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# Three Essays On: Cancelling Liquidity, Information Generation And Learning By Holding Privately Placed Securities, And Information Generation, Learning And The Trading Dynamics Of Institutional Traders During The 2007-2008 Financial Crisis

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# THREE ESSAYS ON:

# CANCELLING LIQUIDITY,

# INFORMATION GENERATION AND LEARNING BY HOLDING PRIVATELY PLACED SECURITITES,

# AND

# INFORMATION GENERATION, LEARNING AND THE TRADING DYNAMICS OF INSTITUTIONAL TRADERS DURING THE 2007-2008 FINANCIAL CRISIS

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ABSTRACT

This dissertation consists of three essays on cancelling liquidity, information generation and learning by holding private placements, and information generation, learning and the trading dynamics of institutional traders during the 2007-2008 financial crisis. The first essay examines cancellation activity of limit orders. We document a two-fold increase in limit order cancellation activity over the last decade, and study the determinants of cancellations and the change in cancellation activity through time. We also examine the impact of order cancellation on market quality. We use an instrumental variable approach and estimate a simultaneous equations model to overcome simultaneity in the trading process. We find significant differences in cancellation activity in the post Reg NMS environment, and differences in cancellation activity between exchanges. However, we fail to find evidence that the increase in cancellations is detrimental to market quality, despite concerns from regulators and traders.

In the second essay we examine how relationships influence trading behavior. Specifically, we study whether or not financial intermediaries (insurance companies) produce information via relationships with publicly traded firms established by investing in the public firm's privately placed securities (privately placed debt, or equity). We contribute to the literature that asserts that financial intermediaries generate information via relationships that they establish with their clients. We find some evidence that suggests

insurers do generate information via the private placement relationship and use this information to trade.

In the third essay, we study if institutional traders acquire information from the assets that they hold and how this impacts trading decisions around the 2007-2008 financial crisis. Specifically, we test if insurance companies who hold mortgages exhibit different trading behavior in their mortgage backed securities portfolio than insurers who do not hold mortgages. We examine insurers' trading behavior in light of several theories of how institutions trade during crisis periods. We document that insurers who hold mortgages have higher odds of being net disposers of MBSs prior to the crisis, than are other insurers. We also find that, on average, insurers exhibited a flight to safety during the crisis.

DEDICATION

To Elizabeth and Anna Kathryn

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I wish to thank the co-chairs of my committee, Dr. Robert Van Ness and Dr. Andre Liebenberg, for their guidance and mentoring. I am truly indebted to both. I also wish to thank the rest of my committee Dr. Bonnie Van Ness, Dr. Rich Gentry, and Andy Puckett (University of Tennessee). Their guidance has been invaluable. Additionally, I would like to recognize and thank Dr. John Bentley for his assistance and advice through the writing of this dissertation.

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father has been a faculty member and administrator at Mississippi State University, Oklahoma State University, and the University of Arkansas. They inspired me to pursue a career in academics and are great examples of what it means to follow a tri-part mission of research, teaching, and service.

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# ESSAY 1: CANCELLING LIQUIDITY

## 1.1 Introduction

Limit orders play a significant role in the market, making up one or both sides of the bid-ask spread a majority of the time (see Chung, Van Ness, and Van Ness, 1999). Figure 1 of our paper shows that the number of limit order shares submitted and subsequently cancelled more than doubles over the last decade. The premise of our paper is that the increase in cancellations represents a substantive change in the manner in which liquidity is provided to the market. Aided in recent years by computerized trading, liquidity can be added and subtracted from the market in nano-seconds. This ability to quickly add and remove liquidity leads to an increased level of cancellations.

We divide our study into four main sections. First, we study the impact of increased order cancellations on market quality (as measured by effective spread, realized spread, depth at the inside quote, size of the limit order book, or price impact). Second, we study the determinants of cancellation activity and test theoretical predictions of the causes of cancellations. Third, we examine the change in the sensitivity of order cancellations to stock-level market conditions over time and how cancellation activity differs across exchanges. Further, we investigate common, market-level, factors that determine order cancellations, similar to the documented commonality in liquidity[1].

We recognize that our research questions have causality running in both directions, where market quality determines cancellation activity and cancellation activity determines market quality. We address the issue of potential simultaneity in the trading process by

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[1] See Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001), who show, for example, that the spread of a particular stock is influenced by the spread for all other stocks, excluding the stock of interest, which suggests market-level or common factors determine the liquidity of a stock.

[2] See page 47 of the January 14, 2010 SEC CFTC Concept Release on Equity Market structure. The document calls for comments on several aspects of trading strategies that are used in today's market environment including asking for comments on topics such as market structure, policy, dark liquidity, etc.

using an instrumental variable approach and estimate a set of simultaneous equation models. We document changes in the dynamics of cancellation activity over the last decade and differences between exchanges with regard to cancellation activity. However, we find no evidence that the increase in cancellation activity has a detrimental impact on market quality.

The remainder of this paper proceeds as follows: We develop our hypotheses in the next section. We discuss out data sources and resulting sample in Section 3. We present the empirical results in Section 4. Section 5 concludes.

## 1.2 Hypothesis Development:

### *1.2.1 Market Quality and Cancellations:*

Market quality is of significant importance to exchange executives, traders, and regulators, and is the frequent focus of academic research. For example, on January 14, 2010, the Securities and Exchange Commission (SEC) published a Concept Release on Equity Market Structure. Concerned by how quickly liquidity is removed from the market, the document raises questions about requiring traders to stand behind their limit orders for a minimum amount of time – that is, instituting a minimum duration for limit orders.[2] In response to the Flash Crash, the SEC, the Commodity and Futures Trading Commission (CFTC), along with exchange representatives held a joint meeting on June 22, 2010. The purpose was to discuss issues of market quality that arose from the Flash Crash, where orders were cancelled rapidly and size of the order book decreased dramatically. The

[2] See page 47 of the January 14, 2010 SEC CFTC Concept Release on Equity Market structure. The document calls for comments on several aspects of trading strategies that are used in today's market environment including asking for comments on topics such as market structure, policy, dark liquidity, etc.

various exchanges reported on the functionality of their markets during the Flash Crash. In a subsequent report from the SEC and the CFTC dated February, 18. 2011, regulators recommend implementation of a, "uniform fee across all exchange markets that is assessed based on the average of order cancellations to actual transactions effected by a market participant."

In addition to regulators' concerns, institutional traders express concern about unstable liquidity, coining terms such as "false liquidity" and "fake liquidity" to describe orders that appear in the book, but are quickly cancelled. Anecdotally, institutional investors also complain about getting "pennied" and "walked-up the book" when trying to execute their trades. Similarly, traders voice concerns about market quality measures such as price impact. The traders' argument is that a highly liquid market should be able to absorb large trades with minimal price impact. We spoke with a concerned institutional trader who feels that he has a larger price impact, when working his trades, than he did ten years ago.

In light of these concerns, we seek to test whether or not increased cancellation activity has a detrimental effect on market quality. A problem when investigating market quality is there is more than one way to measure market quality. As we discuss in more detail in the Data section below, we consider multiple measures of market quality such as measures of round-trip trading costs, measures of the resiliency of the limit order book, and measures of price impact. We posit the following hypothesis regarding cancellations effect on market quality (stated as a null):

$H_1$: There is no impact on market quality (measured as effective spread, realized spread, depth at the inside quote, size of the limit order book, and price impact) from the increasing level of cancelled limit orders.

*1.2.2 The determinants of Cancellations:*

Having stated that we believe there is a significant change in liquidity provision, we now seek to understand why limit order traders cancel orders. Theoretical literature suggests that limit order traders face risks because they are offering free options to other traders, and must monitor their limit orders to avoid non-execution risk (when prices move away from their orders and their orders become stale, see Copeland and Galai, 1983, and Liu, 2009). According to Liu (2009), limit order traders also face the risk of their orders being "picked off" by more informed traders, and must constantly monitor for changes in market conditions and cancel or modify their orders to avoid these risks. The following theoretical literature guides our choice of predictors of cancellations. Biais and Weill (2009) build a dynamic competitive equilibrium model of the limit order book and describe the dynamics of prices, spreads, order submissions, and cancellations. In the Biais and Weill model, order cancellations increase with the frequency with which traders contact the market. Similarly, in Large (2004), uncertainty about the arrival rate of impatient market order traders can cause cancellations. Liu (2009) builds a model that incorporates other market conditions such as spread, arguing that order cancellations should decrease as spreads widen. Additionally, Liu predicts that larger stocks are associated with more order cancellation activity.

These models lead to the second focus of the paper, which deals with the determinants of cancellation activity. Since the above models describe conditions in the market that are specific to a stock, we refer to the determinants collectively as stock-level market conditions. Stock-level market conditions include measures such as, but not limited to, the number of impatient orders submitted for a particular stock to the market center (measured as the number of market orders and marketable limit orders), the number of limit orders for a particular stock submitted to the market center, the stock's spread at the market center, and the market capitalization of the stock.[3] We form the following hypothesis (stated in the null):

$H_2$: Stock-level market conditions have no impact on order cancellations.

As mentioned previously, cancellation activity changes through time, as evidenced by the doubling of the rate of limit order cancellation (see Figure 1). We argue that one external factor that induces more cancellation activity is the passing of Regulation NMS (Reg NMS) in June, 2005. Among other things, Reg NMS makes the national, market-wide limit order book more accessible (see Petrella, 2009; Smith, 2010 and McInish, Upson, and Wood, 2010). Reg NMS Rule 611 mandates that orders be executed at the best price that is immediately and automatically accessible (Petrella, 2009).[4] This rule opens the door for programmatic trading, which allows for high speed strategies and also allows traders to monitor their submitted orders. With better monitoring, traders can avoid non-execution

[3] See the Methodology section below for a complete list and definition of the stock-level market factors that we include.

[4] There are exemptions to Rule 611, for example, orders that are not immediately and automatically accessible such as orders entered manually by dealers or specialists (Petrella, 2009).

risk and the risk of being picked off by cancelling their orders. We seek to more formally test the assertion of a change in cancellation activity by investigating if there is a change in the sensitivity of cancellation activity to its' determinants (stock-level market conditions) in the pre- and post- Reg NMS environments. To do so, we divide our sample into two periods (pre and post) based on the passing of Reg NMS.

$H_3$: There is no difference in sensitivity of cancellation activity to its determinants (stock-level market conditions) between pre- and post- Reg NMS periods.

We also study whether or not there are differences in cancellation activity between exchanges. Numerous studies document differences between exchanges with regards to measures such as spreads and price impact (Huang and Stoll, 1996), patterns of intraday spreads (see Chan, Christie, and Schultz, 1995; and McInish and Wood, 1992), and quoting behavior (Chung, Van Ness, and Van Ness, 2001). We follow the tradition of comparing across exchanges and investigate whether or not there are differences in cancellations between exchanges. To investigate the differences in cancellation activity across exchanges, we use a series of dummy variables for each exchange, dropping the New York Stock Exchange (NYSE), so that each venue is compared to the NYSE. We form the following hypothesis (stated as a null):

$H_4$: There is no difference in the order cancellation activity between exchanges.

### *1.2.3 Commonality in Cancellations:*

We further investigate if there are common, market wide, factors that determine order cancellations. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Brockman, Chung, and Perignon (2009) show that there are common factors that determine spreads and depths. Specifically, they show that the spread (depth) of a particular stock is influenced by the spreads (depths) of all other stocks, excluding the one of interest. In other words, liquidity provision in a particular stock is influenced by spillover effects from other stocks on the same exchange. This phenomenon is termed commonality in liquidity. We investigate if there is commonality in another aspect of liquidity provision, cancellation activity. We formulate the following hypothesis for cancelling liquidity and follow similar research methods to that of Chordia et al. to test the following hypothesis (stated as a null):

$H_5$: There is no commonality in order cancellations.

## 1.3 Data and Descriptive Statistics:

The main source of data for our study is the SEC's Dash-5 data. We supplement the Dash-5 data with variables such as price and volatility from the Center for Research in Security Prices (CRSP) data. We also obtain variables such as number of trades and average trade size from the Trade and Quote (TAQ) database.

The SEC's rule 605 (formerly known as 11Ac1-5) implemented on November 17, 2000 mandates that market centers make available market quality statistics on a monthly basis. The SEC requires that each market center report stock-level statistics such as orders received, number of shares received, number of shares cancelled, effective spreads, realized spreads, and speed of execution. These variables are reported for groups of order types (market orders, marketable limit orders, inside the quote limit orders, at the quote limit orders, and near the quote limit orders). Each order type classification, is further categorized by order sizes (100-499 shares; 500-1999 shares; 2000-4999 shares; 5000 or more shares). Therefore, while the stratification of the data offers a high level of detail, it necessitates that we aggregate the variables across order types and order size categories to arrive at a market center, stock level data set. For other studies that use the Dash-5 data set and give detailed explanations of the data set, see Boehmer (2005) and Boehmer, Jennings, and Wei (2007).

### *1.3.1 Market Quality Measures:*

To examine the impact of cancellation activity on market quality, we first define our measures of market quality. According to Kyle (1985), the finance literature distinguishes three forms of market liquidity; 1) round-trip transaction costs (typically measured as the bid-ask spread) 2) market depth or the size of the limit order book, and 3) resiliency of the book. We attempt to capture these aspects of market quality by looking at effective spread (a transaction costs measure), depth at the inside quote (a depth measure), size of the limit order book (a size of book measure), realized spread (a resiliency measure) and price impact (a resiliency measure), which are described in more detail below.

Market micro-structure literature uses the transaction cost of a round-trip trade, i.e. bid-ask spread, to measure market quality. Effective spread, as opposed to bid-ask spread, represents a better measure of the out-of pocket cost to a trader of completing a round trip trade, since effective spreads accounts for the execution price and the price improvement that might be obtained. Therefore, we use effective spread, which is reported in the Dash-5 data. The effective spread reported in the Dash-5 data is computed as twice the difference between execution price and the National Best Bid and Offer (NBBO) midpoint. Because this value can be positive or negative, we take the absolute value of effective spread, when performing our analysis.

Another measure of market quality is resilience. A limit order book is considered resilient if it recovers quickly from large trades. There are several factors that can impact the resilience of the limit order book, such as sufficient activity (arrival of limit orders) with sufficient depth to dampen the price impact of large executions. We use depth at the inside quote and size of the limit order book as proxies for resilience. We calculate depth at the inside quote from the Dash-5 data set as follows. We divide the number of shares entered by the number of orders entered for the at-the-quote limit orders to give an average size of each order. We then aggregate across order size categories for each stock by calculating a weighted average where the weight is the number shares executed in the order size category divided by the number of shares executed across all order size categories. To calculate the size of the limit order book we sum the number of shares entered in the "inside the quote," "at the quote," and "near the quote" order type categories (i.e. we aggregate the shares of orders that are intended to enter the limit order book).

Traders who are making large trades are concerned with the price impact that they have while working the trade to enter or exit a position. We therefore consider price impact as one of our market quality measures. We follow Boehmer (2005) to calculate price impact from the Dash-5 data. Price Impact is calculated as half the difference of effective and realized spreads.

$$price\ impact = \ .5(EffectiveSpread - RealizedSpread)$$

In addition to price impact, another measure of the resiliency of the limit order book is realized spread. Realized spread is reported in the Dash-5 data set and is computed as twice the difference between the execution price and the NBBO midpoint five minutes later. A resilient limit order book is not affected by trading and should, all else equal, have a small realized spread. Since both realized spread and price impact can be negative we take the absolute value of these measures when conducting our analysis.

### *1.3.2 Descriptive Statistics*

The sample period for our study is from June, 2001 to December, 2010. In selecting our sample, we apply the following filters to our dataset. First, we remove any records with noticeably incorrect values from Dash-5 such as negative volume executed, negative orders submitted, or negative shares submitted. We also remove records where the market center, the exchange, the date, or the ticker is missing or unidentifiable. Second, we require that the firm be in both the TAQ and CRSP database. Third, the ticker must have a CRSP share code of 10 or 11. Fourth, we require that the stock trade above three dollars. Lastly, we trim the dataset at the one and ninety-ninth percentiles for any variable constructed from Dash-5 data to remove outliers. Our final data set has 1203 NASDAQ-listed stocks and 960 NYSE-listed stocks.

Table 1 lists descriptive statistics for our market quality measures, cancellation measures, and other variables used in our analysis. Our market quality measures are in Panel A. We report a mean effective spread, averaged across all stocks on all market centers, for our sample of $0.047 (median $0.027). Similarly average realized spread is $0.017 (median $0.008), and price impact averages $0.015 (median $0.009). The mean depth is approximately 900 shares (median 534 shares). The statistics for cancellations and cancellation rate are in Panel B. The average cancellation rate for the sample is 44.7%, measured as the number of shares cancelled divided by the number of shares entered for all limit order types. While not a direct comparison, our average cancellation rate seems in line with percentages of orders cancelled reported by Fong and Liu (2009) and Hasbrouck and Saar (2009). Descriptive statistics for the other determinant variables are in Panel C.

Hasbrouck and Saar (2009) and Fong and Liu (2009) document that cancellations are a relatively frequent phenomena. Table 2 reports the mean and median cancellation rate by each year in our sample. There is a noticeable increase over time, doubling from 2001 to 2010. Figure 1, also shows the time trend of the cancellation rate. The increase in the cancellation rate points to a significant change in the nature of liquidity provision in the last decade. In the next section we investigate how this change impacts market quality and study what factors determine cancellation activity.

