Investor Attention and Municipal Bond Returns*

Kimberly Cornaggia†[1], John Hund‡[2], and Giang Nguyen§[3]

[1,3]Pennsylvania State University
[2]University of Georgia

May 31, 2018

Abstract

We adapt a novel empirical methodology to analyze the informational efficiency of the municipal bond market and find robust evidence that municipal bond investors ignore the steep deterioration in the equity market capitalization (and corresponding spikes in CDS prices) of the companies insuring their investments. These investors devalue the coverage provided with significant delay after these insurers lose their Aaa certification from credit rating agencies. Institutional investors react to news slightly faster than retail investors, but the market remains highly segmented. If we assume rational investors and efficient markets, then our results indicate either that bond insurance has little value to investors or that transactions costs prohibit price discovery.

JEL classification: G01, G12, G14, G24

Keywords: Market segmentation, market efficiency, municipal bonds, bond return indices, bond insurance, investor attention

*We thank Ryan Israelsen for comprehensive historical municipal bond ratings, Brent Ambrose, Alon Brav, Jess Cornaggia, Pab Jotikasthira, Spencer Martin, Anh Le, Liang Peng, SEC Commissioner Michael Piwowar, Syrena Shirley, Tim Simin, Michael Schwert, Charles Trzcinka, and audience members at the Federal Reserve Board, Penn State University, University of Georgia, the Michigan State University Federal Credit Union Conference on Financial Institutions and Investments, and the United States Securities and Exchange Commission for helpful comments and insights. We thank Brian Gibbons, Dan McKeever, and Zihan Ye for research assistance.

†Department of Finance, Smeal College of Business, Pennsylvania State University. Email: kcornaggia@psu.edu

‡Department of Finance, Terry College of Business, University of Georgia. Email: jhund@uga.edu

§Department of Finance, Smeal College of Business, Pennsylvania State University. Email: giang.nguyen@psu.edu

1 Introduction

Among developed securities markets, municipal bond (muni) markets have been historically been characterized as especially illiquid and opaque; e.g., Downing and Zhang (2004) Harris and Piwowar (2006), Green et al. (2007), and Schultz (2012). Because the $4 trillion muni market is also dominated by retail investors, who are generally thought to be less sophisticated than institutional investors, regulators including the U.S. Securities and Exchange Commission (SEC) and the Municipal Securities Rulemaking Board (MSRB) have worked at least since 2005 to improve its operational and informational efficiency.[1]

In this paper we examine the informational efficiency of the muni market prior to, during, and following the demise of the insurance companies providing credit enhancement to roughly half of the pre-crisis general obligation (GO) bonds issued by U.S. municipalities. Constructing bond return indices by insurer allows us to isolate the impact of informational shocks to the insurer on the muni market. Using the portfolio of Aaa-rated uninsured bonds ("true Aaa" bonds) as a benchmark, we estimate cumulative abnormal returns (CARs) to portfolios of insured bonds of varying underlying credit quality that obtain Aaa-certification through credit enhancement provided by Aaa-rated bond insurers (bonds with "purchased Aaa"). We formally test whether the returns on insured bonds (treated group) differ from returns on uninsured bonds (benchmark) in event time as the insolvency of the insurers is realized in other markets and by the credit rating agencies (CRAs). Finally, we perform vector auto-regressions (VARs) to test whether the muni market is generally informed by equity and credit default swap (CDS) markets. We also examine trade patterns of institutional and retail investors to isolate differences in market segmentation across different investor classes.

[1] See, for example, SEC Commissioner Aguilar's February 2015 statement on making the muni market "more transparent, liquid, and fair" at http://www.sec.gov/news/statement/making-municipal-securities-market-more-transparent-liquid-fair.html. Commissioner Piwowar's 2014 comments on muni market inefficiencies are available at https://www.sec.gov/news/speech/2014-spch080114msp. We discuss particular regulatory efforts to improve this market's efficiency in Section 2.1.

Important for our empirical strategy, we observe that (1) the sharp decline in insurer stock prices and spikes in insurer CDS prices significantly precede insurer credit rating downgrades, and (2) stock price movements, changes in CDS premia, and ratings announcements for the monoline insurers were all very well publicized.[2] The largest monoline insurer in early 2007, Municipal Bond Insurance Association (MBIA), lost 70% of its stock market value from 6/1/2007 to 1/2/2008 but retained its critical Aaa rating until Moody's downgraded to A2 on 6/19/2008.[3] Suggesting *investor* inattention, we observe virtually no reaction in the bond portfolio insured by MBIA until well after the downgrade. Suggesting at least some *issuer* inattention, we observe that MBIA collected nearly $58 million in new US public finance insurance premiums in the first half of 2008.

Also important for our study is the fact that the analyzed shocks to the insurers are largely exogenous to the credit quality of the insured municipal bonds. Over the 39-year period from 1970 to 2009 (we calculate return indices for bonds through 2009), two unlimited GO bond issuers (Baldwin County, AL and Harrisburg, PA) defaulted and direct GO bondholders received 100% of par in both cases, leading to a cumulative default rate for general obligation bonds of less than 1 basis point.[4] The financial distress of the monoline insurers was a result of their controversial foray into non-municipal structured finance products, primarily collateralized debt obligations (CDO), not a contemporaneous increase in municipal bond credit risk.[5]

[2]The New York Times for instance, describes a public press conference on 12/1/2007 where William Ackman of Pershing Square Capital presented a 145 slide presentation on the potential bankruptcy of MBIA. (See for instance: http://www.nytimes.com/2007/12/01/business/01nocera.html) Mr. Ackman was well known for publishing a detailed report on the internet in 2002 which directly questioned MBIA's Aaa rating. See Appendix A for downgrade dates and other announcement dates.

[3]The designation "monoline" follows a 1989 ruling by the New York State Insurance Board that essentially restricts insurers covering financial contracts from writing any other type of insurance (e.g. property, casualty, life or health).

[4]The default rate for GO bonds has increased since 2009, incorporating defaults by Jefferson County, AL (non-bank held limited GO bonds in 2012) and Detroit, MI (2013). Still, the 10-year cumulative default rate for investment-grade GO bonds from 1970-2015 (the last year Moody's separately calculates GO cohorts) is less than 2 basis points. For comparison, the comparable corporate investment-grade cumulative default rate over the same period is over 100 times larger, at 2.81%.

[5]Municipal plaintiffs point to CDO business to support their allegations of negligent misrepresentation by the monoline insurers; see e.g., The Olympic Club vs MBIA (California Superior Court case number CGC-09-487058) and Contra Costa County vs AMBAC (case number CGC-09-492055).

We make three primary contributions to the literature. Our first contribution is a clean and rigorous analysis of cross-market information flow. We find no evidence that insurer stock returns or changes in insurer CDS spreads affect insured bond returns in either the pre-crisis or post-crisis period and conclude that muni investors largely ignored the financial distress of insurers implied by equity and CDS markets. While certain large institutional investors capitalized on the imploding monoline insurance industry, the retail investors holding the bonds enhanced by an insurance guarantee that was rapidly dissipating in value respond only with significant delay following the insurers' loss of Aaa certification.[6] These results point to continued segmentation of the muni market, despite earlier regulatory efforts to improve its informational and operational efficiency.

Second, we address the question of whether insurance is valuable to municipal issuers in a novel manner. Using the bond return indices we develop, we test whether bonds of varying underlying credit quality that are insured by a common insurer have statistically different return patterns. If the insurance "wrap" is perfect, then we should observe that bonds insured by a common insurer have similar return dynamics, irrespective of their underlying credit quality. If this insurance further conveys signaling, liquidity, or tax advantages (as in Thakor (1982), Pirinsky and Wang (2011), and the Association of Financial Guaranty Insurers (2008)), then required returns on insured bonds should be lower than returns on uninsured bonds with identical underlying ratings (since the insurance improves liquidity, lowers default risks, and/or signals greater credit quality within broad rating categories).

In the pre-crisis period, we cannot reject the hypothesis that bonds insured by a common insurer have identical returns, irrespective of their underlying credit quality, or that insured and "true Aaa" uninsured bonds have identical returns. These results suggest that muni investors care about the Aaa rating, but care not whether it is inherent to the issuer or purchased from an insurer. Because lower credit quality bonds are priced similarly to the true Aaa bonds, we conclude that insurance is valuable, as long as the insurer is rated Aaa. Only

[6] Pershing Square Capital made a well-publicized $1.1 billion profit from their short positions in MBIA equity and CDS.

after the insurers lose their Aaa certification do return patterns reflect the bonds' underlying credit quality.

Third, we outline a robust methodology for constructing both return indices and their associated standard errors for highly illiquid bond markets. Our empirical tests are complicated by this market's illiquidity. Previous studies use cross-sectional or pooled panel regressions on yields, both of which are problematic in the muni market because the infrequent trades are endogenous to the event date examined. For example, consider an attempt to gauge the value of bond insurance with an analysis of insured bond yields around an insurer's credit rating downgrade. In this case, trades of insured bonds are much more likely and more informative around the event, whereas trades of comparable benchmark uninsured bonds may not occur simultaneously. Without adjusting for the propensity to trade, portfolios of bonds traded in a single cross-section will not be similar to bonds traded in even the next cross-sectional period. This bias will be most extreme around major events such as the ones we study here.

To overcome this problem we employ the repeat sales regression (RSR) methodology common in real estate economics to construct return indices, as motivated by Spiegel and Starks (2016) in their analysis of the corporate bond market. Because our setting is further complicated by the need to create characteristic-based (credit quality and insurer) return indices in an even more illiquid market, and we adapt the generalized repeat sales regression (GRSR) method of Peng (2012). This GRSR methodology allows us to construct return indices at a high degree of granularity and facilitates formal hypothesis testing of differences between sub-indices. With particular modifications for the muni market, we are able to construct bond return indices by rating, insurer, and other bond characteristics. Our adaptation of Peng (2012) allows the construction of sub-indices to calculate and test hypotheses across multiple characteristics of illiquid bonds. Our GRSR indices maintain constant characteristic-matched portfolios of bonds over (overlapping) rolling windows of one year and thus provide estimates of informational shocks that mitigate the confounding selection into trade bias.[7] An ancillary contribution of our paper is a straightforward method for conducting event studies in highly illiquid markets across a large number of characteristics.

Our paper proceeds as follows. We briefly describe recent regulatory efforts to improve the efficiency of the muni market, the demise of the monolines during the financial crisis, and related literature in Section 2. Section 3 describes the data. In Section 4, we provide descriptive statistics for the market, including the variation in insurance and extent of retail investor participation. We discuss our empirical strategy and its core component, the construction of GRSR bond indices and their standard errors in Section 5. In Section 6, we test the differential return dynamics of insured and uninsured bonds and formally test the informational efficiency of the municipal bond market using event studies and vector auto-regressions. In Section 7, we discuss alternative explanations for our empirical results, including potential confounding effects associated with the Lehman Brothers bankruptcy. Section 8 concludes.

2 Background and Related Literature

2.1 Regulatory efforts to improve municipal market efficiency

Regulatory efforts to improve muni market efficiency fall broadly into two categories: operational and informational efficiency. Recent efforts to improve operational efficiency include the 2016 MSRB Rule G-18 on best execution and the new markup disclosures approved by the SEC in November 2016. Recent efforts by the MSRB to improve informational efficiency include the 2005 public launch of the Electronic Municipal Market Access (EMMA) trade price data and the 2008 release of a vast archive of muni issuer disclosures.

[7] Appendix B provides a detailed self-contained description of this methodology, which should prove valuable for studying return behavior in illiquid markets at higher levels of granularity than previously available.

Additional efforts by the SEC aim to reduce the mechanistic reliance of investors on credit ratings. The SEC Office of Investor Education and Advocacy specifically warns muni investors:

> *While some investors find it helpful to consider credit ratings when making an investment decision, it is important that you not rely solely on credit ratings when deciding whether to purchase municipal bonds. Investors need to undertake their own independent review of the municipal bonds' risk by reading the official statement and other relevant information...*

Our empirical results suggest that regulatory concern over informational efficiency is well founded. However, our results do not indicate that municipal investors respond mechanically to credit rating changes.

2.2 Monoline insurer financial distress

Because insuring munis with low default rates resulted in zero-loss underwriting, the monolines historically operated with very high leverage. The leverage ratio, which is total future value of principal and interest insured divided by statutory capital, was 216 and 195 for privately-held FSA and FGIC, respectively. Publicly-traded insurers AMBAC and MBIA had leverage ratios of 125 and 136, respectively, although on portfolios with much larger gross outstanding par value.[8] Despite such leverage, the monoline insurance market was uniformly rated Aaa and AAA by Moody's and S&P respectively, and by March 2007 had CDS spreads hovering around 20-30 bp.

Expanding their business into structured finance products jeopardized the zero-loss model. Although prohibited from writing property, casualty, life and health insurance, the monoline insurers are allowed to write insurance on different types of financial contracts. Most began insuring asset-backed securities (ABS) and selling protection via CDS as early as the 1990s. By the end of 2006, the monolines collectively insured nearly $448 billion of structured financial products including the now notoriously risky subprime CDOs. For example, the

[8]All the leverage ratios are taken from Exhibit 99.2 from FSA's Form 8-K filed with the SEC at: `https://www.sec.gov/Archives/edgar/data/913357/000110465907027165/a07-5921_38k.htm`

following table demonstrates the change in MBIA's portfolio from 2005 to 2007. In 2005,

MBIA Selected Financial Information

	2007	2006	2005
CDO par insured (US)	48,640	18,951	7,830
GO bond insured	20,742	20,777	27,586
Equity	2,336	9,849	8,065
Distance to Default	0.97	5.60	3.77
"Naive" Probability of Default	17%	0%	0%
Implied Moody's Rating	Caa	Aaa	Aaa
Actual Moody's Rating (12/31)	Aaa	Aaa	Aaa

Source: MBIA's 2007 10-K filing.

MBIA insured approximately $27.6 billion in GO bonds and $7.8 billion in CDOs with $6.6 billion in equity capital. By 2007, MBIA insured only $20.7 billion in GO bonds and $48.6 billion in CDOs with only $3.7 billion in equity capital.[9] MBIA's distance to default in 2007 implies a probability of default (PD) of approximately 17% using a simple normal distribution approximation. Using Moody's published PD tables, this PD is commensurate with a very speculative-grade credit rating (approximately Caa using 2008 realized values) rather than the Aaa ratings awarded by Moody's and S&P into June 2008. Moody's ultimately downgraded MBIA to Caa1 on December 19, 2008.

As subprime housing and securitization markets deteriorated, equity and CDS markets indicated severe distress for AMBAC as well as MBIA. These insurers lost 75% and 70% of their stock market valuation by the end of 2007, respectively, with CDS spreads reaching nearly 500bp by April 2008. By stark contrast, the other publicly traded monoline, Assured Guaranty Corp, had no exposure to CDOs and ended 2007 with no loss in market value. Appendix A summarizes key dates in the collapse and subsequent consolidation of the monoline insurance industry.[10]

[9] All values from MBIA's 2007 10-K filing. Equity values use the balance sheet shares outstanding with the last closing price of the calendar year, and distance to default is calculated using a standard Merton Model with default trigger at short-term liabilities plus half of long-term liabilities and realized equity volatility during the calendar year.

[10] See Moldogaziev (2013) for additional details on the monoline insurers through the crisis period.

