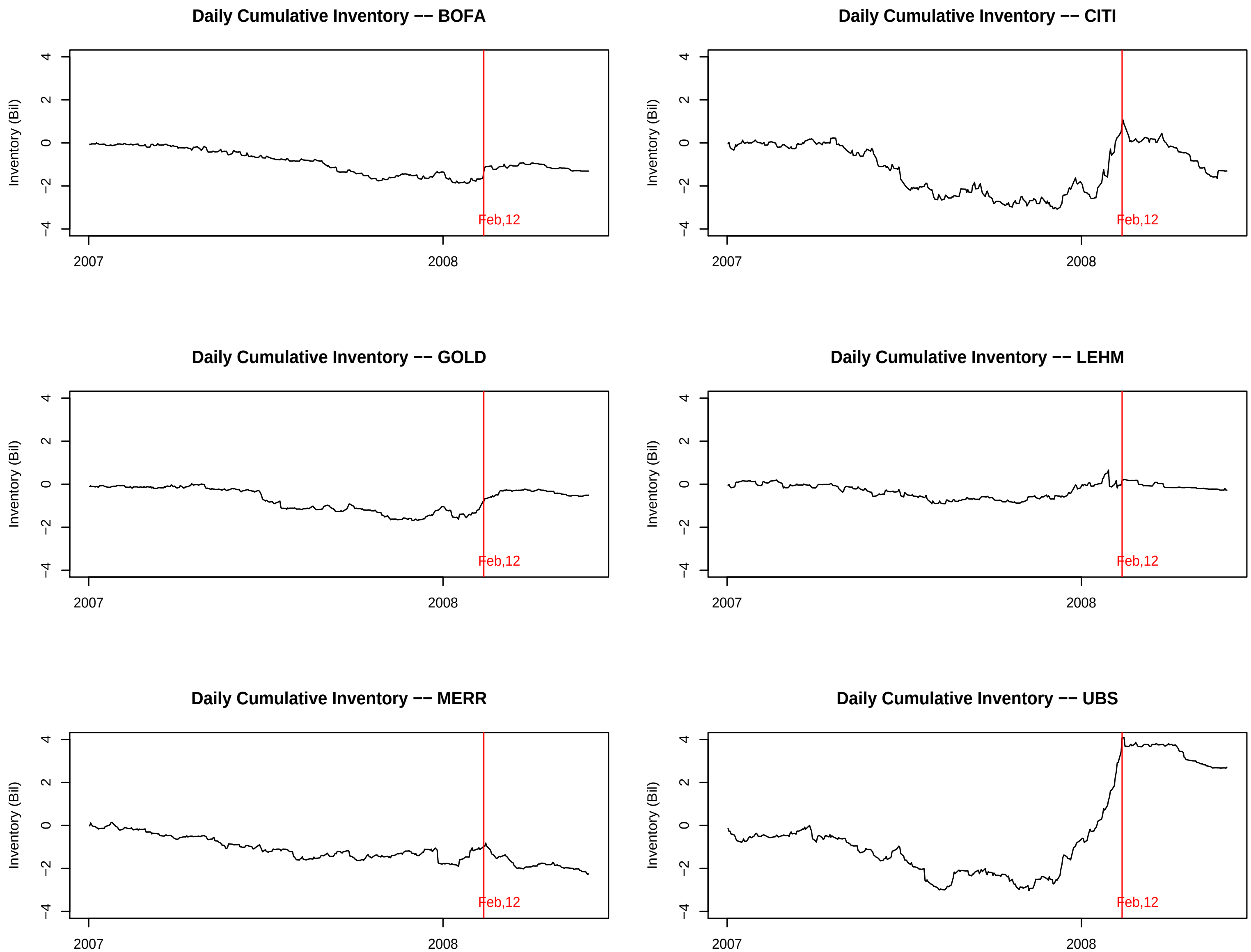


Figure 12: **Changes in Major Broker-Dealers' Inventories**