## 1.4 Empirical Results:

### *1.4.1 Cancellations effect on Market Quality:*

We recognize that hypotheses 1 and 2 have causality running in both directions. For example, we hypothesize that stock-level market conditions, such as effective spread, predict order cancellations, and order cancellations predict effective spreads (where effective spread represents a measure of market quality). To address or work around simultaneity, researchers frequently use techniques such as Granger Causality or introduce lagged variables to establish temporal precedence. For example, it can be argued that effective spread is determined by the level of cancellations in the previous five minute period. The monthly frequency of the Dash-5 data is not suited for using a lagged variable approach because it is unlikely that effective spread is determined by the level of cancellations in the previous month.

We therefore address the issue of simultaneity by using a Two Stage Least Squares (2SLS) method to estimate a two equation simultaneous equation model similar to that used in Hasbrouck and Saar (2011). We use the average market quality measure for stock *j* on all other market centers, excluding market center *i* ($mktqltynotmktctri_{j,t}$) as an instrumental variable for the market quality measure ($mktqlty_{i,j,t}$) of stock *j* on market center *i*,. Similarly, we use cancellations for stock *j* not on market center *i* ($cancelsnotmktctri_{j,t}$) as an instrumental variable for cancellations of stock *j* on market center *i*.[5] We use the following general model:

$$mktqlty_{i,j,t} = a_0 + a_1 lnavgcancels_{i,j,t} + a_2 lnvol_{i,j,t} + a_3 volt_{j,t} + a_4 inverseprc_{j,t} + a_5 tradesize_{j,t} + a_6 mktqltynotmktctri_{j,t} + u$$

[5] Market quality is measured as effective spread, realized spread, depth at the inside quote, size of the limit order book or price impact

$$
\begin{aligned}
&lnavgcancels_{i,j,t} \\
&\qquad = b_0 + b_1 mktqlty_{i,j,t} + b_2 lnvol_{i,j,t} + b_3 volt_{j,t} + b_4(1 - hhi_{j,t}) \\
&\qquad + b_5 lnmktcap_{j,t} + b_6 lnnumorders_{i,j,t} + b_7 lnimpatientorders_{i,j,t} \\
&\qquad + b_8 cancelsnotmktctri_{j,t} + u
\end{aligned}
$$

where $mktqlty_{i,j,t}$ is our market quality measure for stock *j*, on market center *i*, at time *t*. The variable ln$avgcancels_{i,j,t}$ is the natural log of the number of cancellations for stock *j* on market center *i*, at time *t*.

In the model where market quality is our dependent variable, our main variable of interest is ln$avgcancels_{i,j,t}$. In the equation where market quality is the dependent variable we are testing our hypothesis regarding the impact of increasing limit order cancellations on market quality. In this model, we also control for the stock-level characteristics that are shown to impact market quality measures: price ($inverseprc_{i,t}$), volume (ln$vol_{i,j,t}$), volatility ($volt_{i,j,t}$), and trade size ($tradesize_{i,t}$).

In the model where cancellation activity is the dependent variable, we follow the aforementioned theoretical literature in specifying the model (see our development of Hypothesis 2). We use the number of limit orders ($lnnumorders_{i,j,t}$) placed at the market center to proxy for the frequency with which traders contact the market as in Biais and Weill (2009). $lnnumorders_{i,j,t}$ is defined as the natural log of the number of limit orders for stock *j* submitted to market center *i* at time *t.* If $lnnumorders_{i,j,t}$ increases (i.e. traders arriving at higher frequency), then we expect cancellations to increase.

Next, we use the number of market orders and marketable limit orders ($lnimpatientorders_{i,j,t}$) entered at the market center to proxy for the uncertainty in the arrival rate of impatient traders as in Large (2004). We define $lnimpatientorders_{i,j,t}$ as the natural log of the number of market orders and marketable limit orders for stock *j* submitted to market center *i* at time *t*. We contend that an increase in the number of impatient orders (market orders and marketable limit orders) reduces the uncertainty discussed in Large (2004). Hence, $lnimpatientorders_{i,j,t}$ is an inverse proxy of uncertainty, and we expect as $lnimpatientorders_{i,j,t}$ decreases that cancellations will increase.

For the model where effective spread is our market quality measure, our specification is consistent with Liu (2009), who predicts that spread and market capitalization play a role in determining cancellation activity. Following the theoretical predictions of Liu (2009) we expect that cancellations will increase as spreads decrease and as market capitalization increases. We also add other control variables based on previous empirical research investigating the decision to cancel orders, such as trade volume, volatility, and market fragmentation (see, for example, Ellul et al., 2007; Yeo, 2005; Brusco and Gava, 2006; Liu, 2009; Hasbrouck and Saar, 2009; and Fong and Liu, 2010). We include year dummies (not shown) in both the market quality model and the cancellation model to remove any time trend.

We report the results of our analysis of cancellations' impact on market quality in Table 3, Panel A. We estimate the model using five different measures of market quality: effective spread (model 1 – column 3), depth (model 2 – column 4), size of the book (model 3 – column 5), realized spread (model 4 – column 6), and price impact (model 5 – column 7). Our main variable of interest in our market quality model is $lnavgcancels_{i,j,t}$. We start our discussion of the impact of cancellations on market quality by examining our measure of round trip trading costs, effective spread. Our estimation of Model 1 shows a negative relation between cancellations and effective spread, implying increased levels of cancellations are associated with improved market quality. However, the economic significance of the improvement is small. For example, a ten percent increase in cancellations is associated with one tenth of a cent ($0.001) decrease in effective spread.

Another of our market quality measures, resiliency of the limit order book, is proxied by depth at the inside quotes and size of the limit order book. In model 2, where the dependent variable is depth, we find that cancellations have a positive impact, increasing depth at the inside quote. To illustrate, a ten percent increase in cancellations increases depth by 2.2%. Consider the average depth at the inside quote reported in Table 1. A ten percent increase in cancellations means that depth increases by about 20 shares (.022*900 shares). We find that cancellations are positively associated with the size of the limit order book. Model 3 (column 5) estimates imply that a ten percent increase in cancellations is associated with a 14.26 percent increase in the limit order book. Our estimation results thus far are inconsistent with an increase in cancellations being associated with reduced market quality.

Besides having sufficient size and depth of the limit order book, another aspect of the resiliency of the limit order book is how much (or how little) a trade moves prices. In our final analysis of the impact of cancellations on market quality, we consider two additional measures of the resiliency of the limit order book: realized spread and price impact in models 4 and 5, respectively. The results are mixed from the standpoint of statistical significance, with cancellations leading to smaller realized spreads but larger price impacts. However, the economic significance of the coefficients is minuscule. Overall, we fail to find evidence that the increased level of cancellations has a meaningful detrimental impact on market quality despite concerns from regulators and traders.

### *1.4.2 The determinants of cancellations:*

We test the theoretical predictions of the determinants on cancellations with hypothesis 2. We find a positive relation between effective spread and the level of cancellation activity (see Table 3, Panel B). This finding is consistent with previous empirical work such as Yeo (2005) and Ellul, Holden, Jain, and Jennings (2007), but is inconsistent with the theoretical predictions of Liu (2009). In Liu's model, wide spreads are associated with decreased marginal benefit to monitoring the limit order, and therefore, are associated with decreased cancellation or revision activity. We find the opposite, that increased levels of cancellations are associated with more narrow spreads.

Biais and Weill (2009) predict that order cancellations increase when the frequency with which traders contact the market increases. We proxy for the frequency with which traders contact the market with the number of limit orders placed within a month ($lnnumorders_{i,j,t}$). If more traders are accessing the market within a set time frame, the frequency with which they are contacting the market should also increase. We find a positive effect between the number of orders and number of cancellations in all five model specifications. Therefore, our results are consistent with the predictions of Biais and Weill (2009).

Large (2004) predicts that uncertainty about the arrival rate of impatient traders (market order and marketable limit order traders) can lead to increased cancellations. If fewer market and marketable limit orders are submitted, then limit order traders' uncertainty regarding the arrival rate of impatient traders should increase and lead to more cancellations. Therefore, we proxy for uncertainty in arrival rate by using the number of market and marketable limit orders submitted to market center *i*, for stock *j*, in month *t*. We find that a decrease in the number of impatient orders (i.e. increased uncertainty) of ten percent is associated with an increase in cancellations of 2.16 percent (-10*-2.16). Hence, the results of our analyses favor of the theoretical prediction of Large (2004).

*1.4.3 The evolution of liquidity provision:*

In this section we study the relation of changes in the patterns of cancellations with respect to the determinants through time. We suggest that the implementation of Reg NMS makes the limit order book more accessible and further opens a door for programmatic trading to monitor market conditions and build trading algorithms. If computerized trading allows limit order traders to more effectively monitor their limit orders, then we expect that cancellation activity may differ later in our sample period. To test if there is a change in sensitivity following the implementation of Reg NMS, we create an indicator variable (*igeRegNMS*), which is one if the time period is after the implementation of Reg NMS and zero otherwise. We then create a series of interaction terms, interacting the *igeRegNMS* variable with each determinant of cancellations. The interaction terms allow us to test if there are changes in sensitivity between cancellations and the determinants of cancellations in the pre- and post-Reg NMS periods. We expect that if the post-Reg NMS period is associated with better monitoring and more cancellations, then the coefficients of the interaction terms will be statistically significant and in the direction observed in Table 3, Panel B. We estimate the following simultaneous equations model via a 2SLS method with year dummies (not shown) added to both the market quality model and the cancellations model to control for a potential time trend:

$$
\begin{aligned}
|effspread|_{i,j,t} \\
&= a_0 + a_1 lnavgcancels_{i,j,t} + a_2 lnvol_{i,j,t} + a_3 volt_{j,t} + a_4 inverseprc_{j,t} \\
&+ a_5 tradesize_{j,t} + a_6 |effspreadnotmktctri|_{j,t} + u
\end{aligned}
$$

$$
\begin{aligned}
lnavgcancels_{i,j,t} \\
&= b_0 + b_1 |effspread|_{i,j,t} * igeRegNMS + b_2 lnvol_{i,j,t} * igeRegNMS \\
&+ b_3 volt_{j,t} * igeRegNMS + b_4 hhi_{j,t} * igeRegNMS + b_5 lnnumorders_{i,j,t} \\
&* igeRegNMS + b_6 lnimpatientorders_{i,j,t} * igeRegNMS + b_7 lnmktcap_{i,j,t} \\
&* igeRegNMS + b_8 igeRegNMS + b_9 |effspread|_{i,j,t} + b_{10} lnvol_{i,j,t} \\
&+ b_{11} volt_{j,t} + b_{12} hhi_{j,t} + b_{13} lnnumorders_{i,j,t} + b_{14} lnimpatientorders_{i,j,t} \\
&+ b_{15} lnmktcap_{j,t} + b_{16} cancelsnotmktctri_{j,t} + u
\end{aligned}
$$

The results of our analysis are in Table 4. The indicator variable *igeRegNMS* shows that the number of cancellations is 109 percent larger (100*[exp(.739)-1]) in the post-Reg NMS period. We find that cancellations are significantly more sensitive to increases in effective spread and volatility in the post-Reg NMS environment compared to the earlier period. Cancellations are also more sensitive for larger stocks and stocks that have more impatient orders submitted in the post-Reg NMS period compared to the earlier period, a result that is consistent with the predictions of Liu (2009) and Biais and Weill (2009). Overall, the results of Panel B in Table 3 and Table 4 lead us to conclude that a change in the nature of liquidity provision occurs between the pre and post periods with regards to cancellations.

*1.4.4 Differences in Cancellations between exchanges:*

Next we investigate if exchanges exhibit different cancellation activity (hypothesis 4). The Dash-5 data lists the exchange where each market center reports trades. All major exchanges are represented in the data, and we create indicators for each exchange (NYSE, NASDAQ, Amex, Boston, National (NSX), International (ISE), Chicago, ARCA, CBOE, and BATs) dropping the New York Stock Exchange (NYSE) so that coefficients are interpreted in relation to the NYSE.[6] We estimate the following model via 2SLS and include dummy variables for the year (not shown) to account for a potential time trend:

[6] For NASDAQ and Bats there are multiple exchange codes. NASDAQ has exchange codes Q, T, and X. Exchange code X is NASDAQ OMX which used to be the Philadelphia Stock Exchange. Bats has exchange codes Z and Y. For our analysis, we created dummy variables for each exchange code.

$$
\begin{aligned}
&|effspread|_{i,j,t} \\
&\qquad = a_0 + a_1 lnavgcancels_{i,j,t} + a_2 lnvol_{i,j,t} + a_3 volt_{j,t} + a_4 inverseprc_{j,t} \\
&\qquad + a_5 tradesize_{j,t} + a_6 |effspreadnotmktctri|_{j,t} + u
\end{aligned}
$$

$$
\begin{aligned}
&lnavgcancels_{i,j,t} \\
&\qquad = b_0 + b_1 mktqlty_{i,j,t} + b_2 lnvol_{i,j,t} + b_3 volt_{j,t} + b_4 (1 - hhi_{j,t}) \\
&\qquad + b_5 lnmktcap_{j,t} + b_6 lnnumorders_{i,j,t} + b_7 lnimpatientorders_{i,j,t} \\
&\qquad + b_8 cancelsnotmktctri_{j,t} + b_9 iAmex + b_{10} iBoston + b_{11} iNational \\
&\qquad + b_{12} iISE + b_{13} iChicago + b_{14} iARCA + b_{15} iQNasdaq + b_{16} iTNasdaq \\
&\qquad + b_{17} iCBOE + b_{18} iNasdaqOMX + b_{19} iBATS + b_{20} iYBATS + u
\end{aligned}
$$

The results of our estimation are in Table 5. All exchange indicator variables are statistically significant, which shows that the cancellation activity on each exchange is different than cancellation activity on the NYSE (the omitted exchange). Additionally, results of a Wald test (unreported) between each pair-wise combination reveals that cancellation activity is different on all exchanges from all others. Therefore, we conclude that exchanges exhibit differences in cancellation activity.

*1.4.5 Commonality in Cancellation Rates:*

Finally, to test for commonality in order cancellations, we follow Chordia et al. (2000) and Brockman, Chung, and Perignon (2009). We estimate the following model using firm-by-firm time series regressions:

$$
\begin{aligned}
\Delta CancelRate_{j,t} \\
&= \beta_0 + \beta_1 \Delta CancelRate_{E,t} + \beta_2 \Delta CancelRate_{E,t+1} + \beta_3 \Delta CancelRate_{E,t-1} \\
&+ \beta_4 Return_{E,t} + \beta_5 Return_{E,t+1} + \beta_6 Return_{E,t-1} + \beta_7 \Delta Volt_{j,t} + u
\end{aligned}
$$

where $CancelRate_{j,t}$ is the volume-weighted average (i.e. aggregated to the stock level) cancellation rate for firm j, in month t. Our main variable of interest, $CancelRate_{E,t}$ is the equally-weighted average cancellation rate of all other stocks on exchange E, excluding stock *j*, in month *t*. We also add a series of control variables. $Return_{E,t}$ is the equally-weighted average return of all other stocks on exchange E, excluding stock *j*, in month *t*. Lead and lag values of the exchange-level variables are also included. $Volt_{j,t}$ is the average volatility of stock *j* in month *t*. Following the model specification of Chordia et al. (2000) and Brockman et al. (2009), the control variables are included to isolate the effect of the commonality factor (the contemporaneous *CancelRate* variable) by holding constant market-wide price movements and firm specific volatility. The symbol Δ denotes the proportional change in the variable across successive trading months.

The results of the firm-by-firm estimation are in Table 6. The primary variable of interest is the contemporaneous cancellation rate and its corresponding coefficient ($\beta_1$). If $\beta_1$ is positive, then the stock's cancellation rate is influenced by the cancellation rate of all other stocks on the exchange, i.e. there is a spillover effect. Table 6 reports the percentage of stocks where $\beta_1$ is positive (column 4), not significantly different from zero (column 5), and negative (column 6). We also report means and medians for the coefficients and $R^2$s for the firm-by-firm regressions.

We find that all eleven exchanges have positive median coefficients, and that ten of eleven have positive mean coefficients. Eight of the eleven exchanges have ten percent or more of their firms with positive coefficients (see column 4). The NYSE leads this trend with 70.6 percent of firms exhibiting positive coefficients. Our findings reject the null hypothesis that there are no common, market wide factors that influence the cancellation activity of a particular stock, and conclude that there is commonality in the cancellation rates.

## 1.5 Conclusion:

We document a significant change in the nature of liquidity provision. The rate at which shares of limit orders are submitted and subsequently cancelled increases two-fold over the last decade. Additionally, cancellation activity reacts to its determinants differently in the post-Reg NMS environment than in the earlier period.

We believe our study is timely in light of the continued discussion by regulators, exchange officials, and traders concerning false liquidity and resulting market quality. The debate is heated and evidence is largely anecdotal with little concrete evidence on the impact of the changing nature of liquidity provision. We contribute to this discussion by providing empirical evidence that speaks to concerns that have been raised. We find no evidence that the increase in cancellation activity results in harmful effects on market quality.