2.3 Related literature

Early muni market research focused primarily on the puzzling empirical evidence that long-term tax-exempt yields are too high relative to after-tax yields on taxable bonds.[11] The improved disclosure of trade prices and issuer fundamentals discussed in Section 2.1 helped expand the literature to analyze determinants of muni credit ratings (as in Hajek (2011) or Palumbo and Zaporowski (2012)), real economic effects of muni rating changes (as in Cornaggia et al. (forthcoming) and Adelino et al. (2017)), the relative importance of default, liquidity, and tax components in muni credit spreads (e.g., Wang et al. (2008), Ang et al. (2014), and Schwert (2017)), municipality financial constraints (Ang et al. (2017)), and market segmentation (e.g., Pirinsky and Wang (2011), Schultz (2012) and Babina et al. (2017)). To this growing literature, we contribute analysis of this market's informational efficiency. Specifically, we analyze the links between the muni market and related equity and CDS markets.

Similar analysis examines links between the *corporate* bond and equity markets (e.g., Kwan (1996), Downing et al. (2009)), and the links between these developed markets and the relatively young CDS markets (for instance, Blanco et al. (2005), Longstaff et al. (2005) and Norden and Weber (2009)). Even though we study a more recent time period–marked by rapid increases in information technology–our analysis indicates a greater degree of market segmentation than prior papers. Indeed, we find that the cross-market informational efficiency in the muni market is orders of magnitude smaller than that previously observed in the corporate bond market.

We also contribute to an existing literature examining the value of bond insurance. The general consensus of the early literature (e.g., Cole and Officer (1981) and Kidwell et al. (1987)) is that insurance provides issuers a net benefit, potentially due to signaling effects as

[11] For examples, see Trzcinka (1982), Kidwell and Trzcinka (1982), Skelton (1983), Buser and Hess (1986), Kochin and Parks (1988), Green (1993), Green and Oedegaard (1997), Chalmers (1998)Chalmers (2006), and Longstaff (2011). Related papers appeal to the tax-sensitivity of the muni investor to explain other puzzling phenomena; see Starks et al. (2006) and Landoni (forthcoming) regarding the "January effect" and the original issue premium, respectively.

in Thakor (1982), tax effects as in Nanda and Singh (2004), or information production as in Gore et al. (2004). More recent papers present mixed evidence. Several papers suggest less benefit (or even negative benefit) over time (e.g., Bergstresser et al. (2010), Lai and Zhang (2013), Bronshtein (2015), and Chun et al. (2015)). An exception is Wilkoff (2013) who concludes a stable gross benefit of eight basis points.

The effect of bond insurance on bond returns, however, has not been investigated. Using our comprehensive data over the pre-crisis, crisis, and post-crisis periods, we are able to investigate differential return dynamics for insured and uninsured bond portfolios of similar underlying credit quality. After the downgrade of the monoline insurers, insured bonds substantially underperform uninsured bonds which seems to indicate a "flight-to-quality" dynamic in the municipal market which may help explain the yield inversion puzzle documented in Bergstresser et al. (2010) and Chun et al. (2015).

Also related is work by Brune and Liu (2011) who analyze the change in tax-adjusted yield spreads on a limited set of insured bonds on particular dates before and after insurer downgrades. Our contribution relative to their study is a more thorough analysis of return dynamics across insurers and underlying rating classes for the universe of municipal bonds over the entire period covering monoline demise. Our approach allows us to isolate the effects and evolution of insurers' equity, CDS, and ratings changes on matched return indices and statistically evaluate Granger causality within a full VAR setting.

Finally, a related study by Chung et al. (2015) examines the impact of insurer CDS information on the yields of insured munis in a panel regression setting. However, they are unable to separately identify the speed of transmission across markets over time and they fail to control for time variation in the underlying credit risk of the issuer. Additionally, by studying only yields of bonds that trade in each monthly period, their methodology is potentially biased by the differential informativeness of the insured and uninsured bond trades. Our contribution relative to their paper is the creation of bond return indices allowing estimation of insurer effects at the daily level and controlling explicitly for time variation in underlying credit quality.

3 Data

We construct our sample from a variety of sources to describe the municipal bond universe from 2005 to 2016. At times, we focus on specific subperiods, most notably the 2007-2009 crisis period, or the entire period before Moody's municipal bond recalibration in April 2010. We begin with the Mergent Municipal Bond Securities database (Mergent) which covers all municipal bonds issued by June 2016 (our end of sample period). The database consists of 3,555,964 bonds issued by 53,045 municipal issuers across different levels of government. From there, we limit our sample to include only bonds that are unlimited tax general obligations (GO bonds), issued between 1960 and June 2016, have a positive offering amount and coupon rate, and represent new borrowing (i.e. not for re-funding purposes).[12] We also exclude all bonds that are offered via unconventional channels (e.g. limited offerings, private placements, and remarketing), and a small number of bonds that are issued by U.S. territories other than Puerto Rico.

Two key limitations of the Mergent data are important to note. The Mergent database retains only the most recent value of a bond rating and insurer; the history of its insurer and underlying rating is overwritten with each update. Because each bond's underlying rating and the contemporaneous identity of its insurer are both critical factors in our analysis, we supplement the Mergent data with several sources. We find that the majority of municipal bonds have changes in insurer, credit rating, or both over our sample window. We conclude that relying exclusively on Mergent data will result in erroneous inferences regarding original insurer and credit quality at issuance.

[12] We focus on GO bonds because they have the full faith and backing of the local government, which can raise taxes to pay coupons if necessary. In contrast, revenue bonds have a claim on funded project revenues, but no recourse if the project fails.

3.1 Supplementing bond insurers and ratings

As noted above in Section 2.2, the financial crisis resulted in the bankruptcy, sale, or restructuring of the monoline insurers' portfolios. To reconstruct the original and subsequent insurers of each bond, we perform the following steps:

- Because the municipal bond portfolio of FSA was acquired in whole by Assured Guaranty and merged into a newly created subsidiary (AGM) on July 1, 2009, we assign FSA as the insurer for all bonds that are insured by AGM but are issued prior to that date.
- Both Radian and CIFG were likewise acquired by Assured Guaranty, in 2015 and 2016 respectively. We collect from Assured Guaranty the bond CUSIPs of the portfolios transferred from CIFG and Radian and reattribute the original insurer to each.
- MBIA re-insured FGIC's investment grade municipal bond portfolio in 2008; MBIA then carved out NATL as a wholly-owned subsidiary to hold its monoline insurance business on February 18, 2009; NATL subsequently novated the FGIC portfolio on August 19, 2013. We collect from FGIC the CUSIPs of all bonds transferred from FGIC to NATL and attribute these bonds to FGIC as the original insurer. All other NATL-insured bonds (not associated with FGIC) issued prior to the creation of NATL on February 18, 2009 are assigned to MBIA as the original insurer.

Because we cannot track the complex web of all reinsurance agreements, our reconstructed insurer data, by issue, is likely incomplete. However, given the novation data obtained directly from the insurers (and the fact that virtually no new bond insurance was written in late 2008-2010) we believe that our database effectively undoes the overwriting of data by Mergent and correctly assigns the contemporaneous insurer appropriate for each bond-month (or bond-trade) pair.

We backfill the credit ratings histories overwritten by Mergent with a comprehensive history of S&P and Moody's ratings for municipal bonds obtained directly from these rating agencies' websites.[13] Combining these hand-collected insurer and rating histories with the bond characteristics provided by Mergent results in a comprehensive muni database with accurate contemporaneous information on the underlying rating of the issuer and the identity

[13]We are grateful to Ryan Israelsen for providing us these data. Given the magnitude of rating updates even prior to Moody's scale recalibration in 2010, the ratings data provided by Mergent proved inadequate for our analysis.

of its insurer. Ratings are coded from 21 (highest) to 1 (lowest). Many bonds are rated by more than one CRA; when ratings are available from multiple CRAs, we employ the harshest as our measure of underlying credit quality.

3.2 Bond trade data

We obtain trade data for the bonds in the sample from the MSRB available via WRDS from January 2005 to present and merge with the Mergent data by individual bond CUSIP. This merge results in 9,502,128 customer trades for 445,440 bonds. (We do not include intermediate dealer-to-dealer trades because our primary research question is about investor behavior; only the prices investors ultimately pay for these bonds are relevant). We then filter the trade data by removing primary market transactions, trades that occur less than one year prior to maturity, and price outliers (bonds with prices less than 50 or higher than 150).

After cleaning, the trade sample has 7,284,088 trades in 281,882 bonds. For the purpose of describing the data and secondary market trends, our summary statistics are based on this sample. If a bond has multiple trades in a day, we compute the price for the bond on that day using the volume-weighted average of prices, resulting in 4,784,935 CUSIP-day observations. Our methodology (described later) requires a minimum of two data points per bond as our unit of observation is the change in price between two trade price observations. Converting from trades to trade pairs, we obtain 4,503,053 observations. Because rating changes are priced, we exclude pairs of trades between which a change in credit rating of the underlying bond occurs. This requirement reduces the sample size to 4,456,041 observations spanning 2,891 days from 1/5/2005 through to 6/16/2016. We estimate insurer-by-credit rating daily bond return indices with this final sample.

3.3 Other data

We obtain data on the monoline insurers themselves from a variety of sources. For publicly traded insurers, we obtain daily stock prices from CRSP and collect available daily data on 5-year CDS contracts on insurers from Datastream. From Moody's press releases and news updates available on their website, we obtain the credit rating history of the insurers. We obtain data on corporate restructuring dates from a wide variety of sources, including Moldogaziev (2013) and from insurers' websites. An overview of this chronology is in Section 2.1 and key dates are listed in Appendix A. Finally, we merge our universe of bond characteristics, historical credit ratings, insurers and trades with mutual fund holdings data available from CRSP.

4 Characteristics of the Municipal Bond Market

4.1 Variation in credit quality

There is substantial heterogeneity in the usage of bond insurance across states, as can be seen in Table 1. For instance, 71% of California domiciled issuers' GO bonds are insured, whereas only 34% of Texas domiciled issuers are. To some extent, this reflects differential credit quality between issuers; throughout much of the period, the State of California had a credit rating more than six notches below the State of Texas.[14] It is therefore of critical importance to control for contemporaneous changes in municipal issuers' underlying credit quality in our empirical analysis of insured vs. uninsured bonds.

Figure 1 shows the underlying credit quality at issuance for all GO bonds in Panel A, and all insured GO bonds in Panel B. Obvious in Panel A is the proportional increase in Aa rated bonds following Moody's 2010 scale recalibration (we limit our empirical analyses in Section 6 to the period ending in 2009 for this reason). We also observe that a substantial portion of GO bonds did not obtain credit ratings prior to the financial crisis. Following the crisis, the portion of unrated bonds falls significantly. In Panel B, we observe substantial heterogeneity in the underlying credit quality of insured bonds over time, reinforcing the conclusion from

[14] This is a generalization since there are many cities and counties within each state that are also issuing GO bonds. However, examination of the average ratings by state confirms the broad pattern discussed here.

Table 1. Figure 1 actually understates the variability of underlying credit, since it plots the issuer rating at time of issuance, but not the evolution of that issuer's credit quality.

Table 2 depicts the differences in characteristics between issuers purchasing insurance and uninsured issuers. Bonds without insurance are approximately 70% larger in issue size (although mean issue size is very small in both samples). Intuitively, insured bonds have lower underlying ratings by almost two notches on average, which is preliminary evidence that poorly rated issuers are more likely to purchase insurance. Our finding that insured bonds are issued on average at lower ratings is consistent with the result reported by Bergstresser et al. (2015) that insured bonds have significantly higher ratings transitions (upgrade more) than uninsured bonds. Insured bonds are *less* likely than uninsured bonds to be held by mutual funds: 1.20% versus 1.44%.[15] This finding is consistent with insured bonds being primarily held and traded by retail investors–an assertion we investigate more formally by trade size analysis in the next section.[16]

4.2 Liquidity and retail investors

Table 3 reports differences in secondary market liquidity measures (number of trades and average trade size) for GO bonds with and without insurance. The table also reports differences (between insured and uninsured bonds) in the percentage of trades attributable to retail investors (e.g. in blocks smaller than $100,000). All statistics are reported over the entire 2005-2016 period and the significance of differences is based on two-sided test statistics.

Comparing first the Aaa rated bonds, we observe as expected that the overwhelming majority are uninsured (issuers with Aaa quality have less incentive to purchase a Aaa certification than lower-rated issuers). The average trade size among the insured Aaa bonds

[15] We merge GO bond CUSIPs with CRSP mutual fund holding data to calculate the percentage of each bond being held collectively by mutual funds. The low level of mutual fund ownership reported here reflects the fact that mutual funds have ownership interest in only about 3% of bonds in our sample. Conditional on a bond being held by mutual funds, the extent of mutual funds' ownership averages to about 44%.

[16] According to SIFMA statistics, individuals held 43.3% of the entire muni market in 2017Q1. Mutual funds held 23.8%, insurance companies held 13.5% and banks held 15.2%. SIFMA does not, however, provide statistics on the proportional holding of insured versus uninsured or revenue versus GO bonds. SIFMA data is available here: http://www.sifma.org/research/statistics.aspx.

is significantly smaller than the uninsured, consistent with the conjecture that insurance is preferred by retail investors even at this level of credit quality.[17] Indeed, the average trade size is smaller for insured bonds at every investment grade group (Aaa, Aa, A, and Baa) and for the non-rated bonds (although the difference at the Aa level is insignificant).[18]

Consistent with primary market statistics provided by SIFMA, we observe that secondary market trading is likewise dominated by retail investors (more than 50% of trades are less than $100,000 blocks) at every rating level. Again consistent with the conjecture that insurance is preferred by retail investors, we observe even greater retail participation in insured bonds than we observe in uninsured bonds among investment grade bonds.

5 Empirical Methodology

5.1 Event study

To test whether muni investors react to information readibly available from other markets, we examine insured municipal bond returns in response to particular events in the demise of the monoline insurance industry in 2007-2008. Specifically, we test the extent to which the muni market is informed by equity and CDS markets. Therefore, we focus on the publicly traded MBIA and AMBAC. Uniformly rated Aaa prior to 2008, these insurers were downgraded over the course of 2008, following shocks to their equity and CDS markets. Figure 2 plots cumulative stock returns and five-year CDS premiums for MBIA and AMBAC in Panels A and B, respectively. We identify the "equity distress date" as the date of the largest loss in market capitalization. This distress date occurs on October 25, 2007 for MBIA and November 1, 2007 for AMBAC. These dates are represented as vertical dashed lines in Figure 2. Also marked is the initial downgrade (from Aaa) on June 19, 2008.[19]

[17]The purchase of insurance by Aaa issuers is puzzling, and we find little evidence later in the paper that these bonds have lower returns than their uninsured counterparts. In conversation, a former MBIA employee explained that retail investors view "belts and suspenders" as complements and not substitutes, somewhat confirming that at least some retail investors have a preference for doubly insuring their holdings.

[18]We do not tabulate the 25 bonds with non-investment grade rating.

[19]Given the complexity surrounding the structure of the insurers there is some ambiguity whether the downgrade date for the insurance subsidiary (6/5/2008 in the case of MBIA) or the downgrade of the holding

We define three sub-periods based on these dates. Sub-sample 1 runs from the beginning of the data sample (January, 2006) until the insurer's stock market distress date. Sub-sample 2 runs from the distress date until the issuer downgrade. Sub-sample 3 runs from the downgrade to the end of the sample period (December, 2009). The following sections examine the returns on the municipal portfolios insured by MBIA and AMBAC across these periods.