**Table 1**
This table presents summary statistics for our sample. Panel A reports summary statistics for the market quality measures used in the study. $Effspread_{mktctri}$ is the effective spread of liquidity demanders (market and marketable limit orders) on market center i, $RelSpread_{mktctri}$ is the realized spread of liquidity demanders on market center i, $DepthAtQuote_{mktctri}$ is the average order size of quotes submitted at the quote on market center i, $AvgSizeOfBook_{mktctri}$ is the sum of the number of shares entered via limit orders to market center i, $PriceImpact_{mktctri}$ is the price impact measured as half of the difference between effective spread and realized spread at market center i. Panel B reports summary statistics for cancellations ($Cancels_{mktctri}$) at market center i and the cancellation rate ($CancelRate_{mktctri}$), measured as number of shares cancelled divided by number of shares entered, at market center i. Panel C reports summary stats for control variables used in the study. $Volume_{mktctri}$ is the sum of the number of shares executed at market center i, *Volatility* is measured by the standard deviation of price as reported in the TAQ database. *TradeSize* is the monthly average trade size measured from TAQ. *Herfindahl Index* is Herfindahl Index to measure the fragmentation of trading of a stock. $\#of\ Orders_{mktctri}$ is the sum of the number of limit orders submitted to market center i. *Impatient Orders* is the sum of the number of market and marketable limit orders submitted to market center i. *MktCap* is the market capitalization of stock j calculated from the CRSP database.

| Panel A: Market Quality Summary Stats | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Mean | $25^{th}$ Pctl | Median | 75th Pctl | Std Dev | N |
| $Effspread_{mktctri}$ | 0.047 | 0.014 | 0.027 | 0.053 | 0.062 | 2,746,800 |
| $RelSpread_{mktctri}$ | 0.017 | -0.006 | 0.008 | 0.031 | 0.060 | 2,746,800 |
| $DepthAtQuote_{mktctri}$ | 899.141 | 229.063 | 534.571 | 1,111.430 | 1,036.010 | 2,160,781 |
| $AvgSizeOfBook_{mktctri}$ | 3,628,687.720 | 7,817.000 | 64,843.000 | 1,099,619.000 | 11,743,895.600 | 2,746,763 |
| $PriceImpact_{mktctri}$ | 0.015 | 0.002 | 0.009 | 0.023 | 0.029 | 2,746,800 |

| Panel B: Cancellation Summary Stats | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Mean | 25th | Median | 75th | Std | N |
| $Cancels_{mktctri}$ | 3,249,692.790 | 1,050.000 | 24,490.000 | 850,515.000 | 10,936,007.660 | 2,746,763 |
| $CancelRate_{mktctri}$ | 0.447 | 0.079 | 0.416 | 0.790 | 0.358 | 2,551,456 |

| Panel C: Control Variables Summary Stats | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Mean | 25th | Median | 75th | Std | N |
| $Volume_{mktctri}$ | 477,824.010 | 10,600.000 | 51,460.000 | 249,135.000 | 1,438,357.290 | 2,746,800 |
| Volatility | 0.212 | 0.117 | 0.174 | 0.257 | 0.237 | 2,746,800 |
| TradeSize | 299.402 | 160.063 | 195.981 | 309.126 | 283.277 | 2,746,798 |
| Herfindahl Index | 0.390 | 0.204 | 0.271 | 0.553 | 0.249 | 2,746,800 |
| $\#\ of\ Orders_{mktctri}$ | 16,884.900 | 74.000 | 503.000 | 6,586.000 | 50,103.920 | 2,746,800 |
| Impatient Orders | 2,045.250 | 39.000 | 209.000 | 1,304.000 | 5,235.280 | 2,746,800 |
| MktCap | 8,055,867.000 | 492,012.800 | 1,381,711.140 | 4,685,124.120 | 25,890,517.440 | 2,745,435 |

**Table 2**
This table lists descriptive statistics for cancellation rates by year.

| Year | Mean | Median | Std | Minimum | Maximum |
|---|---|---|---|---|---|
| 2001 | 0.291 | 0.207 | 0.299 | 0 | 0.998 |
| 2002 | 0.318 | 0.241 | 0.310 | 0 | 0.998 |
| 2003 | 0.399 | 0.326 | 0.344 | 0 | 0.998 |
| 2004 | 0.396 | 0.327 | 0.341 | 0 | 0.998 |
| 2005 | 0.380 | 0.319 | 0.332 | 0 | 0.998 |
| 2006 | 0.351 | 0.297 | 0.312 | 0 | 0.998 |
| 2007 | 0.376 | 0.301 | 0.332 | 0 | 0.998 |
| 2008 | 0.478 | 0.515 | 0.359 | 0 | 0.998 |
| 2009 | 0.528 | 0.589 | 0.366 | 0 | 0.998 |
| 2010 | 0.604 | 0.745 | 0.367 | 0 | 0.998 |

**Table 3**
This table presents the results of: 1) an analysis of cancellations affect on market quality and 2) the results of the analysis of the determinants of cancellations. Due to simultaneity, we estimate the following simultaneous equations model via a two stage least squares (2SLS) method.

$$mktqlty_{i,j,t} = a_1 + a_2 lnavgcancels_{i,j,t} + a_3 lnvol_{i,j,t} + a_4 volt_{j,t} + a_5 inverseprc_{j,t} + a_6 tradesize_{j,t} + a_7 mktqltynotmktctri_{j,t} + u$$
$$lnavgcancels_{i,j,t} = b_1 + b_2 mktqlty_{i,j,t} + b_3 lnvol_{i,j,t} + b_4 volt_{j,t} + b_5 (1 - hhi_{j,t}) + b_6 lnmktcap_{j,t} + b_7 lnnumorders_{i,j,t} + b_8 lnimpatientorders_{i,j,t} + b_9 cancelsnotmktctri_{j,t} + u$$

As an instrumental variable for our market quality measure at market center i, we use the average market quality measure across all other market centers except market center i. Likewise, as an instrumental variable for cancellations at market center i, we use the average cancellations at all other market centers except market center i. The market quality measure ($mktqlty_{i,j,t}$) is measured as absolute value of effective spread in model [1], the natural log of depth at the inside quote in model [2], the natural log of the size of the limit order book in model [3], absolute value of realized spread in model [4], and absolute value of price impact in model [[5]. Year dummies are included (not shown) to both models to control for a time trend. Panel A holds the coefficients and p-values from the market quality model. Panel B reports the coefficients and p-values from the cancellations model.

Panel A: Results of Market Quality Model

| | | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|---|
| a1 | Intercept | 0.145*** | 1.580*** | -13.138*** | 0.178*** | 0.086*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a2 | $lnavgcancels_{i,j,t}$ | -0.010*** | 0.229*** | 1.426*** | -0.003*** | 0.003*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a3 | $lnvol_{i,j,t}$ | -0.001*** | 0.148*** | 0.944*** | -0.008*** | -0.002*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a4 | $volt_{j,t}$ | 0.003*** | -0.078*** | -0.070*** | 0.024*** | 0.018*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a5 | $inverseprc_{j,t}$ | 0.004*** | 2.077*** | 0.538*** | -0.065*** | -0.103*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a6 | $tradesize_{j,t}$ | 0.000*** | 0.000*** | 0.000*** | 0.000*** | -0.004*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| a7 | $mktqltynotmktctri_{j,t}$ | 0.649*** | 0.001*** | 0.000*** | 0.003*** | 0.006*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |

**Table 3 cont**

Panel B: Results of Cancellations Model

| | | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|---|
| b1 | Intercept | 5.069*** | 3.555*** | 8.882*** | 5.541*** | 11.117*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b2 | $\vert effspread\vert_{i,j,t}$ | 1.046*** | | | | |
| | | (<.0001) | | | | |
| | $lndepthatlimit_{i,j,t}$ | | 0.379*** | | | |
| | | | (<.0001) | | | |
| | $lnsizeofbook_{i,j,t}$ | | | 0.156** | | |
| | | | | (0.003) | | |
| | $\vert respread\vert_{i,j,t}$ | | | | -6.470*** | |
| | | | | | (<.0001) | |
| | $\vert priceimpact\vert_{i,j,t}$ | | | | | -23.428*** |
| | | | | | | (<.0001) |
| b3 | $lnvol_{i,j,t}$ | -0.225*** | -0.259*** | 0.000*** | -0.227*** | 0.000*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b4 | $volt_{j,t}$ | -0.298*** | -0.157*** | -0.057*** | -0.251*** | -0.055*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b5 | $1\text{-}hhi_{j,t}$ | -0.629*** | -0.580*** | -1.291*** | -0.592*** | -1.267*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b6 | $lnnumorders_{i,j,t}$ | 1.859*** | 1.779*** | 0.000*** | 1.864*** | 0.000*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b7 | $lnimpatientorders_{i,j,t}$ | -0.216*** | -0.124*** | 1.559*** | -0.223*** | 1.559*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b8 | $lnMktCap_{j,t}$ | -0.239*** | -0.260*** | -0.637*** | -0.249*** | -0.635*** |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| b9 | $cancelsnotmktctri_{j,t}$ | 0.000*** | 0.000*** | 0.000** | 0.000*** | 0.000*** |
| | | (<.0001) | (<.0001) | (0.048) | (<.0001) | (<.0001) |

**Table 4**
This table reports the results of an analysis examining whether the sensitivity of cancellations to its' determinants changes after the implementation of Reg NMS. We estimate the following simultaneous equations model via 2SLS:

$$|effspread|_{i,j,t} = a_0 + a_1 lnavgcancels_{i,j,t} + a_2 lnvol_{i,j,t} + a_3 volt_{j,t} + a_4 inverseprc_{j,t} + a_5 tradesize_{j,t} + a_6 |effspreadnotmktctri|_{j,t} + u$$

$$lnavgcancels_{i,j,t} = b_0 + b_1 |effspread|_{i,j,t} * igeRegNMS + b_2 lnvol_{i,j,t} * igeRegNMS + b_3 volt_{j,t} * igeRegNMS + b_4 hhi_{j,t} * igeRegNMS + b_5 lnnumorders_{i,j,t} * igeRegNMS + b_6 lnimpatientorders_{i,j,t} * igeRegNMS + b_7 lnmktcap_{i,j,t} * igeRegNMS + b_8 igeRegNMS + b_9 |effspread|_{i,j,t} + b_{10} lnvol_{i,j,t} + b_{11} volt_{j,t} + b_{12} hhi_{j,t} + b_{13} lnnumorders_{i,j,t} + b_{14} lnimpatientorders_{i,j,t} + b_{15} lnmktcap_{j,t} + b_{16} cancelsnotmktctri_{j,t} + u$$

Where igeRegNMS is an indicator variable that is 1 if the date is greater than the implementation of RegNMS (June, 2005), and zero otherwise. Year dummies are included (not shown) to both models to control for a time trend. Since our main concern is the model for cancellations, we omit the coefficient estimates for the first equation, and only report the coefficients for the second model. P-values are reported in parenthesis.

| | | $lnavgcancels_{i,j,t}$ |
|---|---|---|
| b0 | Intercept | 3.491*** |
| | | (<.0001) |
| b1 | $\|effspread\|_{i,j,t}$ *igeRegNMS | 1.483*** |
| | | (<.0001) |
| b2 | $lnvol_{i,j,t}$ *igeRegNMS | -0.279*** |
| | | (<.0001) |
| b3 | $volt_{j,t}$ *igeRegNMS | 0.089*** |
| | | (<.0001) |
| b4 | $hhi_{j,t}$*igeRegNMS | -0.814*** |
| | | (<.0001) |
| b5 | $lnnumorders_{i,j,t}$ *igeRegNMS | -0.250*** |
| | | (<.0001) |
| b6 | $lnimpatientorders_{i,j,t}$ *igeRegNMS | 0.443*** |
| | | (<.0001) |
| b7 | $Lnmktcap_{j,}t$*igeRegNMS | 0.135*** |
| | | (<.0001) |
| b8 | igeRegNMS | 0.739*** |
| | | (<.0001) |
| b9 | $\|effspread\|_{i,j,t}$ | 0.093* |
| | | (0.061) |
| b10 | $lnvol_{i,j,t}$ | -0.003 |
| | | (0.309) |
| b11 | $volt_{j,t}$ | -0.379*** |
| | | (<.0001) |
| b12 | $hhi_{j,t}$ | 0.998*** |
| | | (<.0001) |
| b13 | $lnnumorders_{i,j,t}$ | 2.053*** |
| | | (<.0001) |
| b14 | $lnimpatientorders_{i,j,t}$ | -0.578*** |
| | | (<.0001) |
| b15 | $lnMktCap_{j,t}$ | -0.307*** |

| | | |
|---|---|---|
| | | (<.0001) |
| b16 | $cancelsnotmktctri_{j,t}$ | 0.000*** |
| | | (<.0001) |

**Table 5**
This table presents the results of an analysis of whether there are differences in cancellation activity between exchanges. We estimate the following simultaneous equations model via 2SLS:

$$|effspread|_{i,j,t} = a_0 + a_1 lnavgcancels_{i,j,t} + a_2 lnvol_{i,j,t} + a_3 volt_{j,t} + a_4 inverseprc_{j,t} + a_5 tradesize_{j,t} + a_6 |effspreadnotmktctri|_{j,t} + u$$

$$lnavgcancels_{i,j,t} = b_0 + b_1 mktqlty_{i,j,t} + b_2 lnvol_{i,j,t} + b_3 volt_{j,t} + b_4 (1 - hhi_{j,t}) + b_5 lnmktcap_{j,t} + b_6 lnnumorders_{i,j,t} + b_7 lnimpatientorders_{i,j,t} + b_8 cancelsnotmktctri_{j,t} + b_9 iAmex + b_{10} iBoston + b_{11} iNational + b_{12} iISE + b_{13} iChicago + b_{14} iARCA + b_{15} iQNasdaq + b_{16} iTNasdaq + b_{17} iCBOE + b_{18} iNasdaqOMX + b_{19} iBATS + b_{20} iYBATS + u$$

Where indicator variables for the different exchanges are included. For example iAmex is one is the exchange is Amex and zero otherwise. Year dummies are also included (not shown) in both models to control for a time trend. P-values are reported in parenthesis.

| | | lncancels |
|---|---|---|
| b0 | Intercept | 0.038*** |
| | | (<.0001) |
| b1 | $\vert effspread\vert_{i,j,t}$ | -0.001*** |
| | | (<.0001) |
| b2 | $lnvol_{i,j,t}$ | 0.000*** |
| | | (<.0001) |
| b3 | $volt_{j,t}$ | 0.001*** |
| | | (<.0001) |
| b4 | $(1\text{-}hhi)_{j,t}$ | 0.009*** |
| | | (<.0001) |
| b5 | $lnMktCap_{j,t}$ | 5.362*** |
| | | (<.0001) |
| b6 | $lnnumorders_{i,j,t}$ | 0.000*** |
| | | (<.0001) |
| b7 | $lnimpatientorders_{i,j,t}$ | 0.708*** |
| | | (<.0001) |
| b8 | $cancelsnotmktctri_{j,t}$ | 1.246*** |
| | | (<.0001) |
| b9 | iAmex | -0.232*** |
| | | (<.0001) |
| b10 | iBoston | -0.319*** |
| | | (<.0001) |
| b11 | iNational | -0.486*** |
| | | (<.0001) |
| b12 | iISE | 1.865*** |
| | | (<.0001) |
| b13 | iChicago | -0.201*** |
| | | (<.0001) |
| b14 | iARCA | -0.226*** |
| | | (<.0001) |
| b15 | iQNasdaq | 0.000*** |
| | | (<.0001) |
| b16 | iTNasdaq | 1.463*** |
| | | (<.0001) |
| b17 | iCBOE | -4.367*** |

| | | |
|---|---|---|
| | | (<.0001) |
| b18 | iNasdaqOMX | 0.723*** |
| | | (<.0001) |
| b19 | iBATS | -0.755*** |
| | | (<.0001) |
| b20 | iYBATS | 0.878*** |
| | | (<.0001) |

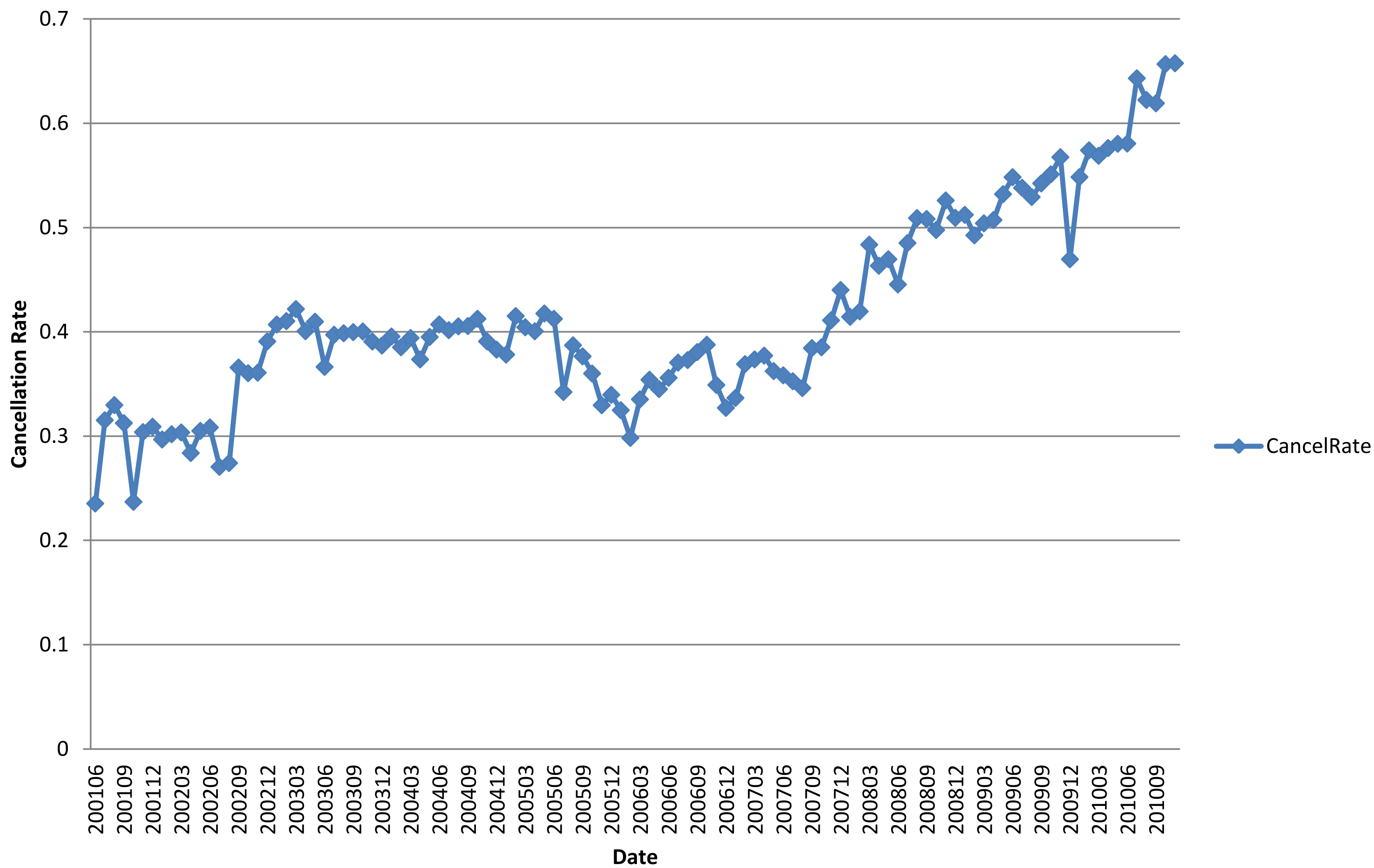
**Table 6**
Reports the results of firm by firm time-series regressions which are estimated using the following model:

$$\Delta CancelRate_{j,t} = \beta_0 + \beta_1 \Delta CancelRate_{E,t} + \beta_2 \Delta CancelRate_{E,t+1} + \beta_3 \Delta CancelRate_{E,t-1} + \beta_4 Return_{E,t} + \beta_5 Return_{E,t+1} + \beta_6 Return_{E,t-1} + \beta_7 \Delta Volt_{j,t} + u$$

Where $CancelRate_{j,t}$ is the volume weighted average (i.e. aggregated to the stock level) cancellation rate for firm j, in month t. $CancelRate_{E,t}$ is the equally weighted average cancellation rate of all other stocks on exchange E, excluding stock *j*, in month *t*. $Return_{E,t}$ is the equally weighted average return of all other stocks on exchange E, excluding stock *j*, in month *t*. Lead and lag values of the exchange-level variables are also included. $Volt_{j,t}$ is the average volatility of stock *j* in month *t*. The symbol Δ denotes the proportional change in the variable across successive trading months. The main variable of interest in the above model is $\beta_1$. The second and third columns report the average and the median for the $\beta_1$ coefficients. Columns 4,5,6 and 7 report the percentage of firms with positive and significant coefficients, percentage of firms with positive but not significant coefficients, percentagae of firms with negative but not significant coefficients, and percentage of firms with negative and significant coefficients, respectively. The last two columns report the average and median $R^2$'s for the firm by firm regressions.

| Exchange | Avg. Coeff. | Median Coeff. | Significantly Positive Coefficient | Coefficient Not Significantly Diff. from Zero | Significantly Negative Coefficient | Avg $R^2$ | Median $R^2$ |
|---|---|---|---|---|---|---|---|
| Amex | 0.932 | 0.665 | 30.120 | 68.675 | 1.205 | 0.285 | 0.235 |
| Boston | 8.469 | 1.467 | 4.811 | 92.44 | 2.749 | 0.343 | 0.257 |
| National | 3.744 | 1.254 | 26.061 | 73.091 | 0.848 | 0.620 | 0.649 |
| International | 0.782 | 0.572 | 8.269 | 91.455 | 0.276 | 0.416 | 0.399 |
| Chicago | 2.368 | 1.159 | 16.677 | 82.128 | 1.195 | 0.277 | 0.232 |
| NYSE | 1.123 | 0.899 | 70.576 | 29.317 | 0.107 | 0.815 | 0.998 |
| NYSE ARCA | 0.913 | 0.915 | 42.792 | 57.107 | 0.102 | 0.169 | 0.138 |
| Nasdaq Q | 0.693 | 0.677 | 18.633 | 80.54 | 0.827 | 0.260 | 0.236 |
| Nasdaq T | 0.976 | 0.093 | 26.670 | 73.182 | 0.147 | 0.212 | 0.175 |
| CBOE | 1.144 | 0.572 | 11.700 | 86.608 | 1.692 | 0.553 | 0.538 |
| Nasdaq OMX | -0.423 | 0.552 | 6.615 | 92.218 | 1.167 | 0.422 | 0.375 |
| BATS | 1.198 | 1.238 | 57.321 | 42.453 | 0.226 | 0.624 | 0.651 |

**Figure 1: Cancellation Rate by month**



# ESSAY 2: INFORMATION GENERATION AND LEARNING BY HOLDING PRIVATELY PLACED SECURITITES

## 2.1 Introduction

There is growing interest in how relationships or affiliations affect the flow of information among financial market institutions and how this information is used to trade. For example, Massa and Rehman (2008) study portfolio holdings of bank affiliated mutual funds and find that these mutual funds appear to be the beneficiaries of information generated by the bank in the corporate loan market, increasing their holdings in the firms that borrow from the bank. Ivashina and Sun (2011) and Massoud, Nandy, Saunders, and Song (2011) report additional evidence that supports the passage of information generated from the syndicated loan market, where members of the syndicate use the loan-related information to trade in the equity of the borrowing firm. Bodnaruk, Massa, and Simonov (2009) and Jegadeesh and Tang (2010) report evidence that when a fund is affiliated or has a relationship with a merger advisor, information is passed and used to trade in the target firm. These studies emphasize how relationships can be a conduit for information flow and can impact trading decisions made by financial market institutions.

The purpose of this paper is to extend the research on how relationships affect trading by examining relationships established in the market for privately placed securities. Specifically, we study insurance companies who establish relationships with publicly traded companies by investing in privately placed securities issued by the publicly traded firm. As we contend below, there is reason to believe that relationships established in the market for private placements generate information about the issuing firm, and in turn this information is used to trade in the public equity of the firm. We examine two types of private relationships; 1) private debt relationships and 2) private equity relationships. To examine if information is generated via the relationship we measure the performance of trades (in the public equity of the issuing firm) when there is a private relationship (we shall refer to these trades as "associated trades") and when there is not (we shall refer to these trades as "unassociated trades"). We also compare the performance of trades associated with private equity relationships to the performance of trades associated with private debt relationships.

Previous studies that have examined how relationships affect trading have typically relied on quarterly data from 13F fillings by institutions (Massa and Rehman, 2008; Ivashina and Sun, 2011). With quarterly data researchers are forced to compute changes in holdings and calculate returns from dates (say quarter end) that may be quite different than the date of the transaction. Our data set provides both holdings and transactions for U.S. insurers, and allows us to know the date that an asset is purchased (or sold). By tracking the performance of a trade from the exact date that the trade is executed, we are better able to assess whether or not there are differences in performance between associated trades and unassociated trades. Therefore, our data set provides an advantage over quarterly data because we can more precisely compute returns.

An additional advantage of our study over that of prior studies is that we examine a setting where the financial intermediary generates the information and uses it to trade, i.e. we do not rely on a setting where there is an indirect passage of information. Other studies that examine trading behavior from relationships argue that information is passed from an intermediary to a trading firm such as a mutual fund or hedge fund. For example, in Massa and Rehman (2008) the trading firm is affiliated with a bank that has a lending arm where the information is generated. In Ivashina and Sun (2011) the trading fund is a member of a loan syndicate but may not be the lead intermediary in the loan agreement and the producer of the information. In contrast, our study the insurer generates the information and uses the information to trade.

The motivation for this study is grounded in theoretical literature on financial intermediaries, which suggests that they have comparative advantages in generating information via their private creditor relationships. For example, Fama (1985) argues that financial intermediaries have access to insider information via loan and private placement relationships compared to outsiders who rely on public information such as bond holders. Diamond (1984, 1991) posits that financial intermediaries develop expertise in information production from initiating and monitoring their creditor relationships.[7] Thus, the financial intermediation literature contends that establishing relationships comes with benefits, particularly when those relationships generate information.

The literature on financial intermediation has typically focused on banks and loan relationships, but, like banks, insurance companies are financial intermediaries who aggregate capital and invest in projects. As financial intermediaries, insurers receive "deposits" in the form of premiums on insurance contracts. This capital is then aggregated and used to make investments. Insurers then choose to invest in a wide variety of financial assets, both in public markets as well as private markets. One such private market that insurers invest in is the market for private placements (privately placed equity and debt instruments).

We contend that the relationships established in the private placement market (both private debt and private equity) generate information for the investor and are similar to the intermediary-creditor relationship. For example, the private placement market, like

[7] See Boot (2000) for a review of this literature.

the loan market, is an information intense environment where information asymmetries between the issuer and the investor abound (Carey, Prowse, Rea, and Udell, 1993; Fenn, Liang, and Prowse, 1995).[8] To mitigate these asymmetries, investors undertake a due diligence process to examine the issuing firm and also continue to monitor of the issuing firm through time(Carey et al., 1993; and Fenn et al., 1995). Like banks, insurers can generate information through the due diligence and monitoring process via disclosures by the issuing firm and discussions with management.

We use two different approaches to measure abnormal trading performance, which we will describe in more detail in section V below. Using the two methods, we find some evidence that insurers do appear to generate information via their relationships and are generally able to profit from their associated trades. In our univariate approach (based on the method of Daniel, Grinblatt, Titman, and Wermers, 1997) we document that insurers appear to generate information and use the information when selling the issuers' equity. Additionally, in our multivariate approach, (based on the methods found in Massa and Rehman, 2008; Pormorski, 2009; and Cohen, Malloy, and Pomorski, 2010) we find that trades associated with privately placed debt relationships earn an abnormal return and outperform trades unassociated with a private placement. Additionally we find mixed results that trades associated with private equity relationships outperform trades associated with private debt relationships.

Our study contributes to three streams of literature. First, we add to the financial intermediation literature that examines the benefits of intermediary-borrower relationship. While early empirical evidence of the benefits in the intermediary-borrower

[8] We describe the market for private placements in more detail in the following section.

relationship focuses on the benefits to the borrower (see James, 1987; Lummer and McConnell, 1989; Petersen and Rajan, 1994; and Berger and Udell, 1995), less is known about the benefits to the lenders. One of the recent exceptions is Bharath, Dahiya, Saunders, and Srinivasan (2007) who show that relationship lenders benefit from subsequent loans to the borrowers and relationship lenders also benefit from being chosen to provide other services such as debt/equity underwriting services. Also, the results of Massa and Rehman (2008) suggest that banks pass information to affiliated funds. Hence, it appears that banks benefit from information generated in the loan market and capture this benefit in their trading divisions. We contribute to this literature by showing that private relationships established by investing in private placements lead to benefits for the intermediary in the form of higher trading performance in public equity. Additionally, our investigation of which type of private asset (debt or equity) is associated with higher performance is novel and sheds light on other types of private relationships such as equity based relationships (i.e. non-creditor relationships).

Secondly, our results shed light on the literature that studies cross-market information flow. Several papers examine how information is incorporated into different asset markets. For example, Downing, Underwood, and Xing (2009) examine lead-lag relationships between stock and bond markets. Hotchkiss and Ronen (2002) report that the informational efficiency in the bond market is similar to that in the underlying stocks. Bushman, Smith and Wittenberg-Moerman (2010) study the channels in which information generated in the syndicate loan market impacts price discovery in secondary loan and equity markets. Acharya and Johnson (2007) infer how financial institutions may exploit information of their clients in CDS markets. We extend this research by investigating a channel through which information spill-over between markets can occur. Specifically, we test if information that is generated by holding a privately placed debt or equity results in higher trading performance in that firm's public equity. We also test if information generation differs across the different privately placed asset types, which extends this literature by testing whether or not information spill-over effects are more sensitive in one type of asset than another.

Thirdly, we add to a growing literature on relationships and trading behavior. For example, Massa and Rehman (2008) find evidence that banks affiliated with mutual funds pass information generated in the loan market to the affiliated mutual fund to use to trade profitably in the stock market. Likewise, Ivashina and Sun (2011) show that equity trades of members of loan syndicates outperform the trades of non-syndicate members. Bodnaruk, Massa, and Simonov (2009) and Jegadeesh and Tang (2010) report evidence of funds trading on inside information when they are affiliated with the bidder or target advisor, respectively. Kedia and Zhou (2009) investigate and report that there is some evidence that bond dealers affiliated with takeover advisors trade ahead of the announcements. However, Griffin, Shu, and Topaloglu (2012) examine situations where inside information is likely such as affiliation with takeover advising, IPO and SEO underwriting, or lending relationships and find little evidence that institutional investors use inside information to trade. We add to this literature by examining where a relationship (established by purchasing or monitoring a privately placed asset in a firm) generates information that can be used to trade.

The remainder of this paper is organized as follows. Section 2 describes the market for privately placed securities. Section 3 sets forth our hypotheses and gives a brief review of the literature. Section 4 describes the National Association of Insurance Commissioners (NAIC) data set that we use for our study, as well as the other data sets we use to supplement our analysis. Section 5 presents the main results of our paper. Section 6 concludes.

### 2.2 The Market for Private Placements

The private placement market is a large and growing avenue for firms to raise capital. While accurate data on the private placement market is historically sparse, Carey et al. (1993) report that between 1935 and 1992 the market grew from $390 million to $65.86 billion, peaking in 1988 at $127 billion (see Appendix D of Carey et al., 1993).[9] Likewise, Fenn et al. (1995) report that the 1980's and 1990's saw a rapid growth in the private equity market, more than doubling the levels of the 1970's. More recently, in 2010 there was more than $1 trillion of capital raised through private placements, and it appeared (from the first quarter of 2011) that the private placement market was on pace to exceed $1 trillion again (Ivanov and Bauguess, 2012; and Sjostrom, 2013). The capital raised through private markets exceeded those in public markets in both the number of offerings as well as the total amount of capital raised (Ivanov and Bauguess, 2012).[10] Thus, the market for privately placed securities is a significant means for firms to raise capital.

A firm can issue privately placed debt or equity (common or preferred) instruments. The term "private" refers to a security which is exempt from registration under Regulation

[9] Carey et al. (1993) also document that between 1987 and 1992 the gross volume of privately placed bonds was more than 60% of that issued in the public bond market, and at times has outpaced the issuance of public bonds.

[10] Ivanov and Bauguess also report that there was a preference for private markets over public markets for public firms who can access both markets.

D of the Securities Act of 1933. There are several exemptions that the law provides to registering securities. Rule 506 of Regulation D provides the most used exemption for issuing privately placed securities (Sjostrom, 2013). To qualify for the registration exemption, the offering, can only be purchased by "accredited investors" defined under Rule 501(a) of Section D to be institutions or individuals with a high net worth or high income (Sjostrom, 2013). According to Sjostrom, the legal reasoning underlying the registration exemption is that accredited investors are sophisticated and can "fend for themselves."

Firms issuing private placements typically employ an agent to help design the securities and to locate potential investors (Carey et al., 1993; Fenn et al., 1995).[11] The process for the issuance has several steps which we summarize here, particularly as it relates to the potential for information generation.[12] Once the decision is made to issue a private placement and an agent is appointed, the agent will conduct their own due diligence on the issuing firm. From the agent's due diligence process, the agent then helps the company prepare the offering memorandum and other documents such as the terms sheet.[13] The agent's due diligence process adds value for the investors because it acts as a pre-screen, and much of the initial interest by the investor is based on conversations with the agent and the offering memorandum.[14] Since reputation is important in this market, the agent is vested in generating accurate information about the issuing firm. According to

[11] Carey et al. 1993 estimate that two thirds of private placements are assisted by an agent. The remaining one-third are direct placements between the issuer and the investor, where no agent is involved.
[12] For more detail on the process see Carey et al.,(1993) and Hayter (2010). We summarize the process here.
[13] The offering memorandum is similar to a prospectus for a public issue, but typically includes more information than is found in a prospectus such as forecasts (Carey et al., 1993). It also typically goes into more detail than the Annual Report (Hayter, 2010)
[14] The process of gaining initial interest and commitment from investors is known as "circling." The commitment is contingent on the lender's (such as an insurance company) investment committee and the investor's own due diligence process.

Carey et al. (1993) investors (primarily insurance companies) rely on the agents information to help filter the several hundred private placements that are offered to them each year of which only a small fraction are accepted.