5.2 VAR and Granger causality tests

We examine the extent to which the muni market is informed by linked equity and CDS markets more generally using a VAR model of muni bond returns and insurers' stock returns and changes in their CDS premia. We choose the order of the VAR model based on the Akaike Information Criterion (AIC). From the VAR model, we can then test for Granger causality among the linked markets. Likewise, we also use the VAR to model the interaction between net order flow of retail and institutional investors and perform Granger causality test to infer the relative speed of responses by retail and institutional investors.

5.3 Computing bond returns

To conduct an event study and analyze the time series behavior of insured bonds, it is critical to have a reliable measure of the average return pattern of these bonds over time. The ideal way to obtain a return index is to have the same bonds trade every day, then compute the simple (or weighted) average return for each day. Several problems present in application to the muni market:

- Munis are far less liquid than corporate bonds. Because they do not trade often, data required to compute a day's average is sparse, resulting in unreliable estimates of averages.
- The computed daily average reflects the average return (or yield) of only bonds that trade on a given day. The small subset of traded bonds is not representative of the return (or yield) of bonds in the entire portfolio.

company is most relevant. Since the insurance subsidiaries had recourse to the holding company, and in most cases capital infusions and equity offerings were done at the holding company level, we choose the later "full company" downgrade date. The later date should also bias us against finding post-date CARs; as we demonstrate, the results are not particularly sensitive to that assumption.

- Often, the fact that a bond trades on a given day is not exogenous. When the trade itself is endogenous to the event of interest (such as an insurer downgrade) one cannot infer average effects from observing only the most affected bonds.
- Municipal bonds are heterogeneous; they differ along many dimensions, most importantly credit quality, the presence of insurance, and the credit quality of the insurer.

These problems are exacerbated during the financial crisis, where liquidity may be a complicated and time-varying function of bond characteristics. We find in Section 4.2 that insured bonds are more likely held and traded by retail investors and their liquidity needs may differ markedly from large institutions. The very limited attempts to mitigate the trading selection effects have generally involved estimating a complex functional selection model (as in Liu (2012)) or by focusing only on a subset of highly liquid bonds, as in Chun et al. (2015). Since we are interested in the flow of information daily into the muni market before, during, and after the crisis, neither of these approaches are satisfactory. Instead, we follow the approach taken by Spiegel and Starks (2016) in the corporate bond market and adapt the RSR method to create daily return indices by insurer and rating. The RSR method is commonly employed to construct return indices for real estate assets, another asset class with substantial heterogeneity across characteristics and significant illiquidity. Substantial modifications of these methods are required to adapt them for bond markets (and specifically for muni markets) and we provide a detailed description of our return index construction procedure in Appendix B.

Briefly, we adapt GRSR developed in Peng (2012) to calculate separate returns for house prices in small submarkets. For all bonds insured by a particular insurer, we use duration-weighted yield changes across pairs of trades to approximate returns and regress these returns on daily time dummies in a GLS framework that overweights trade pairs in closer proximity. Simultaneously, for each rating class (still within the set of bonds insured by a specific insurer) we estimate factor sensitivities using an Expectation Maximization (EM) algorithm. From these we are able to construct separate return indices for each insurer and each rating class and compare them to return indices constructed for uninsured bonds by rating class. While similar to the methods of Spiegel and Starks (2016) and Wilkoff (2013) in spirit, our return construction is novel in that it provides a new method for constructing indices for characteristic-based subgroups with very sparsely spaced data. We construct these indices only through the end of 2009 for two reasons. First, Moody's announced its plan to recalibrate municipal bond ratings on March 16, 2010. This recalibration results in a discontinuity in the portfolios of insured bonds by ratings. Second and more importantly, the market for monoline insurance had collapsed by the end of 2009.

The fact that our return indices are estimated complicates statistical inference compared to a standard event study in liquid markets. We address this problem by adapting bootstrap sampling methods from Peng (2012) in order to estimate standard errors for specific submarket return indices.

6 Empirical Results

This section reports the results from our main empirical analysis. First, we document the contemporaneous lack of response in the market for muni bonds with credit enhancement provided by MBIA and AMBAC, both graphically and with formal tests. This section also provides empirical results indicating that muni investors value insurance, but only so long as the insurer maintains a Aaa certification from the CRAs. Next, we compare the relative speed of response between retail and institutional investors. Finally, we test the general information transmission between the muni market and linked equity and CDS markets.

6.1 Tests of return divergence

Figure 3 presents estimated bond return indices for true Aaa uninsured bonds and by insurer for the four year period from January 3, 2006 to December 31, 2009. It is immediately apparent that there is little difference in bond returns between true Aaa uninsured bonds and the insured bond portfolios (purchased Aaa bonds) prior to January 1, 2008. We interpret this result as investor-perceived value in insurance, since the insured bond portfolios include bonds of much lower underlying credit quality, which should command commensurately higher returns otherwise. Insured portfolio returns begin to diverge sharply from their Aaa uninsured benchmark portfolio in August of 2008; thereafter returns on the true Aaa uninsured bonds dominate the insured portfolio returns. This result is what we would expect when the market devalues the insured bonds upon the loss of insurance value.

The comparison of the muni market response to the financial distress of MBIA and AMBAC to that of the equity and CDS markets observed in Figure 2 is striking. The major stock price plunges for MBIA and AMBAC occur in late 2007, and by April 2008, CDS spreads for both MBIA and AMBAC had reached nearly 500bp. Yet the value of the insured portfolios diverge from their true Aaa benchmark only after Moody's and S&P downgrade the insurers several months later in June of 2008, and then with a substantial lag.

Figure 4 depicts the differential return patterns for MBIA and AMBAC stratified by their underlying credit rating.[20] For both insurers, returns in the pre-crisis period are identical across ratings, as would be expected if the value of insurance dominated underlying credit risk. As the insurers' financial distress increases, lower-rated bonds begin to underperform higher-rated bonds insured by a common insurer.

In Table 4 we formally test for differences in the cumulative returns between the Aaa uninsured benchmark and portfolios insured by MBIA and AMBAC over the three distinct sub-periods defined above. Prior to the insurers' downgrade, there is virtually no difference between the returns on the insured bond portfolios and the portfolio of Aaa uninsured bonds. Post-downgrade, the insured portfolios dramatically underperform their Aaa uninsured counterparts, likely indicating a "flight to quality" in the muni market. However, there is no significant difference in the returns of insured and uninsured bonds between the distress date and the downgrade date – the period during which both MBIA and AMBAC lose over 90% of their stock market value (see Figure 2). In short, we show that the return divergence only occurs after the downgrade, which is several months after the equity and CDS markets

[20]Because MBIA was able to sell insurance to 121 Aaa-rated bonds, while AMBAC only to 4, we are able to reliably estimate the Aaa bond return index for MBIA but not for AMBAC.

reflect the insurers' distress. If the muni market were informationally efficient, we should expect to observe the divergence to occur earlier.

6.2 Measuring investors' attention

The value of financial guaranty insurance depends on the credit quality of the insurer. In Section 6.1 we show that in the pre-crisis period, investors valued the insurance provided by the monoline insurers. Here we ask a related question: how quickly did investors in insured municipal bonds realize that the value of the guaranty provided was evaporating? While there was little focus on the monoline insurance market in the years from 1990-2006, some investors (including the widely publicized short position by activist investor William Ackman of Pershing Square Capital) noticed and publicized the risks accumulating in the sector. Still, the stock price performance of the major publicly traded insurers does not indicate that equity investors priced distress risk for these insurers in the first half of 2007 (see Figure 2). In the second half of 2007, the market value of MBIA and AMBAC imply a drastic increase in default risk. If muni investors were paying attention to the equity market, they should infer that the value of their insurance had fallen. This observation should have led to negative relative price pressure as marginal investors either sold insured bonds, purchased true Aaa uninsured bonds, or both. The impact of insurer distress should be greater among bonds with lower underlying credit quality. If instead institutional factors drive municipal bond sales and purchases, the wedge between the true Aaa uninsured bond portfolio and insured bond portfolio returns would manifest following a downgrade of the insurers.

We compute abnormal returns for MBIA- and AMBAC-insured bonds relative to the return on the true Aaa uninsured index. Figure 5 plots these CARs (accumulated from the beginning of 2006) along with bootstrapped standard errors. Two vertical lines mark the equity distress date and the downgrade date.[21] It is immediately apparent that there is no

[21] In an earlier version of the paper, we replicate this exercise for the two primary privately held insurers, FSA and FGIC and see very similar patterns. The privately held nature of these insurers complicates our information emphasis, since no stock return distress date exists for them. In addition, in the spring of 2008, FSA received large equity and credit line infusions from its parent, Dexia, and FGIC entered into an agreement to split the (largely insolvent) company into a "good" portfolio and "bad" portfolio with Goldman

significant difference between returns on insured portfolios and returns on true Aaa uninsured bonds throughout 2007, for either insurer. MBIA and AMBAC portfolios exhibit similar performance, though CARs for MBIA become slightly negative in the spring of 2008.

The figure also demonstrates a dramatic decline in the value of insurance after the downgrade of the insurer, but these negative returns occur very slowly reaching their minimum approximately 125 trading days (half a year in calendar time) after the downgrade event. More surprisingly, the tumult in the monoline insurer equity and CDS markets has virtually no effect on muni CARs. Stock market distress dates are 158 and 163 trading days prior to the downgrade date for AMBAC and MBIA respectively, and no effect in that period is evident in the plot. There is a small downward drift in the CARs several months after the equity market collapse; it is difficult to attribute this to new information about the insurers entering the stock market (prices had already fallen nearly to their lows).

We formally test the hypothesis that insurer ratings matter more to investors than market information about insurer solvency by computing CARs and their associated bootstrapped standard errors over various windows around each event date. The results are reported in Table 5, with Panel A corresponding to the equity distress date and Panel B to the downgrade. For both insurers, no information in the 250 days preceding either the distress date or the downgrade causes any significant abnormal returns for the insured portfolios. However, the behavior of CARs in the post-event windows clearly differ between the two events. The lower part of Panel B shows that there are significant, albeit still small, negative returns in the 20 trading days immediately following the downgrade (of 48 bps and 74 bps for MBIA and AMBAC respectively). These negative returns accumulate to reach a maximum of over 1.84% (MBIA) and 2.55% (AMBAC) over the 120 days post-downgrade. These negative CARs persist for well over a year after the downgrade. On the other hand, as shown in the lower part of Panel A, there is much less evidence of significantly negative CARs following the equity distress date. The CARs only become significantly negative for both insurers if

Sachs acting as sales agent. For these reasons, we focus on the large publicly traded insurers in the text, but results on FSA and FGIC are available from the authors.

we look at the 250-day window after the distress date, which includes the downgrade. We conclude that investors in the muni market ignore easily obtainable information from directly related markets and react with significant delay to institutional news.

6.3 Measuring investors' attention: institutional versus retail

As in Section 4, we define trades smaller than $100,000 as retail. Trades larger than or equal to this amount are classified as institutional. Figure 6 shows buy and sell trading volume in MBIA-insured bonds by institutional and retail investors around the equity distress date and downgrade date. (We observe a similar pattern for AMBAC insured bonds, omitted here to save space and available from the authors). Trade volume among institutional investors indicates net sales on some dates, but remains pretty balanced. In contrast, retail investors are (collectively) always net buyers. Nothing from Figure 6 indicates a strong reaction from either institutions or retail investors to either the equity distress date or the downgrade in the short term, but Figure 6 does indicate differences between these investor types in terms of net order flow.

The results in Figure 7 further indicate a difference (over time) in this cross-sectional difference (between institutions and retail investors). Specifically, Figure 7 plots the ratio of sell volume by institutions scaled by the sell volume by retail investors over time between January 2006 and the end of 2009. The volume is aggregated across all bonds insured by MBIA and AMBAC. Here we observe a spike in the ratio immediately following the distress date in MBIA's stock price suggesting that at least some institutions responded either to the equity market or to the underlying information priced by the equity market. The largest spike in the sell ratio occurs in March 2008, which follows shortly after Moody's confirmed the Aaa rating on February 26, 2008, but with a "negative outlook". This spike provides the most compelling evidence that institutional investors are more responsive than retail investors to information regarding the value of the credit enhancement provided by MBIA and AMBAC. The next subsequent spike occurs with a lag following the downgrade on June 19, 2008.

More formally, we perform Granger causality tests of institutional and retail trade flows in Table 6. Among insured bonds, institutions' and retail investors' net trade flow Granger cause each other in the period prior to the insurer equity distress date. However, neither investor type leads the other in the important period between distress date and downgrade. After the downgrade, institutional net trade flow significantly leads retail net trade flow. We conclude that neither group was timely in the period prior to the downgrade, but institutions respond faster following the downgrade. We report results for the uninsured bonds for comparison. Here, institutions lead retail investors in the important period between distress and downgrade, but we do not draw strong conclusions from this result.

Together, the results in this section support the joint conclusion that the entire market was very slow to update, but that institutions reacted in a more-timely manner than the retail investors.

6.4 Information flows across markets

In addition to testing the flow of information around particular event dates, our bond return indices allow us to test which direction information moves from one related market to another, more generally. Specifically, we estimate a VAR model on the daily insured bond portfolio indices for AMBAC and MBIA, their equity returns, and the changes in their CDS spreads. Table 7 presents the F-statistics from Granger causality tests of the time series VAR. Consistent with the results in Blanco et al. (2005) and Norden and Weber (2009), we find strong evidence that stock market movements Granger cause CDS spread movements, but not the reverse. More importantly for our research question, we find no evidence that either CDS spreads or stock returns of insurers Granger cause any movement in insured bond returns. This result can also be seen in Figure 8, where we plot the impulse response functions from the VAR model for MBIA. Except for the impulse response of each variable to its own shock (in subplots on the diagonal), the only statistically significant impulse response observed is that of CDS spread to shock in stock return.[22] We again conclude that muni investors ignore information provided from equity and CDS markets.

Table 8 presents an expanded VAR model which nests MBIA and AMBAC's stock returns, changes in CDS premium, and insured bond returns and tests for causal flows of information, to account for possible correlation between MBIA and AMBAC. As before, each insurer's stock return Granger causes its CDS changes, but more importantly, no information from CDS or equity markets Granger causes returns in either insurer's municipal bond portfolios. Curiously, we find evidence that changes in MBIA CDS spreads strongly Granger cause changes in AMBAC CDS spreads. We attribute this result to the widely publicized trading of Pershing Square Capital in the CDS of MBIA, which led to that market being the primary source of information on the health of the municipal insurance market.

7 Alternative Explanations

The purpose of this paper is to test the informational efficiency of the municipal bond market. We are motivated by concerns among regulators regarding the operational and informational efficiency of this market, and the empirical results in Section 6 suggest that regulators' concerns are well founded. We consider next a host of alternative explanations for our empirical results.

7.1 Trivial value of insurance

Observing no reaction in the muni market to the lost credit enhancement suggests either that the muni market is highly segmented or that the insurance provided by MBIA and AMBAC was never of any value. Indeed, the probability of default among munis is lower than any other asset class, save Treasuries.[23] The $378 million in 2007 gross premiums written by MBIA in its domestic public finance business provides prima facie evidence that the insurance

[22] The impulse response functions from the VAR model for AMBAC provide similar results, and hence are omitted in the interest of space.

[23] Although low, default probability is not zero. Schwert (2017) finds that the muni spread over Treasury bonds reflects default risk, not just a liquidity premium.

was of some value to the issuers paying premiums. Also of note is that MBIA earned $58 million in US public finance gross premiums in the first half of 2008, *after* its equity distress date. The empirical evidence we document in Section 6 indicates that the insurance was also valued by investors (retail investors in particular) prior to the insurers' downgrade. We leave for future research a more rigorous analysis of the channel(s) by which investors value insurance (lowered credit risk, provision of tax advantages, and/or enhanced liquidity) in the time periods prior to, during, and following the financial crisis and demise of the once dominant monoline insurers. For our purposes, we note that if the insurance never had value, we should observe no reaction in the muni market to the demise of the monolines. Such is not the case. Indeed, we find significantly negative CARs following the downgrade event. We conclude not that the muni market failed to react, but that it reacted with significant delay. This reaction, though delayed, is inconsistent with the explanation that the credit enhancement provided by MBIA and AMBAC was never of any value.

7.2 Lehman Brothers, bailouts, and crisis

Because the demise of the monolines occurs during the financial crisis, we consider the extent to which other crisis-related effects confound our results and interpretations. In particular, although the negative CARs documented in Table 5 and Figure 5 are significantly delayed relative to the information available from equity and CDS markets and insurer downgrades, they do not appear delayed relative to the Lehman Brothers bankruptcy on September 15, 2008, arguably the peak of the financial crisis. However, the significant negative CARs observed in Figure 5 precede the Lehman bankruptcy by more than a month. We also examine the trading pattern around the Lehman bankruptcy, as shown in Figure 9, and find business as usual. We conclude that muni investors were not simply shaken by the Lehman failure.

We also consider that investors' risk aversion increased over this crisis period (apart from any change in default risk). However, because the CARs control for the benchmark return on the uninsured portfolio, which should also be affected, we believe the negative CARs reflect the declining value of insurance. We also note that any "flight to quality" from riskier asset classes, such as corporate bonds and equities, would have the opposite effect on the CARs reported in Table 5 and Figure 5. In addition, increasing risk-aversion should cause investors to value both the presence and the absence of insurance more. Investors with higher risk aversion should react sooner to the devaluation of insurance rather than later. A sudden spike in risk aversion (say coinciding with the Lehman failure) would lead to both a sudden discrepancy between low-rated and high-rated municipals (including the insurance wrap) and commensurate buy-sell trade volumes, neither of which we find in the data. Certainly higher risk-aversion investors would react to a change in the riskiness of their portfolios by the removal of insurance. A spike in risk-aversion would have to be combined with an ignorance of insurance value in order to generate our results, and this combination seems especially unlikely.

Finally, we consider that the delayed reaction of muni investors might reflect an expectation of a federal bailout of MBIA and AMBAC. Although we have no data on investors' beliefs, the reaction in equity and CDS markets indicate that equity and derivative securities investors shared no such expectation of bailout.

7.3 Limits to arbitrage

We consider that any short sale constraints would mitigate price discovery. The apparent non-reaction of the muni market to relevant information available from linked markets may reflect investors' inability to sell these securities short. Although neither the SEC nor the MSRB prohibits short sales, the IRS imposes a quasi-restriction in that it disallows both a borrower and a lender of a muni to claim a tax exemption.[24] Because the security lender would effectively be trading tax exempt interest for taxable interest, the borrower would incur the cost to make the lender whole. We have no evidence to suggest whether this friction imposes greater constraint than the analogous equity short with a dividend payment, but

[24]The only mention of munis in the SEC's publication on Regulation SHO is that the T+3 rule (settlement must occur within 3 days of trade date) applies to municipal securities. MSRB Rule G-8(a)(iii) requires only that all short trading positions be designated as such.

concede that short sellers may face difficulty borrowing munis. To the extent that short sale constraints inhibit price discovery, we argue that the significant negative CARs documented in Table 5 and Figures 5 understate the eventual negative impact of the monoline distress on insured munis. The fact that muni investors eventually sell affected bonds indicates that any potential inefficiency due to short sale constraints cannot be the entire story.

So, what prevents "smart money" from capitalizing on the uninformed retail investors and improving the informational efficiency of this market? We believe the limits to arbitrage follow from the relatively high transactions costs (see e.g., Harris and Piwowar (2006), Green et al. (2007), and Schultz (2012)) coupled with the relatively low yields in this tax exempt market. Indeed, smart money did capitalize on the inflated credit ratings of MBIA and AMBAC (see footnote 2 regarding Pershing Square Capital's big short) in the equity and CDS markets which offer higher potential gains and lower transaction costs. We conclude that this market's operational inefficiency aggravates its informational inefficiency.

8 Conclusion

Financial regulators and policymakers have long been concerned with protecting individual investors participating in financial markets. The operational and informational inefficiency of the municipal bond market is of particular concern.

Affirming this concern, we find robust evidence that the retail-investor-dominated muni market ignores relevant information that is readily available from other financial markets. Specifically, we adapt a novel methodology to examine muni returns around the implosion of the monoline insurance market. Investors holding munis with credit enhancement provided by distressed insurers ignore information from the distressed issuers' rapidly declining equity values and sharply increasing CDS prices. Investors devalue their insured bonds with significant delay following the insurers' loss of Aaa certification. We consider a host of alternative explanations for our empirical results and conclude that the muni market remains highly segmented despite earlier regulatory efforts to improve transparency and efficiency.

A Ratings and Mergers of Monoline Insurers

This appendix provides the history of restructuring and rating of monoline insurers (in alphabetical order).

AMBAC

(Bankruptcy on 11/9/2010, emerged 5/1/2013)

12/14/2007	Affirmed Aaa with outlook stable
01/16/2008	Review for downgrade
02/29/2008	Comment on review for downgrade
03/05/2008	Comment on capital infusion (SEO for $1.5B at $6.75/share)
03/12/2008	Affirmed at Aaa with negative outlook
06/24/2008	Review for downgrade
06/19/2008	Downgrade to Aa3 with negative outlook
09/18/2008	Review for downgrade
11/05/2008	Downgrade to Baa1
03/03/2009	Review for downgrade
07/29/2009	Downgrade to Caa2
06/08/2010	Announces bankruptcy
10/01/2010	Rehabilitation by Wisconsin
11/09/2010	Files for bankruptcy
11/23/2010	Confirms Caa2
05/01/2013	Exits bankruptcy (senior 15 cents recovery; unsecured 10 cents recovery)

ASGC

(Assured Guaranty Corp; IPO 5/6/2004; announced acquisition of FSA 11/2008, completed 7/2009, became AGM)

05/06/2004	Initial rating of Aa1
06/27/2006	Affirmed Aa1 with positive outlook
03/16/2007	Review for upgrade
07/11/2007	Upgraded to Aaa
12/14/2007	Affirmed Aaa
03/14/2008	Affirmed Aaa
07/21/2008	Review for downgrade
11/21/2008	Downgrade to Aa2
11/21/2008	FSA downgraded to Aa3
11/21/2009	Downgrade to Aa3 (FSA, now AGM affirmed at Aa3)
03/20/2012	Review for downgrade
01/17/2013	Downgrade to A2 for AGM, Assured Guaranty to A3
06/01/2013	MAC (Municipal Assurance Corp formed)

ASGTY

(Acquired by Radian Group in 2001, merged to Radian Asset Assurance 6/2004)

BAM

(Build American Mutual, founded 2012; rated AA by S&P, not rated by Moody's)

CIFG

(Merged into AGO on 7/2016)

FGIC

(Financial Guaranty Insurance Company, placed into rehabilitation 11/24/2009)

12/14/2007	Affirmed Aaa, review for downgrade
02/14/2008	Downgrade to A3
03/31/2008	Downgrade to Baa3
06/20/2008	Downgrade to B1
10/24/2008	Review for downgrade
12/19/2008	Downgrade to Caa1
03/24/2009	Downgrade to Caa3
11/24/2009	Rehabilitation by NY (muni portfolio re-insured by MBIA)

FSA

(Financial Security Assurance, sold to Assured Guaranty 7/1/2009, changed to AGM)

12/14/2007	Affirmed Aaa with stable outlook
03/11/2008	Affirmed Aaa
07/21/2008	Review for downgrade
11/21/2008	Downgrade to Aa3
07/01/2009	Sold by Dexia to AGO

MBIA

(Restructured 2/18/2009, forming NATL; reinsured FGIC on that date)

12/14/2007	Affirmed Aaa with negative outlook
01/17/2008	Review for downgrade
02/26/2008	Confirmed Aaa with negative outlook
06/19/2008	Downgrade to A2
09/18/2008	Review for downgrade
11/07/2008	Downgrade to Baa1
06/25/2009	Downgrade MBIA to Ba3; National affirmed at Baa1

NATL

(Formed from MBIA portfolio on 2/18/2009; novated FGIC on 8/19/2013)

06/25/2009	Affirmed at Baa1 with review for upgrade
12/19/2011	Downgrade to Baa2
05/21/2013	Upgrade to Baa1
05/21/2014	Upgrade to A3
05/26/2015	Affirmed at A3 with negative outlook
05/25/2016	Affirmed at A3

RADIA

(Merged into Assured Guaranty on 4/1/2015)

05/24/2004	Assigned Aa3
12/14/2007	Affirmed Aa3
03/28/2008	Affirmed Aa3 with outlook negative
06/25/2008	Downgrade to A3 (A2 for Radian Guaranty)
10/10/2008	Review for downgrade
03/12/2009	Downgrade to Ba1
11/22/2011	Downgrade to Caa1
04/17/2012	Downgrade to Caa2

XLCA

(Became Syncora, rehabilitation on 8/5/2008)

05/17/2008	Affirmed Aaa
02/07/2008	Downgrade to A3
03/04/2008	Review for downgrade
06/20/2008	Downgrade to B2 with outlook negative
10/24/2008	Downgrade to Caa1 (now Syncora)
03/17/2009	Downgrade to Ca

B Construction of municipal bond return indices

The lack of liquidity in the muni market is a major problem bedeviling virtually all research on secondary market behavior. It is important to measure bond portfolio returns employing all available observations for all bonds in the portfolio, including those that do not trade each day. The real estate literature provides helpful tools for this purpose as they face a similar problem computing housing market returns: houses are likewise heterogeneous assets that do not trade often. The two primary methods used in the real estate literature are hedonic regressions and repeated sales regressions (RSR).

In hedonic regressions, we regress prices on asset characteristics and a time trend, which then produces a set of value weights corresponding to the characteristics.[25] Based on these value weights, we can estimate the price for each asset on each day, from which we can estimate a daily average index. However, this method is prone to model mis-specification and requires a great deal of data on asset characteristics, many of which are unavailable. For use in the muni market, liquidity is an important consideration with a sizable effect on trade prices. However, controlling for bond-level liquidity in a hedonic regression implies that one cannot use the regression to infer the price of non-traded bonds on a given day.

The RSR method makes use of pairs of trades to avoid any need for characteristics selection. This method overcomes the disadvantages of the hedonic regression method, provided that the quality of the assets does not change significantly and there is no cashflow between trade dates (e.g.,Case and Shiller (1989)). In a typical RSR model, the dependent variable is the change in price of an asset between two adjacent trades, and the independent variables are time dummies. For each observation, the time dummies for the dates between adjacent trades are equal to 1, and 0 otherwise. The model is estimated using generalized least squares (GLS), in which the error variance is proportional to the duration since the last trade. Intuitively,

[25] Hill (2003) provides a helpful overview of hedonic regression for real estate indices.

returns based on trades that are far apart carry less weight in the estimation than those based on more frequent trades.

Spiegel and Starks (2016) and Robertson and Spiegel (2017) detail the many advantages of the RSR method, which is especially attractive for our setting. However, two important characteristics of bonds require some adaptation to the standard RSR if we are to apply this method to computing municipal bond return indices. Unlike houses, bonds mature. For example, a five-year bond issued six months ago is now a four-and-a-half-year bond, which is arguably not the same asset as the asset traded six months ago. Secondly, there are regular (typically semiannual) coupon payments associated with bonds. Spiegel and Starks (2016) choose to discard pairs of trades with intervening coupon payments. In our setting, this is untenable because (1) doing so necessitates discarding a large portion of our data, and (2) large sample size is critical for reliable estimation of the indices.

We overcome the effects of bond maturing and coupon payments by working with bond yields instead of bond prices.[26] The RSR method is then applied on the change in yields between adjacent trades, after adjusting for the change in duration of the bonds. That is, the dependent variable in our model is duration-adjusted change in yield:

$$\Delta y_{i,b,s} = -(D_{i,s} \times y_{i,s} - D_{i,b} \times y_{i,b}) \tag{1}$$

where b and s are the times of the last trade and current trade respectively, while y and D denote the yield to maturity and duration of a bond at a given time. The negative sign in the above equation is necessary in order that this change approximates the return.[27]

One further consideration is how to deal with differing rates of returns that are correlated with observable characteristics of bonds in an index. Most research since the mid-1990s has focused on how to combine the hedonic and RSR methods (i.e. allowing the appreciation

[26]In many ways, this is similar to the adaptation of the RSR to estimate house rental indices, as in Ambrose et al. (2015).
[27]Using continuously compounding approximation, we can write: $P_{i,s} = e^{-y_{i,s} \times D_{i,s}}$ and $P_{i,b} = e^{-y_{i,b} \times D_{i,b}}$. Thus, the log return between date b and s is: $r_{i,b,s} = log(P_{i,s}) - log(P_{i,b}) = -(D_{i,s} \times y_{i,s} - D_{i,b} \times y_{i,b})$

across sub-groups to be heterogeneous). Spiegel and Starks (2016) is the latest application of this approach to the corporate bond market. More specifically, they control for key characteristics of a bond (maturity, industry, current yield) by creating a custom index for each bond using data on bonds with similar characteristics (based on Euclidean distance to the bond of interest). The idea is to more heavily weight the bond price appreciation of bonds that are similar than that of bonds that are different. Once the observations on other bonds are weighted based on this 'similarity score', the RSR method is used to produce a benchmark return index for the bond.

For our study, we do not need a separate benchmark index for each bond. Our primary purpose is to study the behavior of portfolios of bonds stratified by characteristics such as rating and insurer. We therefore resort to a more parsimonious approach, and adapt the Generalized Repeat Sales Regression method (GRSR) proposed by Peng (2012), to handle heterogeneous rates of returns among different sub-groups of bonds within an index.[28] The idea is to (in the simplest setup) presume that each characteristic has a factor sensitivity to the main price appreciation trend. The sample is partitioned into subgroups along chosen characteristics. This method involves estimating jointly the common return index and the differential factor loadings of the subgroups. From here, the index for each subgroup can be reconstituted using the common index and the subgroup's factor loading. This method is particularly attractive when subgroups have thin data coverage for which the standard RSR is not estimable. Furthermore, the method allows us to test for differential return dynamics among subgroups.

We proceed as follows. We first compute bond return indices for different rating classes for uninsured bonds. We use the rating of bonds at the time of trade to determine which index they belong to. These indices provide useful benchmarks for the insured bonds with similar underlying credit quality. Since we have sufficient data in each rating class for uninsured bonds, we compute these indices straightforwardly using the standard RSR method.

[28]The original application was to calculate different return indices for real estate sub-markets stratified by final sales price.

Next, we compute the return index for bonds insured by the following major insurers before the crisis: MBIA, AMBAC, FSA, and FGIC. The portfolio of bonds insured by a given insurer is homogeneous in terms of carrying the same insurance wrap. However, they differ in underlying credit quality, and an interesting question is whether the market prices them similarly purely due to the insurance. For instance, does a Baa credit price the same as an Aa credit if both are wrapped by the same insurance company? Thus, for each insurer, we apply the GRSR to estimate a common return index for all bonds insured by the said insurer, as well as the loadings for the different underlying credit rating classes.