Once the agent has located ("circled") potential investors, a "road-show" may take place. The road show is a where a few senior officers of the issuing firm visit the investor to pitch their private placement issue (Hayter 2010). After the agent has pitched the private placement via conversations, the offering memorandum, and perhaps a road-show, the potential investors place bids for the issue. Once the bids are accepted the investor can then perform their due diligence process prior to finalizing the deal (Carey et al., 1993). In the due diligence process the investor can travel to tour the issuing firms operations, and have access to management (Carey et al., 1993).

The private placement securities are typically marketed and sold to a small select group of accredited investors. For example Ivanov and Baugeuss (2012) report that the median number of investors in a particular issue is four. Therefore, investment in private placements is highly concentrated, which can be advantageous for issuing firms because renegotiation costs can be lower (Chandra and Nayar, 2008). Also, by issuing to a small group of investors, firms reduce the probability that any proprietary information they reveal to the investor will be released to other parties (Chandra and Nayar, 2008; Bhattacharya and Chiesa, 1995; Yosha, 1995). Since firms issue to a small number of firms who have comparative advantages in monitoring, the literature generally asserts that obtaining capital via private markets is associated with a certification effect. Several studies report evidence consistent with this assertion finding positive stock price reactions on the announcement of a private placement (Wruck 1989; Hertzel and Smith, 1993; Fields and Mais, 1991). While insurers are sizable players in private asset markets, they are not the only players in the private asset markets (see Carey et al., 1993; and Fenn et al., 1995).[15] The potential for higher returns and information generation also attracts other institutions such as pension funds and hedge funds.[16]

The fundamental principle of the risk-reward tradeoff suggests that with the potential for higher returns also come potential risks. The private placement market is information-intensive market where large asymmetries can exist between issuer and investor that pose risks to the investor. In such markets, financial intermediaries build capabilities to produce information regarding the issuing firm and to monitor their investment as a means of mitigating the risks that they face. We next discuss some of the risks faced by investors in private placement markets in more detail.

Sjostrom (2013) argues that regulatory changes in the private placement market over the last two decades have favored firms attempting to raise capital, but have done little to improve investor protections. From a legal perspective, investors in private placements do not have the same recourse as investors in public issues. Investors in public issues can sue a firm (and its officers) for misrepresentation in the prospectus under Section 11 and 12(a)(2) of the Securities Act. Private placement investors cannot sue under Sections 11 and 12(a)(2) since they do not apply to unregistered securities (Sjostrom, 2013). Instead, private placement investors must sue under Rule 10b-5 which

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[15] Carey et al., 1993 report that 83% of the dollar volume of private placements issued in 1990-92 was held by insurance companies.

[16] A 2006 article in Business Week asserts that hedge funds have become more active in private placement markets and that SEC has launched several probes into their activities ("More Heat On Hedge Funds," 2006). In December, 2012 the Tiger Asia Partners settled charges in the amount of $44 million. The SEC had charged the founder of Tiger Asia Partners with breaking insider trading laws based on confidential information he received in a private placement offering. ("Hedge Fund Manager to Pay $44 Million for Illegal Trading in Chinese Bank Stocks," 2012)

requires a higher burden of proof, and thus investors in private placements face the risk of having a more difficult time obtaining legal recourse if there is misrepresentation in the offering documents (Sjostrom, 2013).

Investors in private placements also face risks from information asymmetries. As we stated above, like the market for bank loans, the market for private placements is a marketplace where potentially large information asymmetries exist between the issuer and the investor. In fact, investors may face larger asymmetries in the private placement market due to the differences between bank loans and private placements. Chandra and Nayar (2008) argue that one difference that can lead to larger asymmetries is the maturity differences between bank loans and private debt. Bank loans are usually short term (less than a year), while privately placed debt typically matures between seven and fifteen years. In the bank loan market where maturities are short, a bank can choose not to renew its lending relationship if it learns that the borrower is of poor quality, while in the private placement market the lender is "locked up" for longer periods of time. Since private equity has no maturity and holding periods are theoretically infinite, a similar argument can be made for larger asymmetries existing in the privately placed equity market. To mitigate these asymmetries, investors engage in due diligence and monitoring activities.

Due in part to the informational asymmetries in the private placement market, privately placed assets also tend to be fairly illiquid investments. Therefore, investors in private placements face liquidity risk, where they may not be able to sell the asset when they desire to dispose of it. The reduced liquidity and informational asymmetries lead to issuers to typically offer their private placements at a discount. Regulatory changes and developments in the marketplace that have occurred are aimed at improving the liquidity for private placements. The SEC adopted Rule 144A in 1990 in an attempt (in part) to improve liquidity and decrease the illiquidity discount associated with private placements by giving a regulatory avenue for resale of the privately placed security (Sjostrom, 2008; and Sjostrom, 2013). Rule 144A allows institutions to sell previously acquired private placements without having to register the securities (Chaplinsky and Ramchand, 2004). Additionally, Nasdaq and other investment banks have created secondary marketplaces such as PORTAL to improve liquidity in the private placement market (Sjostrom, 2008). While these actions may have improved liquidity in the market, there still exist large informational asymmetries between issuer and investor which parallel those discussed in the relationship banking literature.[17]

## 2.3 Hypotheses

### *2.3.1 Do private debt relationships generate information?*

The relationship banking literature predicts that there are benefits for the lender to establishing a private creditor relationship (Fama, 1985, Diamond, 1984, Diamond, 1991, Rajan and Winton, 1995). For example, Bharath et al. (2007) report that relationship lenders have a higher probability of getting repeat lending business from the borrower. They also show that the relationship lender is more likely to be chosen to provide other banking services such as underwriting of debt/equity issues.

[17] Huson, Malatesta and Parrino (2009) report evidence of the private placement discount decreasing through time, which would be consistent with increasing liquidity within the private placement market.

Another benefit is that the private information generated could be used to trade profitably in the issuing firm's public equity.[18] The relationship banking literature asserts that private creditor relationships generate private information through screening (Diamond, 1991) and monitoring (Rajan and Winton, 1995, Diamond, 1984) that is not available to non-lenders or public creditors such as public bond holders. We argue that if the insurers obtain private information and use it to trade, then it should be reflected in the performance of their informed trades. We seek to determine if public equity trades made by insurers where a private debt relationship exists outperform public equity trades where no other private relationship (such as a private equity relationship) exists. This leads us to form our first hypothesis.

H1: Public equity trades associated with a private debt relationship outperform public equity trades not associated with a private relationship.

*2.3.2 Do private equity relationships generate information?*

The literature on the financial intermediary-borrower relationship focuses on lending/creditor relationships, but as mentioned earlier other non-creditor private relationships exist. For example, relationships with merger advisors (a non-creditor relationship) can produce information that is used to trade (Bodnaruk, Massa, and Simonov, 2009; Jegadeesh and Tang, 2010). In our context, privately placed securities can be debt or equity instruments. Therefore, private equity relationships exist between

[18] Albeit illegally according to Rule 10b5-1. The potential for the use of material, non-public information generated via private placement transactions has caught the eye of regulators. The SEC has an ongoing investigation of private placement transactions, launched in 2002 (Bengtsson, Dai, and Henson, 2012).

issuing firms and investors, and represent another type of non-creditor relationship. However, according to Fenn et al. (1995) there is reason to believe that investors in the private equity market will behave similar to the private creditor relationships we discussed in the prior section. Private equity investors also undertake a due diligence process and monitoring to mitigate asymmetries between them and the issuer (Fenn et al., 1995). Therefore, the private equity relationship can generate information that could be used to trade in the public equity of the issuing firm. We seek to answer whether or not public equity trades associated with a private equity relationship outperform public equity trades where no other private relationship (such as a private debt relationship) exists. We therefore form the following hypothesis.

> H2: Public equity trades associated with private equity relationships outperform public equity trades not associated with a private relationship.

*2.3.3 Are private debt or private equity relationships associated with better performance?*

Theory suggests that there are differences in the information content of private equity and private debt relationships. The pecking order theory provides insight into why there may be differences (Myers, 1984; Myers and Majluf, 1984). Myers (1984) argues that when asymmetric information costs to a firm are high, firms will avoid raising funds externally when internal funds are available. If firms do raise external funds the firm will choose the security whose value is least sensitive to inside information (Myers, 1984). Myers' argument leads to a pecking order where debt (the least sensitive to inside information) is used first and then equity (the most sensitive to inside information).

According to Myers a security is information-sensitive when the price of the security changes in response to changes in the amount of information about a firm. Equity is more information-sensitive (compared to debt) because the price of equity changes more in response to information about the firm.

Fulghieri and Lukin (2001) extend the standard pecking order theory model to incorporate the ability of investors to generate information about the issuing firm. The Fulghieri and Lukin model is particularly applicable to the private placement market because investors are able to generate information about the issuing firm through the due diligence and monitoring process (Carey et al., 1993; Fenn et al., 1995; and Gomes and Phillips, 2012). According to Fulghieri and Lukin, investors' incentive to produce information depends on the information-sensitivity of the security. Given that equity is more information-sensitive than debt (Myers, 1984), investors in private equity relationships will have a greater incentive to produce information and will produce more information than investors in private debt relationships. Besides the increased incentive to produce information in a private equity relationship, we contend that the informational advantage of private equity (over private debt) will result in public equity trades of privately placed equity holders outperforming the public equity trades of privately placed debt holders. We therefore form the following hypothesis:

> H3: Public equity trades associated with privately placed equity relationships will outperform public equity trades associated with privately placed debt relationships.

## 2.4 Data

The primary data for this study comes from the Schedule D data from the National Association of Insurance Commissioners (NAIC). We supplement the NAIC data with data from the Center for Research in Security Prices (CRSP) when we need to calculate returns on equity trades. We choose the sample period from the NAIC data for this study to be from 2001 to 2010. Schedule D of the NAIC data reports holdings as well as buy and sell transactions for U.S. insurer's general accounts. The data contain a listing, by Cusip number, for each asset held in the portfolio. Our data set is the universe of insurers, and Schedule D holds all bond, preferred stock, and equity holdings and transactions of the insurer. For our study we identify privately placed assets issued by public firms, and then identify public equity trades that occurring during the holding period of the privately placed asset. A more detailed explanation of the data set and how we identify the privately placed assets that we use in our study can be found in Appendix A.

The NAIC data offers three distinct advantages for investigating theories of relationships in financial intermediation. First, our data allow us to examine the passage of information in different types of private relationships. Since our data contains the entire portfolio holdings and transactions (equity and debt) of insurers, we can compare relationships such as the ones established in privately placed debt relationships compared to privately placed equity relationships.

Second, our data provides the date on which a transaction is made, therefore, we are able to see precise dates when the private and public assets were bought or sold (or otherwise disposed of). This is an advantage over studies that rely on 13F filing data which is only reported quarterly, and must infer captured returns from a date that is likely different from the transaction date. Our data allows us to calculate benefits accrued to the intermediary, i.e. returns on trades in public assets in a more accurate manner.

Third, an additional advantage of data is that we can focus on the benefits gained by the provider of capital (the intermediary), such as information generated from the relationship. Early studies that examined relational banking focus on what could be measured in stock prices, and the market's reaction to announcements of a private relationship. Examples, in this vein are James (1987) and Lummer and McConnell (1989) who examine the announcement effect of bank loan initiations and renewals, respectively. Slovin, Sushka, and Hudson (1988) report that a stand-by letter of credit from a bank determines whether the announcement of a commercial paper issue is positive. These papers focus on the benefits to the borrower via the market's favorable reaction to the announcement.

Table 1 reports the number of privately placed assets of public firms held by insurers. Panel A shows that life insurers held 5,880 unique privately placed debt assets and 540 privately placed equity assets, while Property and Casualty (P&C) insurers held 1,019 privately placed debt assets and 305 privately placed equity assets, respectively. For Life insurers, these privately placed asset holdings represented investment in 2,299 unique firms issuing privately placed debt and 349 unique firms issuing privately placed equity. For P&C insurers, investment was made in 712 unique firms issuing privately placed debt and 240 unique firms issuing privately placed equity. These investments in privately placed assets are quite diversified across industries. We classify issuing firms into one of the 49 Fama and French industry classifications found on Ken French's website. Table 1 reports that Life insurers during our sample period hold privately placed assets in every one of the 49 Fama and French industry classifications. This is also almost true for P&C insurers who hold privately placed assets in 42 of the 49 Fama and French industry classifications. On average, the issuers of these privately placed assets are quite large as seen in Panel B of Table 1. The average market capitalization of the issuer is $6.8 billion compared to the average of $2.3 billion for the CRSP database.

Not all insurers in the NAIC dataset hold privately placed assets. Thereare 414 life insurers who hold privately placed debt and 157 who hold privately placed equity. Likewise, there are 259 property casualty insurers who hold privately placed debt and 182 that hold privately placed equity. Of these insurers who hold privately placed assets there are a smaller number that make trades in the public equity of the issuing firm during a period where the insurer also held a privately placed asset of the issuing firm. For life insurers there are 55 insurers that hold privately placed debt and trade in the public equity of the issuing firm and 21 insurers that hold privately placed equity and trade in the public equity of the issuing firm. For P&C insurers there are 18 and 19, respectively. On average the insurers who hold the private asset and transact in the public equity of the issuing firm are larger insurers. Panel C shows that the average size (measured by assets) of insurers making associated trades is $26 billion compared to an average $1.6 billion for the NAIC database. Our data set has 2,944 associated trades made by life insurers and 377 such trades made by property casualty insurers.

To gain further understanding regarding the nature of the privately placed asset holding of insurers we present Figures 1, 2, and 3 and Tables 2 and 3. Figure 1 plots the holdings (in dollars) of privately placed debt and equity assets of life and P&C insurers, respectively. Figure 1 shows that insurers hold a significant aggregate amount of private placements (approximately $80 trillion in 2010). Figure 2 reveals that for the insurers that hold private placements, private placements make up a significant portion of their debt and equity holdings. Among insurers that hold privately placed debt, private placements account for an average of 7% of their total debt holdings. On average, privately placed debt issued by public firms accounts for 2% of these insurers' debt holdings. While private equity placement holdings are not as common in insurers' portfolios (see Table 1), they do make up a significant portion of their equity portfolio. For insurers that hold privately placed equity, on average private placements make up 48% of their equity portfolio based on book value. Of all privately placed equity, 1% of the equity holdings are in privately placed equity issued by public firms. Figure 3 reports the average percentage holdings for the universe of insurers in the NAIC database as opposed to the subset of insurers that invest in private placements. For the universe of insurers, private placements account for 1% of insurer's debt holdings and 1% of their equity holdings.

Table 2 reports the average holding period (in months) for the asset types. The average holding period for privately placed debt assets in our sample is approximately five years for both life and P&C insurers.[19] The holding period for privately placed equity is slightly longer, approximately seven years, for both types of insurers. Conditional on an insurer holding privately placed assets, Table 3 presents the average number of privately placed assets held. Life insurers, on average, hold far more privately placed debt assets than privately placed equity assets (51.19 debt assets compared to 5.24 equity assets). P&C insurers, besides holding fewer privately placed assets than life insurers on average, are more balanced with their holdings between the two asset classes (5.65 debt assets and 2.49

[19] The holding periods we report are close to the maturities of private placements in Carey et al. (1993) who report that maturities for private placements have mean of six to seven years.

equity assets). Since insurers sometimes hold multiple privately placed assets in a single issuer, we present panels C and D of Table 3 which holds the average number of issuing firms insurers are invested in conditional on an insurer holding private placements. Panels C and D shows that (conditional on holding private placements), on average, insurers have debt relationships with 34.8 firms and equity relationships with 3.76 firms. Meanwhile, property casualty firms have debt relationships with an average of 4.88 firms and equity relationships with 2.08 firms.

## 2.5 The Performance of Trades Associated with Private Relationships

In this section we discuss how we measure the relative performance of trades associated with private relationships, and present the results. We measure performance using two methods, a univariate method and a multivariate method. We start our discussion by describing the univariate approach, and then turn our attention to the multivariate approach.

### *2.5.1 Univariate Approach*

The first method we use to investigate the performance of trades associated with privately placed assets is to use a univariate approach that follows Puckett and Yan (2011). A benefit of tracking abnormal performance in this manner is that it takes advantage of a strength of our data set. Our data allows us to calculate the returns with a level of precision that is not possible with other data sets since we know the exact transaction date. We start by identifying the start and end dates when an insurer holds a privately placed asset (debt or equity). We consider the time between the start and end date to be the period where the insurer has a private relationship with the issuing firm. Next, we identify all public equity trades made by the insurer that take place during a private relationship. Henceforth, we shall refer to these trades as associated trades. All other trades that occur outside a private relationship are termed unassociated trades.

For our analysis, we separate the trades into buys and sells. We then track the performance of the trade over 20, 60, 120, and 240 trading days subsequent the execution date. We calculate both holding period compound returns as well as abnormal returns for the specified tracking periods. To calculate the abnormal return, we take the compounded CRSP return for the specified trading periods (holding period compound return) and subtract the Daniel, Grinblatt, Titman, and Wermers (1997) (henceforth DGTW (1997)) benchmark return over the same holding period.