Specifically, denote $R^I_{m,t}$ the expected return for all bonds in the portfolio of insurer I (where $I = \{\text{MBIA, AMBAC, FSA, FGIC}\}$). The portfolio is partitioned by underlying credit rating classes. For each rating class l, denote by $\tau_{l,t}$ the sensitivity of returns of bonds in rating class l to the return of the overall portfolio (we suppress the superscript I for simplicity). The GRSR model is:

$$\Delta y_{i,b,s} = \sum_{t=b+1}^{s} \tau_{l,t} R_{m,t} + \sum_{t=b+1}^{s} \epsilon_{i,t} \tag{2}$$

We choose the most general parameterization of $\tau_{l,t}$ to allow for time-varying factor loadings, as in Peng (2012). That is, $\tau_{l,t} = \tau_{1,l} + \tau_{2,l} R_{m,t}$. A negative $\tau_{2,l}$ indicates that a rating class becomes more sensitive to the overall portfolio in bad times, but less sensitive to the overall portfolio in good times.

We estimate the GRSR model specified in Equation (2) with an iterative Expectation-Maximization (EM) algorithm outlined in Peng (2012). First, assigning starting values of $\tau_{1,l} = 1$ and $\tau_{2,l} = 0$, we estimate Equation (2) by GLS and obtain the overall index $R_{m,t}$ (which are the coefficients on the time dummies). Second, we run a separate regression for each rating class (where the estimated $R_{m,t}$ is plugged into Equation (2) to estimate the sensitivity coefficients $\tau_{1,l}$ and $\tau_{2,l}$). The process is repeated until convergence. Based on the final estimates of $R_{m,t}$ and factor loadings, we construct the return index for each rating class within each insurer's portfolio. For example, for MBIA, apart from the overall return index for all MBIA-insured bonds, we have five sub-indices of returns corresponding to Aaa, Aa, A, Baa, and non-rated bonds.

To facilitate various hypothesis tests on estimated returns, we follow Peng (2012) to produce bootstrapped sampling distributions for our return estimates. Specifically, we draw a random sample of repeated bond trades with replacement from our data sample so that the drawn sample has the same size. We then use this sample to estimate bond returns and obtain one set of return estimates. We repeat this procedure 500 times, which results in 500 sets of return estimates. Statistical tests in the paper are based on standard errors computed from these bootstrapped sampling distributions.

Finally, due to computational constraints, we cannot estimate all the above indices for the entire sample period, so we break the sample period into smaller sub-periods and estimate the indices for each sub-period individually. A feature of the RSR model is that the number of observations available at the beginning and end of the estimation period is low, rendering estimates for these parts of the estimation period unreliable. To mitigate this problem, we follow the strategy of Spiegel and Starks (2016) by estimating the indices on a rolling three-year window. In each three-year window, we keep only the estimates for the middle year, discarding estimates for the first year and third year. Thus, with trade data available from 2005, our indices start in 2006. For our empirical study, we construct these indices only through the end of 2009 for reasons explained in Section 5.3. Table B1 below reports the number of trade pairs occurring during the 2005-2010 period that are used in estimating each credit-quality-insurer index.

Since our sample period bridges the financial crisis, a concern could be that the composition of the tradeable market for municipals changes over the period. For instance, if there were few to no trades in low-rated munis after the crisis but such trades were common before the crisis, then the precision of the estimates might predictably vary. Our rolling window method (dropping the early and late periods) mitigates this effect somewhat. We also examine the

Table B1: Number of observations (trade pairs) used in estimation of return indices

	Uninsured	MBIA	AMBAC	FSA	FGIC
Aaa	245,787	4,053	443	15,501	2,057
Aa	506,469	249,882	42,875	152,143	57,406
A	210,772	242,445	50,335	164,830	54,433
Baa	35,519	36,901	11,004	34,934	8,230
Ba	420	2,796	1,194	1,390	487
Non-rated	62,312	51,842	14,682	42,167	20,762

number of trades by rating and year in Table B2 below and find little variation over time. Therefore, our return indices are not driven by changes in the frequency of trades by rating class through time.

Table B2: Trade composition by trade year and rating

Year	Aaa	Aa	A	Baa	NIG	NR
			Panel A: Non-insured Bonds			
2005	50267	98429	62913	9330	22	12683
2006	56944	108730	63592	7779	18	12471
2007	64520	112989	55409	7525	2	10121
2008	77937	190231	79859	10899	101	9954
2009	68050	183227	68495	30026	252	11966
2010	87196	182248	65330	19131	278	13709
2011	94440	207438	65750	6557	228	12284
2012	74494	176585	54442	11599	209	9572
2013	96656	232266	62364	12598	138	29207
2014	84509	226973	31154	7839	289	26198
2015	82334	252532	27982	5114	3477	12946
2016	35795	115762	19939	2163	2629	2735
			Panel B: Insured Bonds			
2005	13679	101013	132166	25682	1589	34858
2006	12499	114025	144021	27747	1505	35421
2007	9090	133501	148709	27301	1234	34044
2008	6815	175855	165993	36041	2458	32898
2009	4023	158375	163570	39544	2681	27386
2010	7335	178726	130623	19603	3876	21105
2011	7880	187614	120166	17059	3124	15709
2012	5101	132768	81748	17197	3266	10231
2013	4318	118180	84479	18192	3621	8983
2014	2490	93902	52211	10793	1607	4152
2015	1803	77321	45471	4272	923	1607
2016	559	29444	19627	1279	1954	216

References

Adelino, Manue, Igor Cunha, and Miguel A. Ferreira, 2017, The economic effects of public financing: Evidence from municipal bond ratings recalibration, *Review of Financial Studies* 30, 3223–3268.

Ambrose, Brent W., N. Edward Coulson, and Jiro Yoshida, 2015, The repeat rent index, *Review of Economics and Statistics* 97, 939–950.

Ang, Andrew, Vineer Bhansali, and Yuhang Xing, 2014, The muni bond spread: Credit, liquidity, and tax, Working Paper (BlackRock, Inc., Pacific Investment Management Company, and Rice University).

Ang, Andrew, Richard C. Green, Francis A. Longstaff, and Yuhang Xing, 2017, Advance refundings of municipal bonds, *Journal of Finance* 72, 1645–1682.

Association of Financial Guaranty Insurers, 2008, The state of the bond insurance industry, *Presentation to the House Subcommittee on Capital Markets, Insurance, and GSEs,* 277–322.

Babina, Tania, Chotibhak Jotikasthira, Christian T. Lundblad, and Tarun Ramadorai, 2017, Heterogeneous taxes and limited risk sharing: Evidence from municipal bonds, Working Paper (Columbia Business School, Southern Methodist University, University of North Carolina, and Imperial College London).

Bergstresser, Daniel, Randolph Cohen, and Siddharth Shenai, 2010, Financial guarantors and the 2007-2009 credit crisis, Working Paper (Harvard Business School).

Bergstresser, Daniel, Randolph Cohen, and Siddharth Shenai, 2015, Skin in the game: The performance of insured and uninsured municipal debt, Working Paper (Harvard Business School, Harvard Law School, MIT, and Bracebridge Capital).

Blanco, R., S. Brennan, and I. W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* 60, 2255–2281.

Bronshtein, Gila, 2015, Insurance in the municipal bond market, Working Paper (Standford University).

Brune, Chris, and Pu Liu, 2011, The contagion effect of default risk insurer downgrades: The impact on insured municipal bonds, *Journal of Economics and Business* 63, 492–502.

Buser, Stephen A., and Patrick J. Hess, 1986, Empirical determinants of the relative yields on taxable and tax-exempt securities, *Journal of Financial Economics* 17, 335–355.

Case, Karl, and Robert J. Shiller, 1989, The efficiency of the market for single-family homes, *American Economic Review* 79, 125–137.

Chalmers, John M. R., 1998, Default risk cannot explain the muni puzzle: Evidence from municipal bonds that are secured by u.s. treasury obligations, *Review of Financial Studies* 11, 281–308.

Chalmers, John M. R., 2006, Systematic risk and the muni puzzle, *National Tax Journal* 59, 833–848.

Chun, Albert L., Ethan Namvar, Xiaoxia Ye, and Fan Yu, 2015, Modeling municipal yields with (and without) bond insurance, Working Paper (University of Queensland, University of California, Berkeley, University of Bradford, and Claremont McKenna College).

Chung, San-Lin, Chen-Wei Kao, Chunchi Wu, and Chung-Ying Yeh, 2015, Counterparty credit risk in the municipal bond market, *Journal of Fixed Income* 25, 7–33.

Cole, Charles W., and Dennis T. Officer, 1981, The interest cost effect of private municipal bond insurance, *Journal of Risk and Insurance* 48, 435–449.

Cornaggia, Jess N., Kimberly J. Cornaggia, and Ryan D. Israelsen, forthcoming, Credit ratings and the cost of muncipal financing, *Review of Financial Studies* .

Downing, Chris, Shane Underwood, and Yuhang Xing, 2009, The relative informational efficiency of stocks and bonds: An intraday analysis, *Journal of Financial and Quantitative Analysis* 44, 1081–1102.

Downing, Chris, and Frank Zhang, 2004, Trading activity and price volatility in the municipal bond market, *Journal of Finance* 59, 899–931.

Gore, Angela K., Kevin Sachs, and Charles Trzcinka, 2004, Financial disclosure and bond insurance, *Journal of Law and Economics* 47, 275–306.

Green, Richard C., 1993, A simple model of the taxable and tax-exempt yield curves, *Review of Financial Studies* 6, 233–264.

Green, Richard C., Burton Hollifield, and Norman Schurhoff, 2007, Financial intermediation and the costs of trading in an opaque market, *Review of Financial Studies* 20, 275314.

Green, Richard C., and Bernt A. Oedegaard, 1997, Are there tax effects in the relative pricing of u.s. government bonds?, *Journal of Finance* 52, 609–633.

Hajek, Petr, 2011, Municipal credit rating modelling by neural networks, *Decision Support Systems* 51, 108–118.

Harris, Lawrence E., and Michael S. Piwowar, 2006, Secondary trading costs in the municipal bond market, *Journal of Finance* 61, 1361–1397.

Hill, Robert J., 2003, Hedonic price indexes for residential housing: A survey, evaluation and taxonomy, *Journal of Economic Surveys* 27, 879–914.

Kidwell, David S., Eric H. Sorensen, and John M. Wachowicz, 1987, Estimating the signaling benefits of debt insurance: The case of municipal bonds, *Journal of Financial and Quantitative Analysis* 22, 299–313.

Kidwell, David S., and Charles A. Trzcinka, 1982, Municipal bond pricing and the New York City fiscal crisis, *Journal of Finance* 37, 1239–1246.

Kochin, Levis A., and Richard W. Parks, 1988, Was the tax-exempt bond market inefficient or were future expected tax rates negative?, *Journal of Finance* 43, 913–931.

Kwan, Simon H., 1996, Firm-specific information and the correlation between individual stocks and bonds, *Journal of Financial Economics* 40, 63–80.

Lai, Van S., and Xueying Zhang, 2013, On the value of municipal bond insurance: An empirical analysis, *Financial Markets, Institutions and Instruments* 22, 209–228.

Landoni, Mattia, forthcoming, Tax distortions and bond issue pricing, *Journal of Financial Economics* .

Liu, Gao, 2012, Municipal bond insurance premium, credit rating, and underlying credit risk, *Public Budgeting and Finance* 32, 128–156.

Longstaff, Francis A., 2011, Municipal debt and marginal tax rates: Is there a tax premium in asset prices?, *Journal of Finance* 66, 721–751.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market, *Journal of Finance* 60, 2213–2253.

Moldogaziev, Tima T., 2013, The collapse of the municipal bond insurance market: How did we get here and is there life for the monoline industry beyond the great recession?, *Journal of Public Budgeting, Accounting and Financial Management* 25, 199–233.

Nanda, Vikram, and Rajdeep Singh, 2004, Bond insurance: What is special about munis?, *Journal of Finance* 59, 2253–2280.

Norden, Lars, and Martin Weber, 2009, The co-movement of credit default swap, bond and stock markets: an empirical analysis, *European Financial Management* 15, 529–562.

Palumbo, George, and Mark P. Zaporowski, 2012, Determinants of municipal bond ratings for general-purpose governments: An empirical analysis, *Public Budgeting and Finance* 32, 86–102.

Peng, Liang, 2012, Repeat sales regression on heterogeneous properties, *Journal of Real Estate Finance and Economics* 45, 804–827.

Pirinsky, Christo A., and Qinghai Wang, 2011, Market segmentation and the cost of capital in a domestic market: Evidence from municipal bonds, *Financial Management* 40, 455–481.

Robertson, Adriana, and Matthew I. Spiegel, 2017, Better bond indices and liquidity gaming the rest, Working Paper (University of Toronto and Yale University).

Schultz, Paul, 2012, The market for new issues of municipal bonds: The roles of transparency and limited access to retail investors, *Journal of Financial Economics* 106, 492–512.

Schwert, Michael, 2017, Municipal bond liquidity and default risk, *Journal of Finance* 72, 1683–1722.

Skelton, Jeffrey L., 1983, Relative risk in municipal and corporate debt, *Journal of Finance* 38, 625–634.

Spiegel, Matthew I., and Laura Starks, 2016, Institutional rigidities and bond returns around rating changes, Working Paper (Yale University and University of Texas, Austin).

Starks, Laura T., Li Yong, and Lu Zheng, 2006, Tax-loss selling and the january effect: Evidence from municipal bond closed-end funds, *Journal of Finance* 61, 3049–3067.

Thakor, Anjan V., 1982, An exploration of competitive signalling equilibria with third party information production: The case of debt insurance, *Journal of Finance* 37, 717–739.

Trzcinka, Charles, 1982, The pricing of tax-exempt bonds and the miller hypothesis, *Journal of Finance* 37, 907–923.

Wang, Junbo, Chunchi Wu, and Frank X. Zhang, 2008, Liquidity, default, taxes, and yields on municipal bonds, *Journal of Banking and Finance* 32, 1133–1149.

Wilkoff, Sean M., 2013, The effect of insurance on municipal bond yields, Working Paper (Securities and Exchange Commission).

Table 1: Municipal general obligation bonds issued by state and fraction insured

This table reports the number of municipal general obligation bonds issued by each state, and the fraction within each state that are insured by a monoline insurer. Bond characteristics data are from Mergent Municipal Fixed Income Securities Database (Mergent) as of 6/17/2016.

State	No. of Bonds	Percent Insured	State	No. of Bonds	Percent Insured
AK	2,719	63	MT	5,329	23
AL	736	24	NC	11,120	23
AR	3,292	8	ND	2,134	19
AZ	10,443	60	NE	14,821	7
CA	50,218	71	NH	4,803	46
CO	7,688	55	NJ	40,949	62
CT	21,848	36	NM	7,603	29
DC	467	68	NV	473	52
DE	816	25	NY	90,822	55
FL	3,742	43	OH	16,527	43
GA	5,289	22	OK	13,229	5
HI	2,142	57	OR	10,225	40
IA	22,389	32	PA	32,835	82
ID	3,128	45	PR	528	50
IL	33,505	55	RI	3,435	68
IN	6,817	28	SC	9,222	30
KS	18,658	28	SD	1,032	41
KY	3,166	37	TN	9,750	40
LA	10,113	54	TX	97,264	34
MA	18,681	54	UT	3,846	23
MD	7,027	16	VA	7,308	18
ME	4,612	32	VT	1,155	19
MI	27,886	48	WA	13,469	51
MN	46,135	22	WI	27,239	29
MO	14,645	21	WV	739	48
MS	10,521	17	WY	530	26

Sample size: 763,070

Table 2: Summary statistics of GO bonds with and without insurance

The table shows average bond characteristics of GO insured bonds compared to non-insured bonds. *Rating at issuance* refers to the underlying credit rating of the bond at the time of issuance. *Number of issue agents* is the number of agents involved in selling an issue. *Mutual fund holding* is the percentage of a bond held by mutual funds within the first quarter of issuance. Column (7) reports the differences in average characteristics between insured and non-insured bonds. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively. Bond characteristics data are from Mergent as of 6/17/2016. Mutual fund holding data is from CRSP.

	Non-Insured Bonds			Insured Bonds			
	# Bonds	Mean	StDev	# Bonds	Mean	StDev	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)=(5)-(2)
Size ($ million par)	436,980	1.711	25.374	326,090	1.008	3.871	-0.702***
Maturity (years)	436,980	9.766	6.078	326,090	10.523	6.017	0.757***
Coupon (%)	436,980	4.304	1.421	326,090	4.576	1.107	0.272***
Rating at Issuance	232,842	18.393	2.108	185,600	16.395	1.713	-1.998***
Additional Credit Enhancement (1/0)	436,980	0.189	0.392	326,090	0.149	0.356	-0.041***
Bank Qualified (1/0)	436,980	0.550	0.498	326,090	0.523	0.499	-0.027***
State Taxable (1/0)	436,980	0.081	0.272	326,090	0.065	0.247	-0.016***
Number of Issue Agents	434,221	5.414	2.534	325,656	5.297	2.033	-0.117***
Mutual Fund Holding (%)	436,980	1.442	9.915	326,090	1.204	9.414	-0.238***

Table 3: Differences in secondary market liquidity of GO bonds with and without insurance

The table shows secondary market liquidity metrics of insured bonds compared to non-insured bonds in similar credit rating categories. Rating refers to the rating of bonds at issuance. Liquidity metrics are computed from the MSRB database for the period from January 2005 to December 2016. The number of bonds reported in columns (1) and (4) indicate the subset of bonds that trade during the MSRB data period. Column (7) reports the difference in average liquidity between insured and non-insured bonds. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively.

	Non-Insured Bonds			Insured Bonds			
Rating	# Bonds	Mean	StDev	# Bonds	Mean	StDev	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)=(5)-(2)
Number of Trades Per Bond:							
Aaa	21,415	30	67	503	30	73	0
Aa	54,815	30	85	26,203	37	112	7***
A	15,786	41	213	52,908	23	71	-17***
Baa	3,157	44	258	9,170	25	118	-19***
Non-rated	45,496	19	82	52,282	17	58	-2***
Average Trade Size Per Bond:							
Aaa	21,415	281,796	939,469	503	194,709	331,883	-87,087***
Aa	54,815	215,277	849,184	26,203	211,516	909,100	-3,761
A	15,786	172,047	729,063	52,908	124,404	424,372	-47,643***
Baa	3,157	146,069	440,219	9,170	109,813	319,519	-36,257***
Non-rated	45,496	155,965	651,813	52,282	134,054	388,092	-21,910***
Percentage of Retail Trades:							
Aaa	21,415	66.27	34.91	503	64.3	38.59	-1.96
Aa	54,815	69.13	34.57	26,203	70.73	33.21	1.6***
A	15,786	67.12	37.56	52,908	72.92	34.56	5.8***
Baa	3,157	69.03	39.76	9,170	73.55	35.99	4.52***
Non-rated	45,496	71.89	37.55	52,282	68.96	38.52	-2.93***

Table 4: Tests of return divergence from true Aaa uninsured bonds

This table presents the F-statistics (F-stat) and the corresponding 95% χ^2 critical values (c.v.) of tests of the difference in cumulative return on bonds insured by an insurer versus that on true Aaa uninsured bonds. A double-asterisk (**) indicates that the deviation is significant at the 5% level. The tests are performed for three sub-samples: 1) from the beginning of 2006 to the date of the insurer's stock market distress, 2) from the distress date to the downgrade date (off of Aaa rating), and 3) from the downgrade to the end of 2009. The average return of bonds insured by each insurer is computed using the GRSR method. The average return on true Aaa uninsured bonds is computed using the RSR method. Municipal bond trade data are from the MSRB, bond characteristics data are from Mergent, and supplementary credit rating data are collected from the rating agencies' websites.

	MBIA		AMBAC	
	F-stat	χ^2 c.v.	F-stat	χ^2 c.v.
Sub-sample 1: Prior to Distress Date	341.26	507.84	397.83	513.11
Sub-sample 2: From Distress to Downgrade Date	147.83	192.70	42.76	187.24
Sub-sample 3: After Downgrade Date	2889.16**	421.15	928.89**	421.15

Table 5: Cumulative abnormal return around event dates

This table presents estimates of cumulative abnormal return (CAR, in %) of MBIA- and AMBAC-insured bonds around the given insurer's distress date in Panel A, and around the downgrade off of Aaa rating in Panel B. The average return of bonds insured by each insurer is computed using the GRSR method. The benchmark return is the return on true Aaa uninsured bonds. Abnormal return is accumulated over various windows relative to the event date (time 0). Municipal bond trade data are from the MSRB, bond characteristics data are from Mergent, and supplementary credit rating data are collected from the CRAs' websites. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively.

Panel A: CARs around equity distress date

	Pre-event window									
	[-20:-1]		[-40:-1]		[-60:-1]		[-120:-1]		[-250:-1]	
	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.
MBIA	−0.15	0.20	−0.20	0.20	−0.06	0.20	−0.13	0.22	−0.08	0.34
AMBAC	−0.47*	0.31	−0.07	0.31	0.02	0.32	0.23	0.31	−0.10	0.52
	Post-event window									
	[0:20]		[0:40]		[0:60]		[0:120]		[0:250]	
	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.
MBIA	0.85***	0.36	−0.03	0.23	−0.23	0.39	−0.74**	0.39	−2.09***	0.42
AMBAC	−0.15	0.31	−0.68**	0.40	−0.37	0.57	−0.34	0.61	−1.76***	0.61

Panel B: CARs around downgrade date

	Pre-event window									
	[-20:-1]		[-40:-1]		[-60:-1]		[-120:-1]		[-250:-1]	
	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.
MBIA	−0.07	0.25	0.22	0.26	0.28	0.26	−0.34	0.42	−0.32	0.39
AMBAC	−0.33	0.39	−0.27	0.39	−0.07	0.40	0.31	0.64	−0.25	0.60
	Post-event window									
	[0:20]		[0:40]		[0:60]		[0:120]		[0:250]	
	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.	CAR	s.e.
MBIA	−0.48**	0.27	−0.41*	0.28	−0.87***	0.29	−1.84***	0.29	−1.16**	0.52
AMBAC	−0.74**	0.40	−0.79**	0.43	−0.15	0.47	−2.55***	0.47	−1.65**	0.82

Table 6: Granger causality test of institutional and retail trade flows

This table reports the F-statistic of whether institutional trade flow Granger-causes retail trade flow, and vice versa. The tests are based on a VAR model of daily net flow of institutional trades (i.e., trades sized at or above $100,000) and retail trades (i.e., trades sized below $100,000). Daily net order flow is computed as the total par value of buyer-initiated trades minus that of seller-initiated trades, standardized by total trading volume. The order of the VAR is chosen based on Akaike Information Criteria (AIC). Panel A shows the results for bonds collectively insured by MBIA and AMBAC. Panel B shows the results for uninsured bonds for comparison. The full sample data include all secondary market trades in the MSRB database for the period from 1/1/2006 to 12/31/2009. Sub-sample 1 is from the beginning of 2006 to the date of the MBIA's stock market distress. Sub-sample 2 is from the distress date to the downgrade date (off of Aaa rating). Sub-sample 3 is from the downgrade date to the end of 2009. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively.

Causality Direction	Full Sample	Sub-sample 1	Sub-sample 2	Sub-sample 3
Panel A: Insured Bonds				
Institutional → Retail	8.162***	6.350***	2.181	7.891***
Retail → Institutional	4.617***	5.598***	1.500	2.228
Order of VAR Model	3	2	2	1
Panel B: Uninsured Bonds				
Institutional → Retail	2.614*	0.736	6.408***	0.285
Retail → Institutional	1.237	1.818	0.432	2.448*
Order of VAR Model	3	3	2	2

Table 7: Granger causality test of information transmission across markets

This table presents the results of Granger causality test of information transmission among the stock market, the CDS market, and the market for municipal bonds insured by MBIA and AMBAC. The table reports the F-statistic of whether the row variable Granger-causes the column variable. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively. The tests for both MBIA and AMBAC variables are based on VAR model of order 1 (based on AIC), using data for the period from 2006 to 2009. "Insured Bond" is the average daily return on municipal bonds insured by the given insurer. These returns are estimated using the GRSR method and MRSB municipal bond trade data. "Stock Return" and "CDS Change" are the daily stock returns and daily changes in the 5-year CDS premium of the given insurer, obtained from CRSP and Datastream respectively.

	Insured Bond	Stock Return	CDS Change
		Panel A: MBIA	
Insured Bond		1.687	1.665
Stock Return	0.075		55.352***
CDS Change	0.031	0.052	
		Panel B: AMBAC	
Insured Bond		0.047	0.000
Stock Return	0.002		44.400***
CDS Change	0.982	3.123*	

Table 8: Granger causality test of information transmission across markets

This table presents the results of Granger causality test of information transmission among the stock market, the CDS market, and the market for municipal bonds insured by MBIA and AMBAC. The table reports the F-statistic of whether the row variable Granger-causes the column variable. Significance at the 1%, 5%, and 10% level is denoted by ***,**, and * respectively. The tests are based on a VAR of order 2 (based on AIC) of the six variables, using data for the period from 2006 to 2009. "ABK-Bond" and "MBIA-Bond" are the average daily return on municipal bonds insured by AMBAC and MBIA respectively. These returns are estimated using the GRSR method and MRSB municipal bond trade data. "ABK-Stock" and "MBIA-Stock" are the daily stock returns of AMBAC and MBIA respectively, sourced from CRSP. "ABK-CDS" and "MBIA-CDS" are the daily changes in the 5-year CDS premium of AMBAC and MBIA respectively, obtained from Datastream.

	ABK-Bond	ABK-Stock	ABK-CDS	MBI-Bond	MBI-Stock	MBI-CDS
ABK-Bond		0.838	2.234	10.257***	1.124	0.655
ABK-Stock	0.827		4.333**	1.129	0.674	0.447
ABK-CDS	0.271	0.567		0.463	1.235	1.637
MBI-Bond	36.394***	0.451	1.715		1.131	1.566
MBI-Stock	1.013	2.226	2.134	2.212		11.828***
MBI-CDS	1.766	4.789***	21.232***	0.616	0.659	

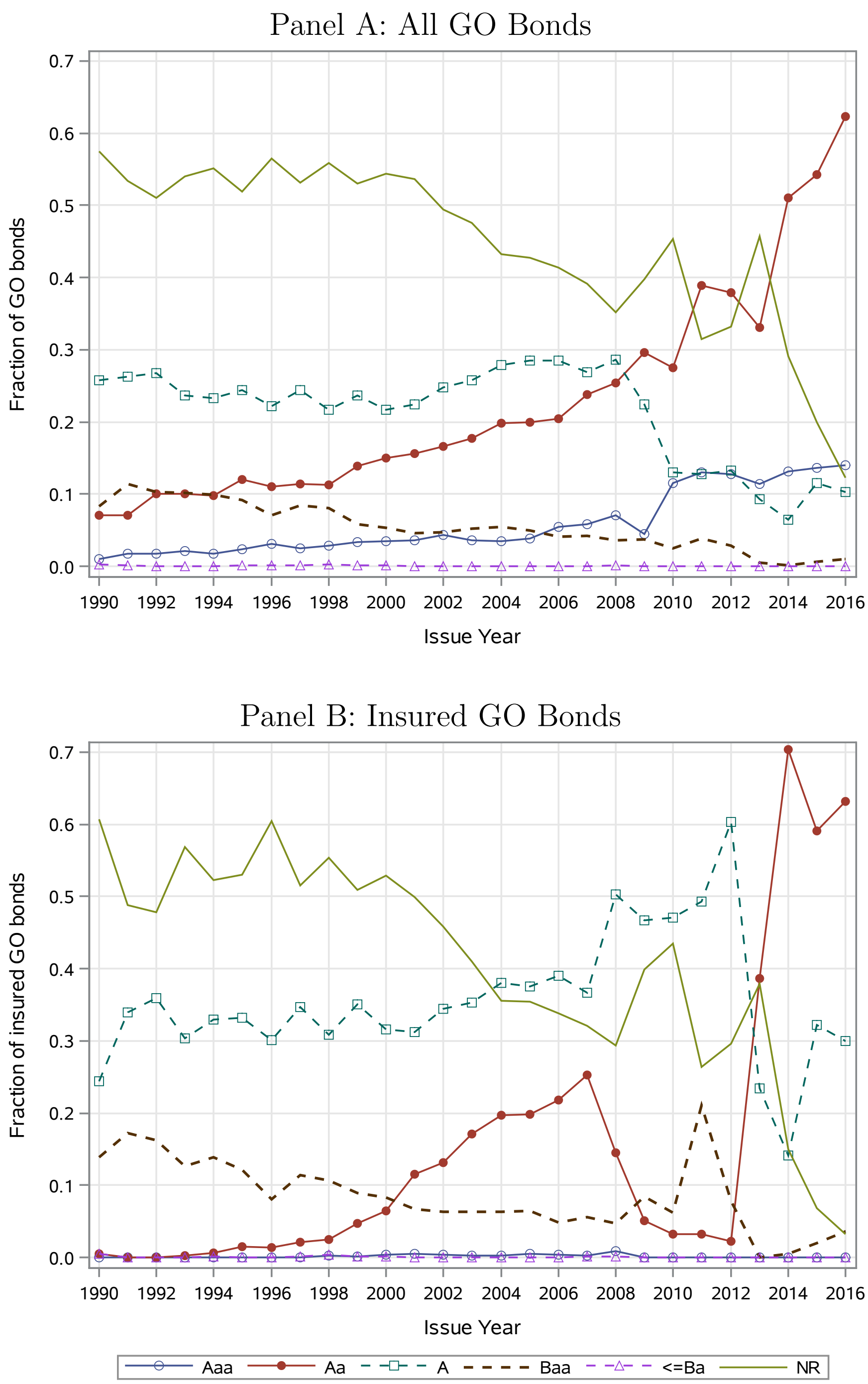


Figure 1: Underlying credit quality by issue year

This figure shows the distribution of underlying credit quality of GO bonds issued between 1990 and 2016. Panel A is based on all GO bonds. Panel B is based on insured GO bonds. Bond characteristics data are from Mergent Municipal Fixed Income Securities Database.