Table 4 reports the results for testing hypothesis 1 which investigates whether or not trades associated with privately placed debt relationships outperform trades not associated with a private relationship. Panel A reports the results for associated and unassociated buy transactions. The results in Panel A indicate that, for tracking periods of 60 days and greater, associated trades outperform unassociated trades for the raw holding period returns. However, the DGTW-adjusted returns show no difference between associated and unassociated trades. Therefore, it appears that the insurers do not benefit from information generated from the private placement relationship when making purchasing decisions. However, the results for sell transactions in Panel B show some evidence that the insurers benefit from information generated in the private relationship when making sell decisions. For a 20, 120, and 240 day tracking period associated trades have significantly different DGTW-adjusted returns compared to unassociated trades in the direction one would expect for sell transactions. To interpret the results consider a sale of a stock. A successful sale of a stock would occur prior to a period of underperformance. The results show that for a 20, 120, and 240 day tracking period, the abnormal performance of associated trades is lower than that of unassociated trades. For example, for a 20 day tracking period, the abnormal performance of associated trades is 47 bps lower than for unassociated trades. Taken together, the results of Panel A and Panel B provide mixed results on whether or not information generated via the private debt relationship is used to trade. If information is used, it appears that insurers use negative information to dispose of equity holdings.

Next we test our second hypothesis which asserts that trades associated with private equity relationships outperform trades unassociated with a private relationship. Table 5 presents the results of testing the hypothesis. Similar to the findings for privately placed debt, we find that there is no difference between associated and unassociated DGTW-adjusted returns. However, we do find for the 20 day tracking period that associated sell trades exhibit abnormal performance, and outperform the unassociated sell trades in the direction expected for sell trades. Again it appears that insurers are generating negative information about the issuing firm and using the information to sell the equity.

We then test the third hypothesis which asserts that trades associated with privately placed equity relationships outperform trades associated with privately placed debt relationships. Table 6 presents the results of this analysis. We find mixed results when considering whether the trade is a buy or sell transaction. We find no difference in

DGTW-adjusted returns between buy transactions associated with privately placed debt and buy transactions associated with privately placed equity. For sell transactions, consistent with our prior expectation, we find that sell transactions associated with private equity outperform sell transactions associated with private debt. We find that the raw returns are significantly different for the 20, 60, and 120 day tracking periods. Additionally we find that the DGTW-adjusted returns for sell transactions associated with privately placed equity outperform those associated with privately placed debt.

Overall our results of our univariate method are suggestive of information being generated via private placement relationships and being used to time sells of the issuing firm's equity. At least for the selling behavior of insurers, the results are consistent with theories of financial intermediation which argue that information is generated in private creditor relationships. Additionally, for sell transactions the results indicate that trades associated with privately placed equity outperform trades associated with privately placed debt, which is consistent with investors having more incentive to produce information in a private equity relationship.

### *2.5.2 Multivariate Approach*

To further test the performance of trades associated with a private placement relationship, we also use a multivariate approach to compare risk adjusted returns. Our multivariate approach is to create calendar time portfolios of associated and unassociated trades. This approach is used in the literature for assessing factor/risk-adjusted returns and similar approaches can be found in Massa and Rehman (2008); Pormorski (2009); and

Cohen, Malloy, and Pomorski (2010). Seasholes and Zhu (2010) describe the benefits of measuring performance using a calendar time portfolio approach.

We form calendar time portfolios that are long buys and short sells. To form the portfolios we collect the buys and sells in the public equity over six month windows (the portfolio formation window) and form a portfolio at the end of the portfolio formation window. We then follow each of the trades for 60 trading days from the end of the portfolio formation window.[20] Next, for each calendar day we calculate an equal-weighted calendar-time portfolio return. We then use standard pricing models such as the Fama and French three factor (Fama and French, 1993), the Fama and French four-factor model (Carhart, 1997), and the Fama and French five-factor model to measure performance (i.e. to find alpha).[21]

Our first test using the multivariate approach estimates alpha for the sub-sample of associated trades only. The goal of this analysis is to test whether or not associated trades earn an abnormal return. Table 7 presents the results of estimating the three, four, and five factor models for trades associated with privately placed debt (Panel A) and for trades associated with privately placed equity (Panel B). Panel A shows that trades associated with privately placed debt earn an abnormal return. Trades associated with privately placed debt earn an abnormal return of 1.6 bps (1.8 bps for the five factor model) per day which equates to approximately 4% per year (1.6 bps*250 trading days). Panel B indicates that trades associated with privately placed equity do not earn an abnormal return.

[20] Other tracking periods such as 20 days were also run, and the results lead to the same inference.
[21] At the time this study was conducted CRSP only had the liquidity factor through December 2010, which limits the number of observations used in the five factor model regressions.

For comparison, we also examine whether or not trades that are unassociated with a private placement relationship earn an abnormal return. The results are found in Panel C of Table 7. We find that there is no abnormal performance for unassociated trades. The coefficient on the intercept is not significant, and therefore indistinguishable from zero abnormal performance. Finding abnormal performance for trades associated with privately placed debt, while finding no abnormal performance for unassociated trades provides initial evidence that supports hypothesis 1.

To address the hypotheses regarding whether or not trades associated with private placements outperform trades unassociated with holding a private placement, we estimate the multi-factor models that we describe previously. The results of estimation are reported in Table 7. We find that there is an abnormal performance associated with privately placed debt (Table 7 Panel A) while the performance of unassociated trades is statistically indistinguishable from zero (Table 7 Panel C). Therefore, we conclude that trades associated with privately placed debt outperform unassociated trades. With regard to whether or not trades associated private equity outperform unassociated trades, we find no evidence that there is a difference in the relative performance between the two groups as both intercept coefficients are insignificant.

Finally, we conclude from our multivariate approach in Table 7 that trades associated with privately placed debt outperform trades associated with privately placed equity. We find a positive and significant abnormal return for trades associated with privately placed debt. However, we find that the return on trades associated with privately placed equity is not different from zero. Therefore we conclude, contrary to our prior expectations, that the trades associated with privately placed debt outperform trades associated with privately placed equity.

## 2.6 Conclusion

In this paper we examine how investors who establish private relationships by investing in privately placed securities produce tradeable information. We add to a growing literature that examines how relationships influence trading performance, and we extend the literature that suggests financial intermediaries are able to produce information via their private relationships. We find some evidence that insurers profit from information gained via a private placement relationship. Using a multi-factor model we find that insurers who invest in privately placed debt instruments and subsequently trade in the public equity of the issuing firm are able to earn an abnormal return. Additionally from the DGTW method, we find some evidence that insurers earn an abnormal return on sell transactions that are associated with privately placed debt and privately placed equity. Overall, we conclude that there is some evidence indicates that insurers are able to produce tradeable information via the process of due diligence and monitoring.

We also extend the financial intermediation literature that focuses on creditor relationships by examining another type of relationship (equity-based relationships). We have argued that the market for privately placed equity is similar to the market for privately placed debt. Both markets are characterized by high degrees of informational asymmetry and should therefore also be characterized by due diligence and monitoring by investors. We find mixed evidence that private equity relationships are associated with increased trading performance. Using a univariate approach we document that sell trades are associated with privately placed equity show some relative performance compared to unassociated trades at the 20 day tracking period. However, we find no such performance using a multi-factor model.

**Figure 1: Private Placement Holdings By Year**

This figure plots the amount of privately placed debt and equity held by life and property casualty, respectively, in each year of the sample. Amounts are measured by actual cost as reported in the NAIC statutory filing

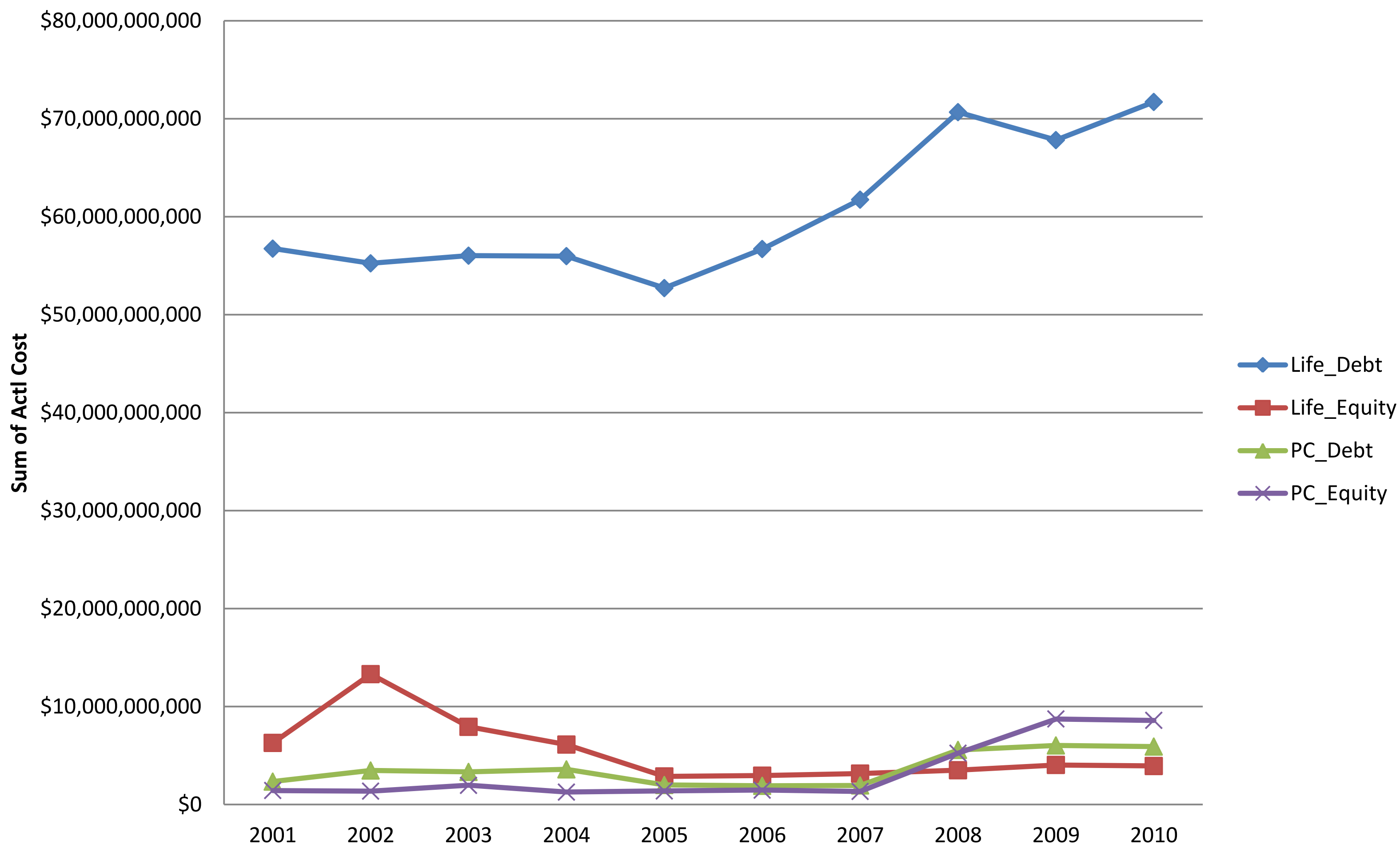
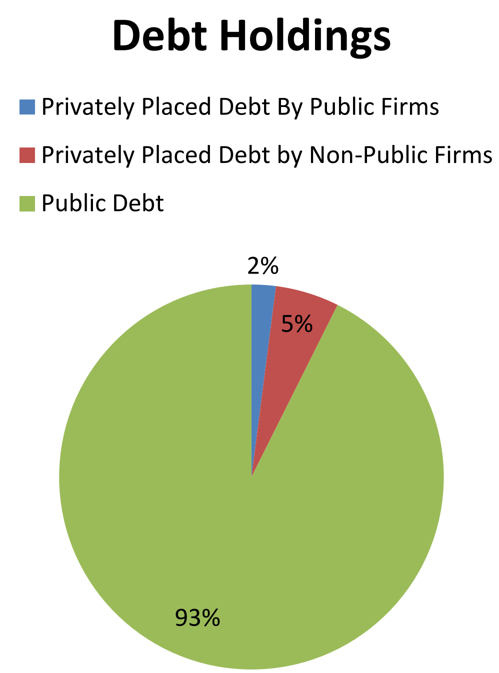


**Figure 2: Public and Privately Placed Asset Holdings Conditional on Holding Private Placements**
These figures show the average percentage holdings for private placements as a part of insurers' debt and equity portfolios, conditional on holding private placements. Holding percentages are based on the book value of the asset as



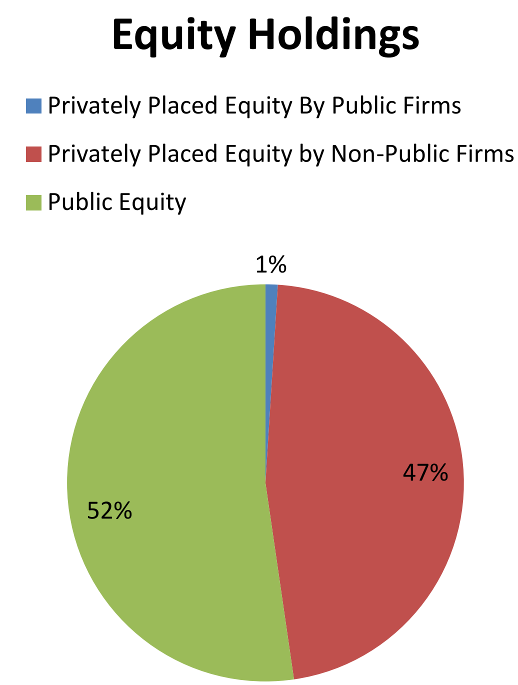
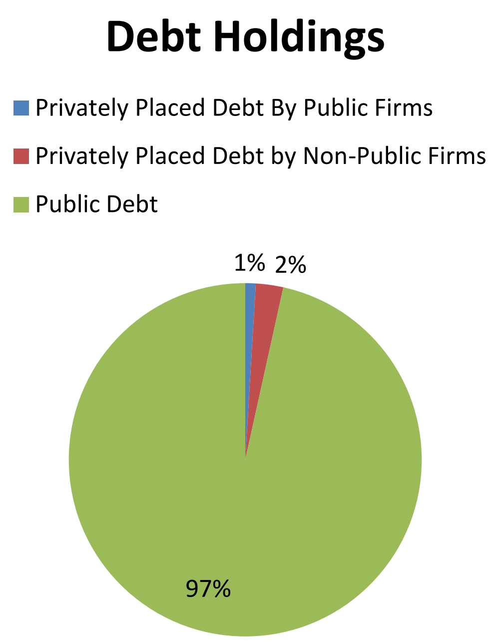



**Figure 3: Public and Privately Placed Asset Holdings Unconditional on Holding Private Placements**
These figures hold the average percentage holdings for private placements as a part of insurers' debt and equity portfolios. Holding percentages are based on the book value of the asset as reported in the NAIC statutory filings.



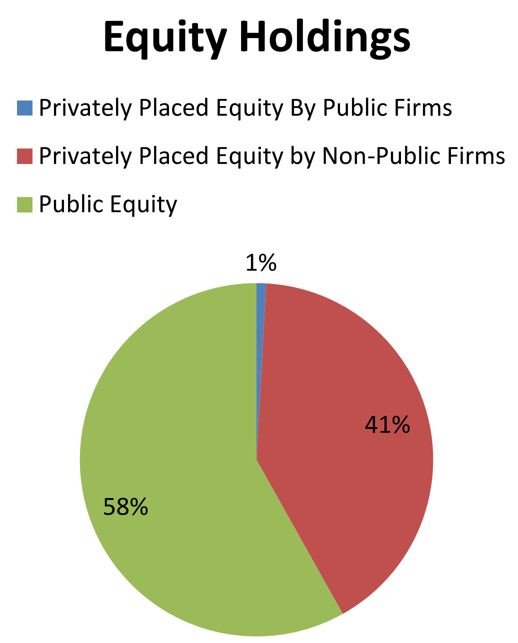



**Table 1: Descriptive Statistics**

The descriptive statistics for privately placed assets below are for those issued by public companies only. Panel A reports descriptive statistics of our sample taken from the NAIC database. The sample period is from 2001 through 2010. Panel B reports the descriptive statistics for market capitalization of trades in public equity that are associated with a private placement relationship. Panel C reports descriptive statistics for the size of insurers making associated trades.

**Panel A -NAIC Data**

| | Life | Prop/Casualty |
|---|---|---|
| # of prv placed debt assets | 5880 | 1019 |
| # of firms issuing prv placed debt assets | 2299 | 712 |
| # of industries represented in prv placed debt assets | 49 | 42 |
| # of prv placed equity assets (Preferred Stock and Common Stock) | 540 | 305 |
| # of firms issuing prv placed equity assets | 349 | 240 |
| # of industries represented in prv placed equity assets | 34 | 23 |
| # of insurers holding prv placed debt | 414 | 259 |
| # of insurers holding prv placed equity (Preferred and Common) | 157 | 182 |
| # of insurers holding prv debt and transacting in public equity | 55 | 18 |
| # of insurers holding prv equity and transacting in public equity | 21 | 19 |
| # of trades of common equity associated with private relationship | 2944 | 377 |

| **Panel B - Stock Characteristics** | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| Market Cap of Associated Trades | $6,808,650,433 | $2,908,257,961 | $10,549,633,405 | $5,116,500 | $151,862,785,992 |
| Market Cap of CRSP database | $2,333,439,319 | $230,567,699 | $12,041,245,580 | $8,340 | $530,426,006,557 |

| **Panel C - Insurer Characteristics** | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| Size of All insurers in the NAIC dataset | $1,639,013,822 | $57,394,971 | $9,712,945,118 | $41 | $297,465,527,467 |
| Size of Insurers making associated trades | $27,158,194,497 | $7,071,500,281 | $45,655,921,404 | $7,902,162 | $297,465,527,467 |

**Table 2: Holding Periods of Private Placements**

This table reports the average holding period (in months) for the different types of privately placed assets. In calculating the holding period, if an asset is held at the end of the sample period we assume that the ending holding date is December 31, 2010. Panel A reports the results for Life insurers and Panel B reports the results for Property Casualty Insurers.

Panel A - Life Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 21192 | 64.63 | 0 | 1 | 24 | 48 | 89 | 238 | 477 | 55.38 |
| Equity | 822 | 77.35 | 0 | 0 | 22 | 45 | 82 | 540 | 1238 | 107.54 |

Panel B - Property Casualty Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 1463 | 58.73 | 0 | 0 | 18 | 41 | 84 | 269 | 347 | 56.30 |
| Equity | 454 | 82.56 | 0 | 0 | 19 | 45 | 96 | 546 | 586 | 113.54 |

**Table 3: Descriptive Statistics for Private Placements**

This table presents descriptive statistics for the number of private placements held conditional on holding private placements, and for the number of issuing firms that the holdings represent. Panel A (Life Insurers) and Panel B (Property Casualty Insurers) presents the results for the number of private placements held conditional on holding private placements. Panel C (Life Insurers) and Panel D (Property Casualty Insurers) hold the descriptive statistics for the number of private placement issuing firms represented in our sample. Our sample period is from 2001 to 2010.

Panel A - Life Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 414 | 51.19 | 1 | 1 | 3 | 15 | 52 | 486 | 1060 | 106.18 |
| Equity | 157 | 5.24 | 1 | 1 | 1 | 2 | 5 | 38 | 64 | 8.93 |

Panel B - Property Casualty Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 259 | 5.65 | 1 | 1 | 1 | 2 | 4 | 69 | 118 | 12.23 |
| Equity | 182 | 2.49 | 1 | 1 | 1 | 1 | 3 | 19 | 21 | 3.17 |

Panel C – Life Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 414 | 34.80 | 1 | 1 | 2 | 12 | 40 | 310 | 645 | 64.09 |
| Equity | 157 | 3.76 | 1 | 1 | 1 | 2 | 4 | 28 | 40 | 5.54 |

Panel D - Property Casualty Insurers

| Private Asset | N | Mean | Min | 1st | 25th | Median | 75th | 99th | Max | Std |
|---|---|---|---|---|---|---|---|---|---|---|
| Debt | 259 | 4.88 | 1 | 1 | 1 | 1 | 4 | 62 | 92 | 10.06 |
| Equity | 182 | 2.08 | 1 | 1 | 1 | 1 | 2 | 18 | 19 | 2.54 |

**Table 4: Trades associated with Privately Placed Debt**
This table reports the raw and DGTW-adjusted returns for public equity trades associated with privately placed debt assets (associated trades) and equity trades unassociated with a private placement (unassociated trades). Panel A reports the results for Buys and Panel B reports the results for Sells. The difference between the means for associated and unassociated trades is tested. T-stats are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

**Panel A – Buys**

| holding period (trading days) | 20 | 60 | 120 | 240 |
|---|---|---|---|---|
| **Associated Trades:** | | | | |
| Raw Return | 0.00384 | 0.0216*** | 0.0461*** | 0.1147*** |
| | (1.21) | (4.32) | (6.84) | (11.10) |
| DGTW Adjusted Return | -0.00197 | -0.00020 | -0.00231 | -0.00350 |
| | (-0.76) | (-0.05) | (-0.40) | (-0.37) |
| | n = 1,473 | n = 1,473 | n = 1,473 | n = 1,475 |
| **Unassociated Trades:** | | | | |
| Raw Return | 0.00471*** | 0.0123*** | 0.0331*** | 0.0661*** |
| | (37.76) | (59.62) | (113.32) | (155.94) |
| DGTW Adjusted Return | 0.00130*** | 0.00217*** | 0.00482*** | 0.00646*** |
| | (12.99) | (12.96) | (20.28) | (18.56) |
| | n = 917,707 | n = 917,713 | n = 917,725 | n = 917,752 |
| **Associated - Unassociated:** | | | | |
| Raw Return | -0.00087 | 0.00933* | 0.0130* | 0.0485*** |
| | (-0.28) | (1.81) | (1.93) | (4.59) |
| | Pooled | Pooled | Satterthwaite | Pooled |
| DGTW Adjusted Return | -0.00327 | -0.00237 | -0.00713 | -0.00996 |
| | (-1.26) | (-0.57) | (-1.20) | (1.06) |
| | Satterthwaite | Pooled | Pooled | Satterthwaite |

**Panel B – Sells**

| holding period (trading days) | 20 | 60 | 120 | 240 |
|---|---|---|---|---|
| **Associated Trades:** | | | | |
| Raw Return | -0.00453 | 0.00264 | 0.0296*** | 0.0683*** |
| | (-1.61) | (0.56) | (4.05) | (6.65) |
| DGTW Adjusted Return | -0.00241 | -0.00018 | -0.00385 | -0.00609 |
| | (-1.03) | (-0.05) | (-0.60) | (-0.63) |
| | n = 1570 | n = 1570 | n = 1570 | n = 1571 |
| **Unassociated Trades:** | | | | |
| Raw Return | -0.00033** | 0.00638*** | 0.0285*** | 0.0713*** |
| | (-2.34) | (28.15) | (89.28) | (150.75) |
| DGTW Adjusted Return | 0.00231*** | 0.00467*** | 0.00833*** | 0.0145*** |
| | (20.58) | (25.46) | (32.14) | (36.70.96) |
| | n = 933,035 | n = 933,052 | n = 933,071 | n = 933,147 |
| **Associated - Unassociated:** | | | | |
| Raw Return | -0.00420 | -0.00374 | 0.00104 | -0.00298 |
| | (-1.49) | (-0.79) | (0.14) | (-0.29) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |
| DGTW Adjusted Return | -0.00472** | -0.00485 | -0.0122* | -0.0206** |
| | (-2.01) | (-1.26) | (-1.93) | (-2.14) |
| | Satterthwaite | Satterthwaite | Pooled | Pooled |

**Table 5: Trades Associated with Privately Placed Equity**

This table reports raw and DGTW-adjusted returns for public equity trades associated with privately placed equity assets (Associated Trades) and equity trades unassociated with a private placement (Unassociated Trades). Panel A reports the results for Buys and Panel B reports the results for Sells. The difference between the means for associated and unassociated trades is tested. T-stats are in parentheses below. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

**Panel A – Buys**

| holding period (trading days) | 20 | 60 | 120 | 240 |
|---|---|---|---|---|
| **Associated Trades:** | | | | |
| Raw Return | -0.0329 | -0.0464 | -0.00107 | 0.0364 |
| | (-1.33) | (-1.59) | (-0.03) | (0.68) |
| DGTW-Adjusted Return | 0.0167 | 0.0100 | 0.0223 | -0.0525 |
| | (0.84) | (0.49) | (0.66) | (-1.16) |
| | n = 115 | n = 115 | n = 115 | n = 116 |
| **Unassociated Trades: :** | | | | |
| Raw Return | 0.00471*** | 0.0123*** | 0.0331*** | 0.0661*** |
| | (37.76) | (59.62) | (113.32) | (155.94) |
| DGTW-Adjusted Return | 0.00130*** | 0.00217*** | 0.00482*** | 0.00646*** |
| | (12.99) | (12.96) | (20.28) | (18.56) |
| | n = 917,707 | n = 917,713 | n = 917,725 | n = 917,752 |
| **Associated - Unassociated:** | | | | |
| Raw Return | -0.0376 | -0.0587** | -0.0342 | -0.0297 |
| | (-1.52) | (-2.02) | (-0.87) | (-0.55) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |
| DGTW-Adjusted Return | 0.0154 | 0.00788 | 0.0175 | -0.0589 |
| | (0.77) | (0.38) | (0.52) | (-1.30) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |

**Panel B – Sells**

| holding period (trading days) | 20 | 60 | 120 | 240 |
|---|---|---|---|---|
| **Associated Trades:** | | | | |
| Raw Return | -0.0798*** | -0.0993** | -0.1045* | 0.00441 |
| | (-3.82) | (-2.34) | (-1.83) | (0.08) |
| DGTW-Adjusted Return | -0.0381*** | -0.00349 | -0.0130 | -0.0158 |
| | (-3.02) | (-.98) | (-0.27) | (-0.36) |
| | n = 159 | n = 159 | n = 159 | n = 159 |
| **Unassociated Trades: :** | | | | |
| Raw Return | -0.00033** | 0.00638*** | 0.0285*** | 0.0713*** |
| | (-2.34) | (28.15) | (89.28) | (150.75) |
| DGTW-Adjusted Return | 0.00231*** | 0.00467*** | 0.00833*** | 0.0145*** |
| | (20.58) | (25.46) | (32.14) | (36.70) |
| | n= 933,035 | n= 933,052 | n = 933,071 | n = 933,148 |
| **Associated - Unassociated:** | | | | |
| Raw Return | -0.0794*** | -0.1056** | -0.1330** | -0.0669 |
| | (-3.80) | (-2.49) | (-2.33) | (-1.25) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |
| DGTW-Adjusted Return | -0.0404*** | -0.0396 | -0.0213 | -0.0304 |
| | (-3.20) | (-1.11) | (-0.45) | (-0.69) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |

**Table 6: Performance of trades associated with privately placed debt compared to privately placed equity**

This table reports the raw and DGTW-adjusted returns for public equity trades associated with privately placed debt (Associated with Debt Trades) and public equity trades associated with privately placed equity (Associated with Equity Trades). Panel A reports the results for Buys and Panel B reports the results for Sells. The difference between the means for trades associated with privately placed debt and trades associated with privately placed equity is tested. T-stats are in parentheses below. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

| **Panel A – Buys** | | | | |
|---|---|---|---|---|
| holding period (trading days) | 20 | 60 | 120 | 240 |
| **Associated with Debt Trades:** | | | | |
| Raw Return | 0.00384 | 0.0216*** | 0.0461*** | 0.1147*** |
| | (1.21) | (4.32) | (6.84) | (11.10) |
| DGTW-Adjusted Return | -0.00197 | -0.00020 | -0.00231 | -0.00350 |
| | (-0.76) | (-0.05) | (-0.40) | (-0.37) |
| | n = 1,473 | n = 1,473 | n = 1,473 | n = 1,475 |
| **Associated with Equity Trades:** | | | | |
| Raw Return | -0.0329 | -0.0464 | -0.00107 | 0.0364 |
| | (-1.33) | (-1.59) | (-0.03) | (0.68) |
| DGTW-Adjusted Return | 0.0167 | 0.0100 | 0.0223 | -0.0525 |
| | (0.84) | (0.49) | (0.66) | (-1.16) |
| | n = 115 | n = 115 | n = 115 | n = 116 |
| **Associated Debt – Associated Equity:** | | | | |
| Raw Return | 0.0367 | 0.0680** | 0.0472 | 0.0782 |
| | (1.47) | (2.30) | (1.18) | (1.43) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |
| DGTW-Adjusted Return | -0.0187 | -0.0102 | -0.0246 | 0.0490 |
| | (-0.93) | (0.49) | (-0.72) | (1.06) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |

| **Panel B – Sells** | | | | |
|---|---|---|---|---|
| holding period (trading days) | 20 | 60 | 120 | 240 |
| **Associated with Debt Trades:** | | | | |
| Raw Return | -0.00453 | 0.00264 | 0.0296*** | 0.0683*** |
| | (-1.61) | (0.56) | (4.05) | (6.65) |
| DGTW-Adjusted Return | -0.00241 | -0.00018 | -0.00385 | -0.00609 |
| | (-1.03) | (-0.05) | (-0.60) | (-0.63) |
| | n = 1570 | n = 1570 | n = 1570 | n = 1571 |
| **Associated with Equity Trades:** | | | | |
| Raw Return | -0.0798*** | -0.0993** | -0.1045* | 0.00441 |
| | (-3.82) | (-2.34) | (-1.83) | (0.08) |
| DGTW-Adjusted Return | -0.0381*** | -0.00349 | -0.0130 | -0.0158 |
| | (-3.02) | (-.98) | (-0.27) | (-0.36) |
| | n = 159 | n = 159 | n = 159 | n = 159 |
| **Associated Debt – Associated Equity:** | | | | |
| Raw Return | 0.0752*** | 0.1019** | 0.1340** | 0.0639 |
| | (3.57) | (2.39) | (2.33) | (1.17) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |
| DGTW-Adjusted Return | 0.0357*** | 0.0348 | 0.00915 | 0.00973 |
| | (2.78) | (0.97) | (0.19) | (0.22) |
| | Satterthwaite | Satterthwaite | Satterthwaite | Satterthwaite |

**Table 7: Multi-Factor Models**
This table reports results of factor models for trades associated privately placed debt (Panel A), trades associated with privately placed equity (Panel B), and trades unassociated with a private placement relationship (Panel C). Calendar time portfolios of trades are formed that are long the buy trades and short the sell trades. The dependent variable is the calendar time portfolio return of associated trades. The independent variables are the variables for Fama and French three, four, and five factor models. The sample period is 2001 to 2010. T-stats are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

**Panel A: Trades Associated with Privately Placed Debt**

| Variable | FF3 | FF4 | FF5 |
|---|---|---|---|
| Intercept | 0.00016** | 0.00016** | 0.00018** |
| | (2.06) | (2.09) | (2.13) |
| SMB | 0.05337*** | 0.05684*** | 0.06052*** |
| | (4.00) | (4.23) | (4.32) |
| HML | -0.05702*** | 0.06004*** | -0.06176*** |
| | (-4.46) | (-4.67) | (-4.65) |
| MKTRF | -0.00661 | -0.01281** | -0.01001 |
| | (-1.13) | (-1.96) | (-1.42) |
| UMD | | -0.01726** | -0.01333 |
| | | (-2.13) | (-1.56) |
| LIQUID | | | 0.00063 |
| | | | (0.33) |
| | | | |
| N | 2,682 | 2,682 | 2,511 |
| $R^2$ | 0.0152 | 0.0168 | 0.0177 |

**Panel B: Trades Associated with Privately Placed Equity**

| Variable | FF3 | FF4 | FF5 |
|---|---|---|---|
| Intercept | -0.00013 | -0.00014 | -0.00030 |
| | (-0.38) | (-0.39) | (-0.80) |
| SMB | 0.26649*** | 0.26068*** | 0.32786*** |
| | (4.46) | (4.33) | (5.31) |
| HML | -0.65620*** | -0.65052*** | -0.64921*** |
| | (-11.38) | (-11.19) | (-10.98) |
| MKTRF | -0.41704*** | -0.40705*** | -0.31642*** |
| | (-15.97) | (-13.97) | (-10.26) |
| UMD | | 0.02813 | 0.09935*** |
| | | (0.77) | (2.64) |
| LIQUID | | | 0.00436 |
| | | | (0.52) |
| | | | |
| N | 2,654 | 2,654 | 2,492 |
| $R^2$ | 0.1544 | 0.1546 | 0.1420 |

**Panel C: Unassociated Trades**

| Variable | FF3 | FF4 | FF5 |
|---|---|---|---|
| Intercept | 0.00001 | 0.00001 | -0.00002 |

| | | | |
|---|---|---|---|
| | (0.48) | (0.34) | (0.73) |
| SMB | -0.00520 | -0.01185*** | -0.00742* |
| | (-1.16) | (-2.70) | (-1.68) |
| HML | -0.10973*** | -0.10394*** | -0.10661*** |
| | (-25.56) | (-24.76) | (-25.50) |
| MKTRF | -0.04066*** | -0.02876*** | -0.02000*** |
| | (-20.73) | (-13.50) | (-9.04) |
| UMD | | -0.03312*** | 0.04016*** |
| | | (-12.53) | (14.98) |
| LIQUID | | | 0.00170*** |
| | | | (2.82) |
| N | 2,682 | 2,682 | 2,511 |
| $R^2$ | 0.3283 | 0.3655 | 0.3811 |

# ESSAY 3: INFORMATION GENERATION, LEARNING AND THE TRADING DYNAMICS OF INSTITUTIONAL TRADERS DURING THE 2007-2008 FINANCIAL CRISIS

## 3.1 Introduction

There is considerable recent interest in institutional trading during bubble, and subsequent crisis, periods. For example, Griffin, Harris, Shu, and Topaloglu (2011) study how institutions appear to drive and burst the Tech bubble in early 2000, and report that hedge funds are the most aggressive traders around the bubble period. Additionally, Cella, Ellul, and Giannetti, (2012) examine a period around the Lehman Brothers collapse, and find that institutions with short investment horizons liquidate more of their equity portfolio than do investors with longer horizons. Manconi, Massa, and Yasuda (2012) show that bond mutual funds that hold mortgage backed securities (MBS) during the 2007-2008 financial crisis sell more liquid assets in the form of corporate bonds. Manconi et al. argue that the selling of corporate bonds by mutual funds explains how the financial crisis is transmitted to the bond market. The aforementioned studies focus on institutional characteristics that help explain their contribution to and trading behavior around crisis periods.