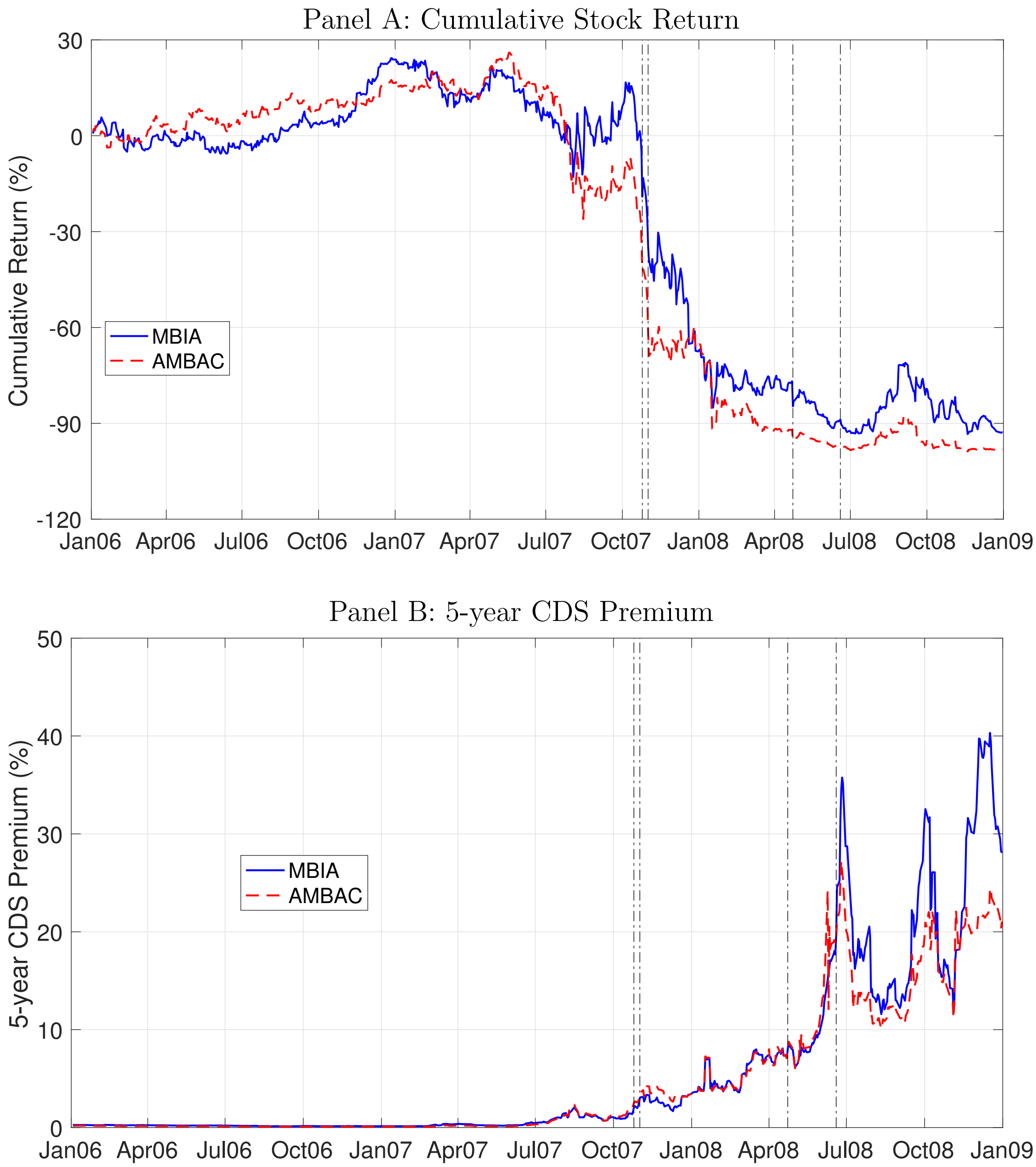


Figure 2: Time series of stock return and CDS premium of MBIA and AMBAC 2006-2008

This figure shows the time series of cumulative stock return and 5-year CDS premium of MBIA and AMBAC from 2006 through 2008. Stock return data are from CRSP and CDS data are from Datastream.

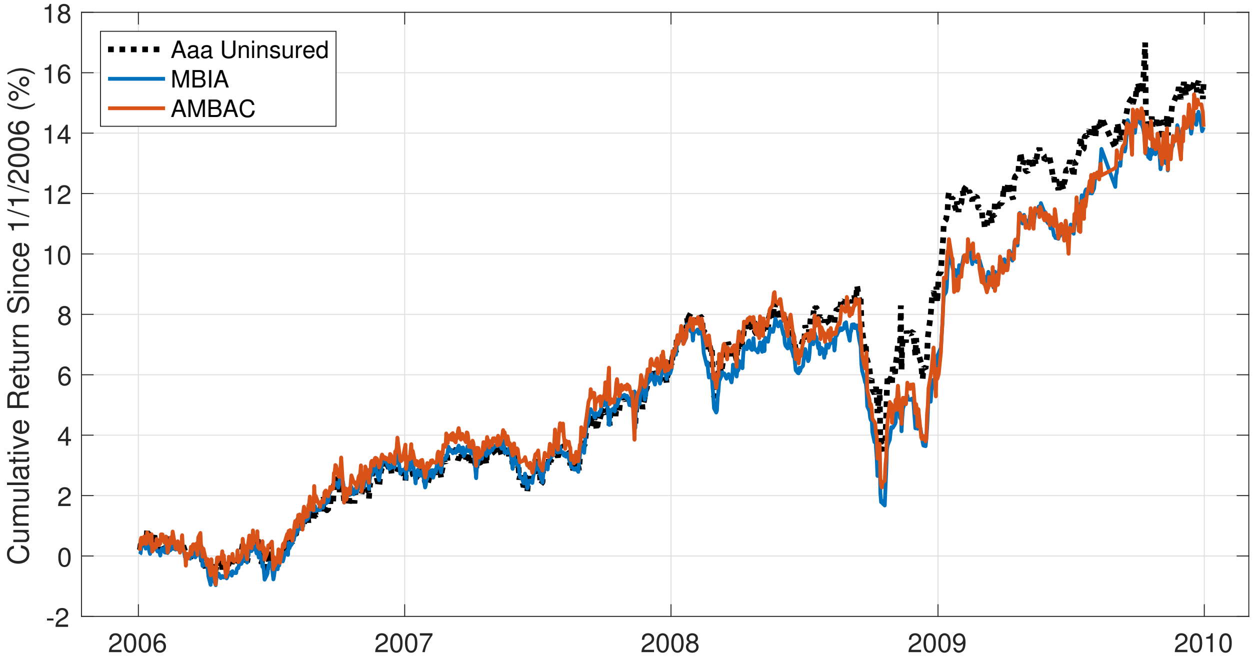


Figure 3: Time series of cumulative bond returns 2006-2009

This figure shows the time series of cumulative returns of true Aaa uninsured bonds versus those of MBIA- and AMBAC-insured bonds from the beginning of 2006 through the end of 2009. Bond returns are estimated by the GRSR method using trade data from the MRSB.

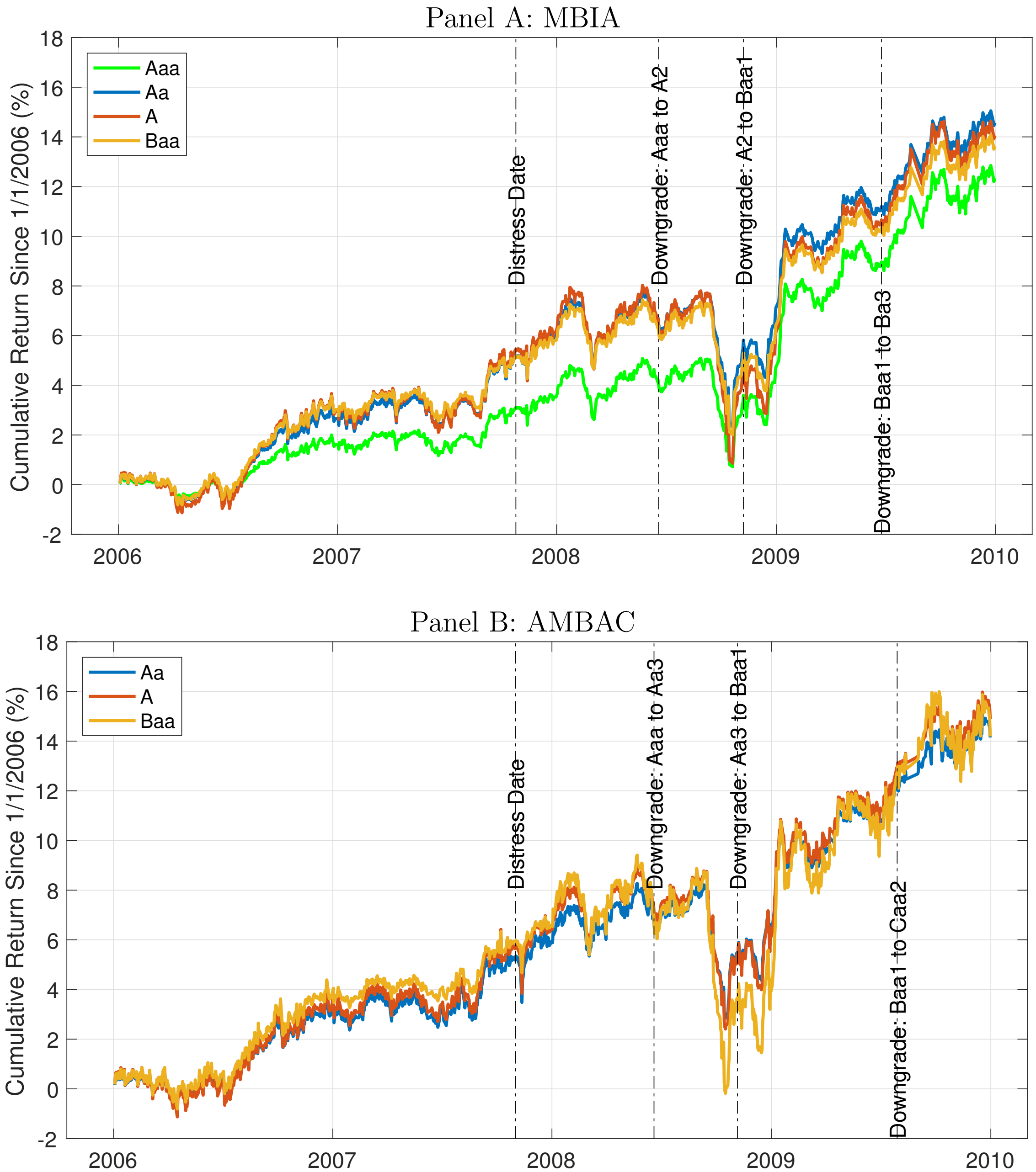


Figure 4: Cumulative returns of insured bonds by rating class 2006-2009

This figure shows the time series of cumulative return of insured bonds by rating classes. Bond returns by rating classes are estimated by the GRSR method using trade data from the MRSB. Because MBIA was able to sell insurance to 121 Aaa-rated bonds, while AMBAC only to 4, we are able to reliably estimate the Aaa bond return index for MBIA but not for AMBAC.

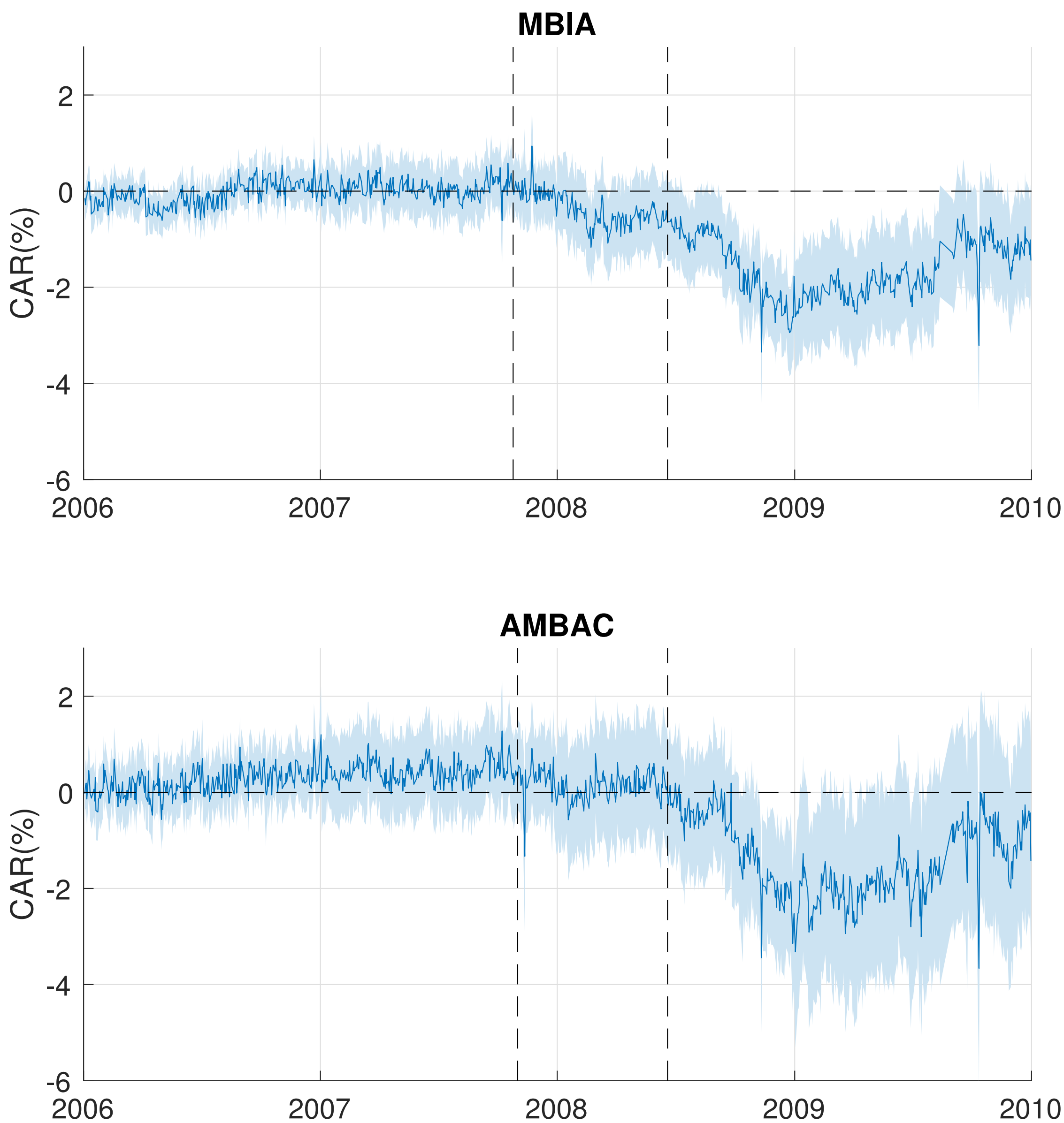


Figure 5: Cumulative abnormal returns of insured bonds 2006-2009

This figure shows the time series of cumulative abnormal return (CAR, in %) of insured bonds from 2006 through 2009. Returns are benchmarked by the returns of true Aaa uninsured bonds, and accumulated since the beginning of 2006. Bond returns are estimated by the GRSR method using trade data from the MRSB. The shaded area represents the 90% bootstrapped confidence band around the estimated CAR. Two vertical lines mark the equity distress date and downgrade date in that order.

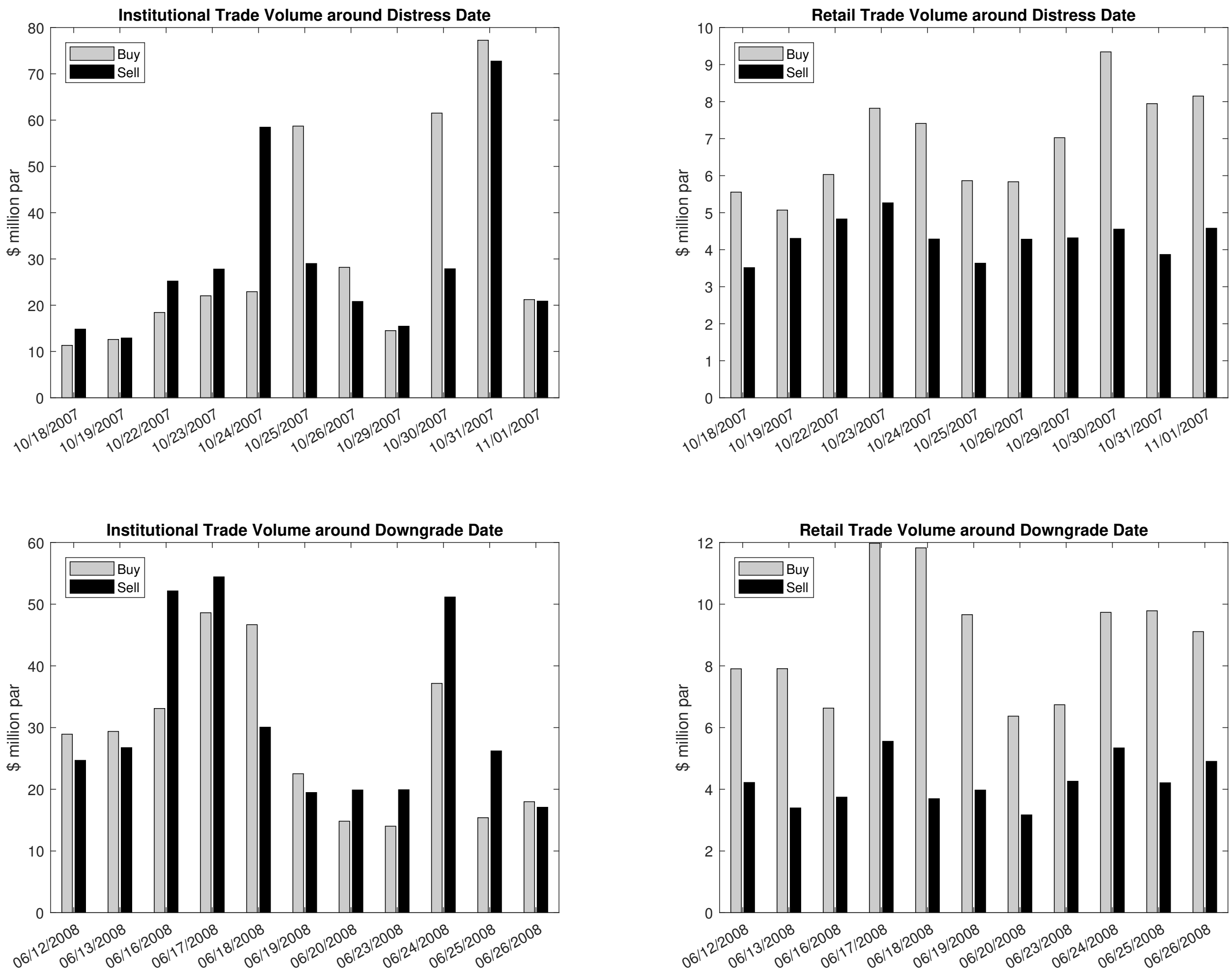


Figure 6: Institutional and retail trading activity in MBIA bonds around event dates

This figure shows daily trading volume of institutional and retail investors around two event dates: the equity distress date and downgrade date. Trades are classified as institutional if they are sized $100,000 and above. Trades that are smaller than $100,000 are classified as retail. Trade data are from the MSRB.

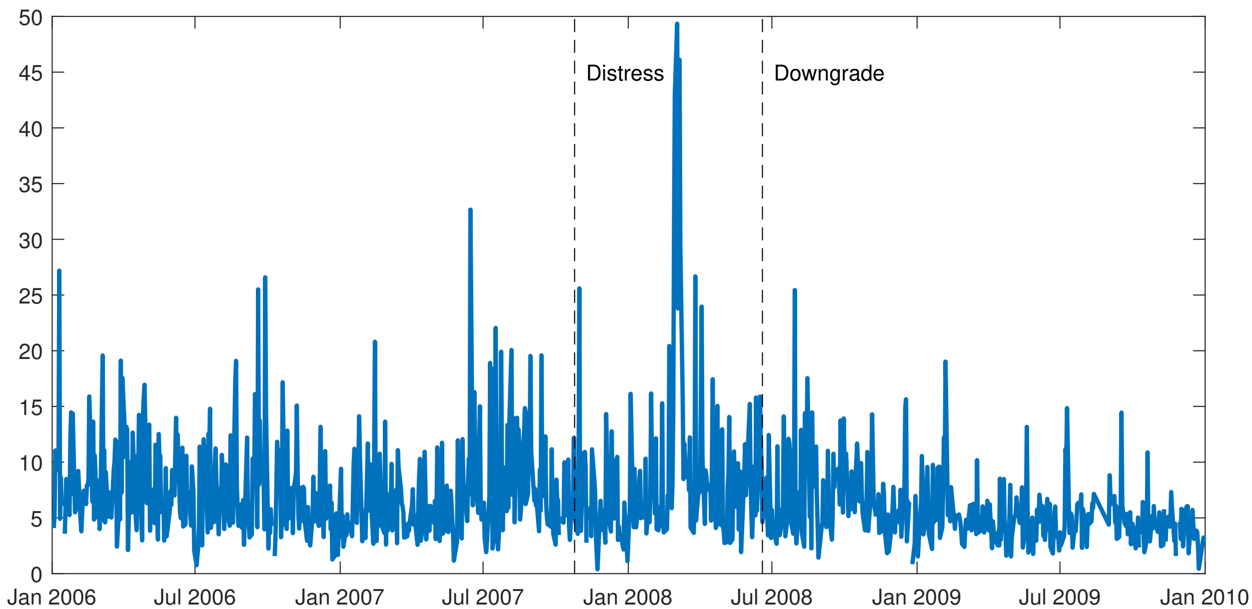


Figure 7: Institutional-to-retail sell volume ratio

This figure shows daily ratio of institutional sell volume to retail sell volume. Two vertical lines mark the equity distress date and downgrade date in that order. Trades are classified as institutional if they are sized \$100,000 and above. Trades that are smaller than \$100,000 are classified as retail. Trade data are from the MSRB.

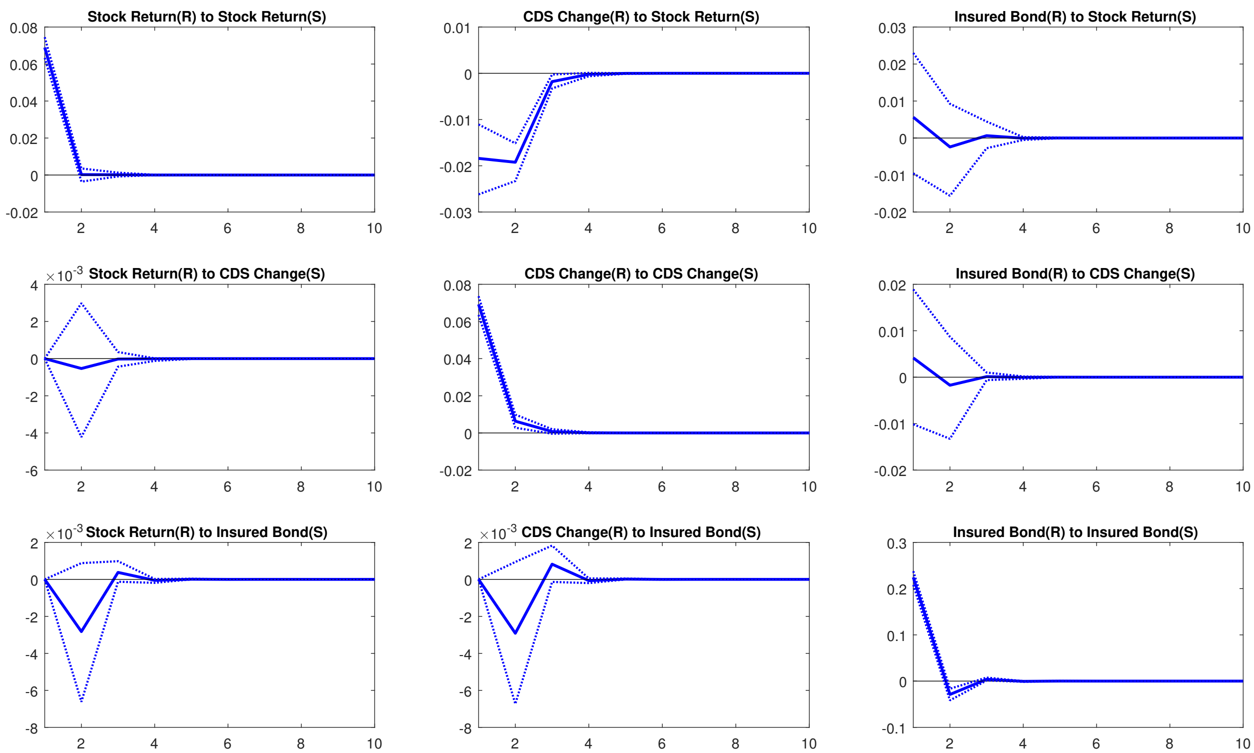
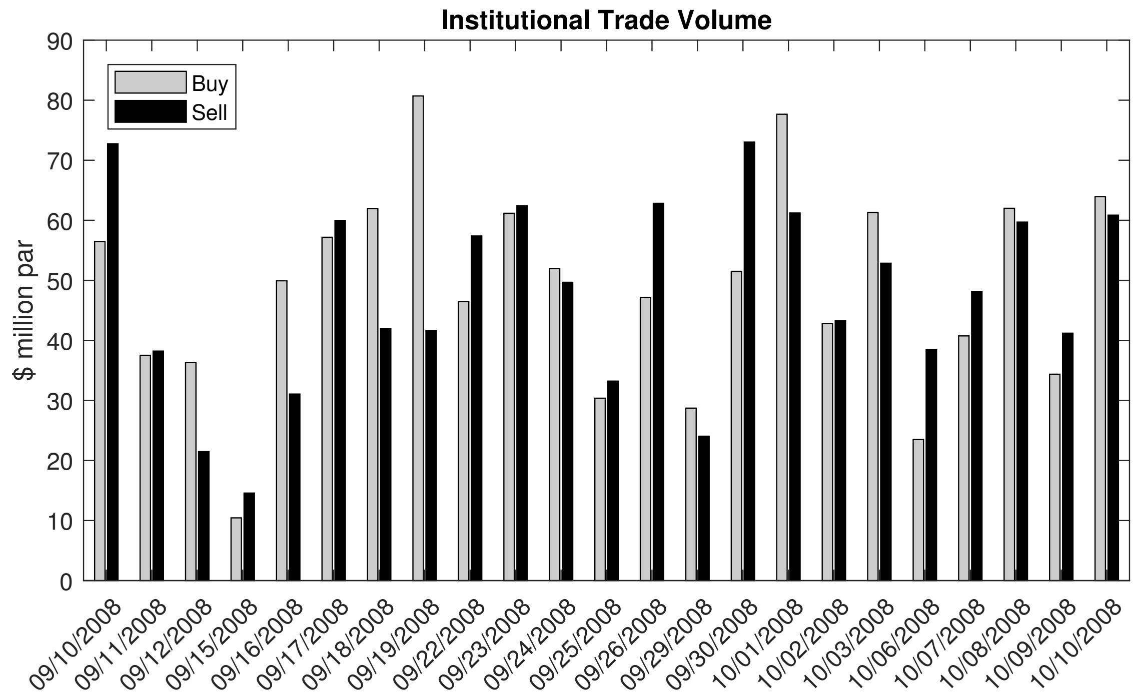


Figure 8: Information transmission across markets related to MBIA

This figure shows the impulse response function (IRF) of variables in a VAR(1) model of stock returns, changes in CDS premium, and returns on bonds insured by MBIA. The response variable is noted with (R), and the shock variable is noted with (S). The shock size is one standard deviation in the shocked variable. The dotted lines represent the point-wise 90% bootstrapped confidence band around the estimated impulse responses. "Stock Return" and "CDS Change" are the daily stock returns and daily changes in the 5-year CDS premium of the given insurer, obtained from CRSP and Datastream respectively. Bond returns are estimated by the GRSR method using trade data from the MRSB.



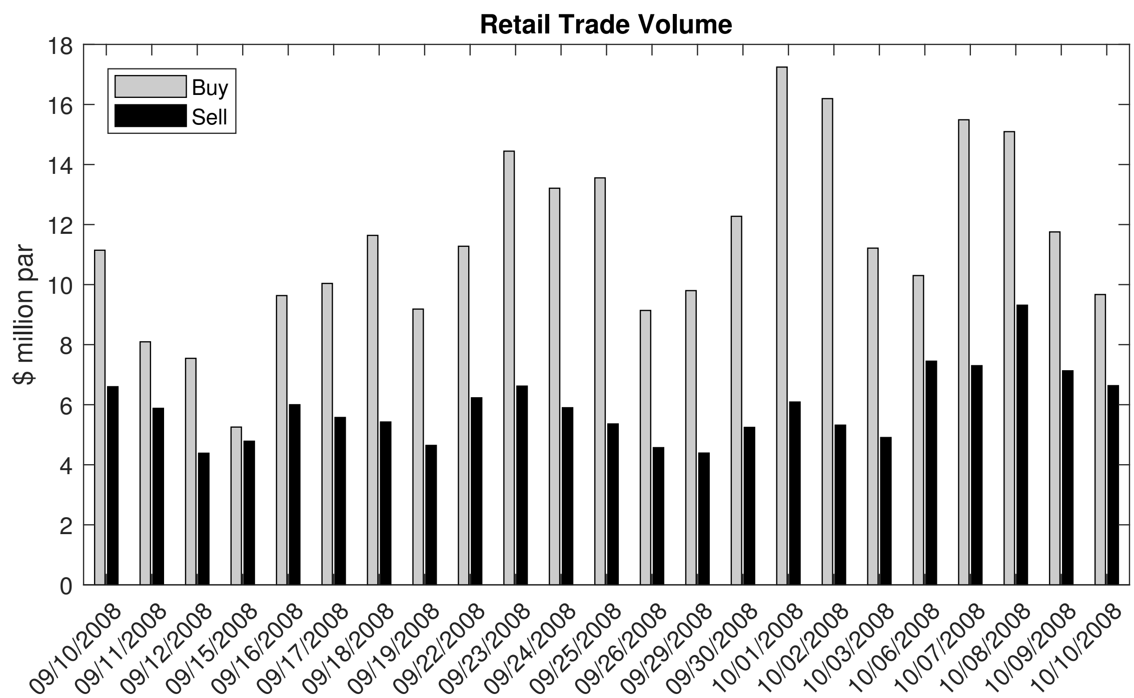


Figure 9: Institutional and retail trading activity in bonds insured by MBIA and AMBAC around Lehman Brothers' bankruptcy

This figure shows daily trading volume of institutional and retail investors around Lehman Brothers' Bankruptcy on September 15, 2008. Trades are classified as institutional if they are sized $100,000 and above. Trades that are smaller than $100,000 are classified as retail. Trade volume is aggregated across all bonds insured by MBIA and AMBAC. Trade data are from the MSRB.