We add to the literature that examines how institutions trade during a crisis period by examining a unique data set that has both portfolio holdings and transactions of U.S. insurers. We focus our analysis on insurer trading behavior around the 2007-2008 financial crisis and examine whether or not insurers learn from the assets they hold. We argue that insurers who hold mortgages are able to acquire and process information such as delinquencies in their own loan portfolio. We hypothesize that these insurers benefit from this mortgage-related information and are more likely to sell MBS before the financial crisis. Additionally, we test if information obtained from mortgage portfolios causes some insurers to adjust their holdings towards government bonds (a prediction made by Gennaioli, Shleifer, and Vishny, 2012).

In aggregate, insurers are significant holders of both MBS and mortgages. For example, Manconi, Massa, and Yasuda (2012) show that insurers hold more securitized assets than mutual funds, measured by dollar volume. Additionally, insurers hold a significant amount of mortgages in their portfolios, representing the second largest asset class in their portfolio behind fixed income securities (Insurance Information Institute, 2011). Therefore, it is reasonable to believe insurers will be attuned to developments in the loan markets.

Brunnermeier (2009) reports that the crisis started in loan markets as early as February 2007, but that it was May before Moody's put certain tranches of structured products based on real estate on downgrade review. Ellul, Jotikasthira, Lundbald, and Wang (2012) report that most of the downgrades of asset backed securities did not start until the third quarter of 2007. Therefore, there appears to be a lag between when the information in loan markets is generated and when this information is fully revealed to the market.[22] However, investors who hold mortgages could reduce the amount of time it took

[22] Information from issuers of MBS regarding the experience of the loan portfolio that backed MBS is acquired with a lag. According to a joint staff report from the Department of Treasury, Office of Federal Housing Enterprise Oversight, and the Securities and Exchange Commission, dated January (2003) issuers of private label MBSs must provide investors with post-offering disclosures, however, there is a lag period between the issuer's realization of information and the investors' realization (receiving the report). In addition, under Section
15(d) of the Exchange Act issuers of MBSs who have less than 300 record holders (which they state is typically the case for private-label MBSs), the issuer may discontinue post offering disclosures. Therefore there is at a minimum some lag period between when issuers of the securities report delinquencies, prepayments etc. There is also a time lag for reporting, for example, by the Federal Reserve reporting foreclosures numbers at the state level.

to acquire information.[23] If they learn from their mortgage portfolio, then they can use this information to reduce their exposure to other real estate they hold in the form of MBSs.

Insurance companies provide an ideal setting for studying how institutional trading behavior in one asset (MBSs) is influenced by holdings of another asset (mortgages). Insurance companies hold substantial amounts of both mortgages and MBSs. The statutory filing of the National Association of Insurance Commissioners (NAIC) reports the detailed year-end holdings of mortgages and MBSs for each licensed U.S. insurer. In addition to the year-end holdings, the NAIC data includes a detailed listing of the transactions of the assets during the year. The detailed holdings and transactions data is a unique feature of the NAIC data that is not found in other institutional data sets such as 13F fillings (which reports quarterly holdings only) or Ancerno (which reports detailed transactions but no holdings data).

Following Ellul, Jotikasthira, and Lundbald, we define the financial crisis for MBS to start in the third quarter of 2007. We document that insurers do appear to learn from their mortgage holdings in the pre-crisis period. We find that insurers who hold mortgages are more likely than those insurers who do not hold mortgages to reduce their MBSs holdings in the eighteen months leading up to the start of the financial crisis. At the onset of the crisis, we find no evidence that insurers who hold mortgages sell with as much urgency as those who do not hold mortgages. Additionally we find that insurers as a group exhibit a flight to safety during the financial crisis, increasing the percentage of their fixed income portfolios that is held in governments bonds. However, we find that those insurers who

[23] There is good reason to believe that lending relationships, such as mortgages, are special and generate information for the lender (Diamond, 1984; Fama, 1985). Even though the mortgages held by insurers were obtained in the secondary market (thus precluding information generation via underwriting), insurers could still generate information through the monitoring process.

hold mortgages do not exhibit a flight to safety, and actually reduced the percentage that government bonds made up of their fixed income portfolios.

The remainder of this paper is organized as follows. In the next section we develop our hypotheses to address the idea of learning from holding an asset, and how insurers use this information to trade around the financial crisis. Section III describes the data set that we use for our study. Section IV presents our results, and section V concludes.

## 3.2 Hypothesis Development

### *3.2.1 Did insurers learn from mortgage holdings and time the financial crisis?*

There are a number of influential papers, both theoretical and empirical, that consider how institutions trade during periods of mispricing, which in the extreme manifest as crisis periods. [24] Early work, arguing for the efficiency of capital markets, such as Friedman (1953) and Fama (1965) theorizes that sophisticated investors trade against irrational agents to eliminate mispricing. In contrast, there is now substantial literature on the limits to arbitrage that explains why periods of mispricing can persist. This literature argues that market frictions such as noise trader risk (DeLong, Shleifer, Summers, and Waldmann, 1990) or synchronization risk (Abreu and Brunnermeier 2002, 2003) may make it optimal to attempt to ride a bubble. For example, in Abreu and Brunnermeier (2002) rational arbitrageurs will attempt to time the market and delay their arbitrage because they are uncertain of when other rational investors will start attempting to correct mispricing. In their model, a single arbitrageur cannot correct mispricing by himself.

[24] Empirical papers in this vein, such as Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu, (2011) have used the tech bubble of the late 1990's and generally found that institutions rode (and burst) the bubble.

Mispricing is only corrected when a critical mass of arbitrageurs act together, which creates a coordination problem. If a trader realizes that he cannot correct the mispricing by himself, then he may choose to "ride the bubble" until the point at which a critical mass of traders exists to trade against the bubble.

The aforementioned literature makes predictions how rational, informed investors trade when mispricing exists. Institutional traders are typically considered to be rational, informed investors. Given that insurers are a class of institutional investors, we relate the trading behavior of insurers to the predictions made in these models.

In addition to the models that make predictions regarding informed trading behavior during bubble and crisis periods, Grossman and Stiglitz (1980) build a model that describes why investors become informed. In Grossman and Stiglitz, investors can choose to acquire information and learn from this information. We argue that insurers who hold mortgages are able to acquire information similar to the investors in the Grossman and Stiglitz model. Insurers who hold mortgages acquire information from their mortgage portfolio by monitoring things such as late payments and default rates. We contend that insurers who become more informed via their mortgage holdings should be in a better position to know that they should exit the bubble, and will be more likely to exit the bubble prior to the financial crisis.[25] Therefore, we form the following hypothesis:

H1: The likelihood of reducing MBS exposure prior to the crisis is greater for insurers that hold mortgages than for those who do not.

[25] There is also some empirical evidence that supports the idea of investors learning. Seru, Shumway, and Stoffman, 2010) find that some individual traders do appear to learn, and become better with trading experience, while some learn that they have poor ability and stop trading.

Additionally, since rational arbitrageurs are competitive in the Abreu and Brunnermeier (2002) model, an arbitrageur who waits too long will miss the chance to trade (if the price corrects in the interim). Hence, Abreu and Brunnermeier emphasize an element of urgency to trade once the crisis starts. To address the urgency suggested by the Abreu and Brunnermeier (2002) theory, we examine if some insurers trade with more urgency at the onset of the financial crisis (where there is a critical mass of traders trading against the mispricing). If some insurers can acquire information and learn, as in the Grossman and Stiglitz model, then we expect that some will act with more urgency. We contend that insurers who hold mortgages will act with more urgency to sell once they realize that a critical mass of traders is starting to trade against the mispricing. We measure the urgency with which traders act via a Cox Proportional Hazard model that measures time until an event. In this case, for each firm-security combination the event will be selling the security. The above discussion leads to the following hypotheses:

> H2: insurers that hold mortgages will seek to sell after the onset of the crisis with more urgency than those that do not hold mortgages.

*3.2.2 Did insurers exhibit a flight to safety?*

There are several theoretical models that consider which assets institutions choose to trade during periods of market stress. For example, models by Vayanos (2004) and Brunnermeier and Pedersen (2009) describe trading by financially constrained institutions (e.g. institutions facing redemptions) when there is a market disruption. Generally, the aforementioned literature makes the following argument. A fund faces a crisis such as a drop in performance due to a market downturn or a crisis in a particular security such as MBS. Investors in the fund demand their money back, causing large outflows for the fund in the form of redemptions. The fund faces a Scholes (2000) liquidation problem and must then choose which assets to sell to cover the redemptions. The empirical results of Manconi et al. (2012) support these theories by showing that mutual funds that face redemptions choose to sell more liquid corporate bonds at the onset of the financial crisis.

While Vayanos (2004) and Brunnermeier and Pedersen (2009) make predictions of trading behavior for financial constrained institutions, Gennaioli et al. (2012) model institutional trading behavior in a framework where there is no financial constraint (such as redemptions). The lack of a financial constraint on the institution in the Gennaioli et al. model is applicable to insurers who do not face the same funding flows problem that other institutions face (Manconi et al., 2012).[26] We argue that an insurer's funding flows should not be as sensitive to its portfolio performance as what funding flows are for other institutions such as mutual funds and hedge funds.[27] The Gennaioli et al. model makes a prediction of which assets an unconstrained institution will choose to buy (instead of sell) when faced by a crisis in a particular asset such as MBS.

Gennaioli, et al. (2012) contend that their model predictions reflect the events of the financial crisis. In the setup for their model they argue that a decrease in government debt during the Clinton administration creates a shortage in supply of safe assets, i.e.

[26] Funding flows refer to where mutual funds and hedge funds must raise capital (inflows) and at times redeem this capital for investors (outflows). The analog for insurers is that they raise capital through the selling of insurance policies (inflows), and must at times redeem these policies in the form of losses (outflows).

[27] We argue here that insurers are less likely to be impacted, but we will still control for the insurers' premiums and losses as we detail in the Methodology section.

government bonds. Financial engineers then create MBS as AAA rated substitutes for government bonds. The MBS are believed to be safe, but at some point bad news enters the market and investors realize that the MBS are not good substitutes for the government bonds. Investors then shift demand back to government bonds in a "flight to safety" mechanism.

The initial prediction from the Gennaioli et al. model is that prior to the financial crisis, before bad news enters the market, there is increased demand for MBS that mimic the safe cash flows of the government bonds. We test the prediction of increased demand for MBS prior to the crisis, and expect that prior to the crisis we should observe that insurers are large net buyers (demanders) of MBS. Therefore, we form the following hypothesize.

H3: Prior to the crisis there was an increase in demand for MBS by insurers.

According to the Gennaioli et al. model, the increase in demand for the MBS is followed by bad news entering the market and a subsequent flight to safety, where investors no longer demand MBS and instead demand government bonds. To test if insurer trading exhibits a flight to safety, we examine insurer holdings across the financial crisis. As we argue above, the Grossman and Stiglitz (1980) model allows some investors to learn and acquire information. We expect some insurers, those who hold mortgages, may be able to acquire and process information in their mortgage portfolio, and receive the bad news earlier. If they receive the bad news earlier, we hypothesize that they realize that MBSs are not good substitutes for government bonds, and exhibit a stronger flight to safety. We therefore form the following hypotheses to test our assertion and the predictions of the Gennaioli et al. model:

H4: After the onset of the crisis, insurers' trading behavior is consistent with a flight to safety.

H5: After the onset of the crisis, insurers that hold mortgages exhibit trading behavior that is more consistent with a flight to safety.

## 3.3 Data

To answer our primary research question, regarding whether or not information is generated in one asset (mortgages) that can be used to trade better in other assets (MBSs), we need detailed institutional holdings and transaction data for both assets. The Insurance industry is an excellent laboratory for testing our research questions because all licensed U.S. insurers are statutorily required to report detailed underwriting and investment data, including mortgage and MBS holdings and transactions. These (quarterly and annual) statutory reports are submitted to insurers' state insurance commissioners, who in turn submit these data to the National Association of Insurance Commissioners (NAIC) for aggregation. The NAIC data have been used in the finance literature by Bessembinder, Maxwell and Venkataraman (2006) to study market transparency around TRACE implementation and Lin, Wang, and Wu (2011) to study liquidity risk and bond returns.

In addition to being subject to unique investment reporting requirements, insurance companies provide an ideal setting for testing the aforementioned theories regarding institutional trading behavior around financial crises because they do not have the same confounding effects that other institutions might have, such as funding liquidity constraints or short investment horizons. For instance, there are numerous theoretical models that investigate exogenous shocks to institutions and its ability to fund itself (e.g. capital withdrawals by investors in a mutual fund).[28] Generally, these models predict an asset substitution where institutions trade (sell) liquid assets, instead of illiquid ones, in order to relieve the funding constraint. These models typically focus on institutions such as hedge funds or mutual funds that are subject to high variation in inflows and outflows of funding capital. In comparison, insurer funding capital (inflows and outflows) arises through the collection of premiums and payment of losses on policies, and these funding flows should not be as sensitive to the insurers' portfolio performance as mutual funds and hedge funds funding flows to their portfolio performance.[29] Besides the sensitivity to funding liquidity, there are other institutional characteristics, such as short investment horizons, that are theorized to play a role in trading decisions (see Allen, Morris and Shin, 2006; DeLong et al., 1990; Dow and Gorton, 1994; Froot, Scharfstein and Stein, 1992; Stein, 2005; and Tirole, 1982). These theories predict that, short horizon traders make trading decisions based on their short horizon and organizational structures, instead of longer run movements in value.[30] Insurers have a relatively long horizon compared to other institutions, and therefore are likely not influenced by the short horizon strategies emphasized in these

[28] See Brunnermeier (2009) for an insightful discussion of examples of these type of shocks. He draws the distinction between funding liquidity (the ability of a firm to finance itself) and market liquidity (the ability dispose of assets). Brunnermeier provides several examples of funding liquidity shocks. For other models that generate financial crisis from funding liquidity shocks see, for example, Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Diamond and Rajan (2009), Froot (2009), Geanakoplos (2010), Krishnamurthy (2009). Generally, in these models funding shocks to the institution causes an amplification process that depresses prices and/or market liquidity, which in the extreme cause asset fire sales and financial crises.

[29] We argue here that insurers are less likely to be impacted, but will still control for it and capture the heterogeneity among insurers as we detail further below.

[30] Cella, Ellul, Giannetti (2012) provides empirical evidence of the short investment horizons influencing trading behavior.

papers. However, there is heterogeneity in the investment horizon of insurers that will be controlled for in our analysis.

For the purposes of this study, we use Schedule B of the NAIC data that reports mortgage holdings at year end and transactions throughout the year. Schedule B provides information about their portfolio experience such as the mortgages which are in good standing, mortgages which are 90 days past due but not in foreclosure, and mortgages that are in foreclosure. For each loan held in the portfolio, the NAIC data reports the type of mortgage (Residential, Farm, Commercial, or Mezzanine), the city and state where the mortgage is located, the date acquired, the rate of interest, appraisal value, and the date of the last appraisal.

Schedule D reports holdings and transactions of debt instruments (bonds, asset-backed securities, etc), preferred stock and common stock in the insurers' general account. Having year end holdings and transactions that occur throughout the year allows us to infer the insurer's quarterly holdings. For each asset held in the portfolio the NAIC data reports the CUSIP number of the asset, a description of the asset, a book value, a fair value (the value that the asset could be sold for at the time of reporting), the actual cost (what the insurer paid for the asset including any transaction costs), the date the asset was acquired, and the NAIC designation.[31] The level of detail of the NAIC data set is not found in other publicly available institutional data sets, where answering our research questions would be infeasible.[32]

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[31] The NAIC designation is a one to six value assigned by the NAIC where assets with NAIC designation of one has the highest credit ratings.
[32] For other studies that use the NAIC data see Campbell and Taksler (2003), Schultz (2001), Bessembinder, Maxwell and Venkataraman (2006), Ericsson and Renault (2006) and Lin, Wang, and Wu (2011)

While the NAIC data has the benefit of providing the holdings and transactions for the mortgages and MBSs, there are a few limitations. We are dependent on the insurer accurately classifying the MBS into the correct line numbers designated for reporting holdings of MBSs in Schedule D of the statutory filing. Also, in some instances other asset backed securities based on assets such as airplane or car leases may be reported in a range of line numbers that also hold MBSs. To remove asset backed securities not based on mortgages we apply a series of filters based on key words such as “airplane,” “auto,” etc. Finally, the NAIC report does not provide security specific characteristics, and therefore we cannot control for security specific characteristics in our analysis.

To test our hypotheses, we select our sample period to be from 2001 to 2010 which allows us to capture the pre-crisis, crisis, and post-crisis period. We define the crisis period to be from the end of second quarter 2007 to fourth quarter 2009. We choose this period because in May of 2007 is when Moody’s announced that they were putting certain structured products on downgrade review. Ellul, Jotikasthira, Lundbald, and Wang (2012) report that most asset backed securities were downgraded within this period with downgrades starting in the third quarter of 2007. Table 1 presents descriptive statistics for our data set. There are 5093 insurers listed in the NAIC database of which there are 3394 who hold MBSs and 893 who hold mortgages. Figure 1 plots the holdings (measured as book value) of MBSs and mortgages for all insurers. Both MBSs and mortgages are reduced later in the sample period, but mortgages appear to be reduced with a lag compared to MBSs.

The mortgages that insurers hold are geographically diverse. There are 508 insurers who hold mortgages in the five states most affected by foreclosure.[33] Panel B of Table 1 reports descriptive statistics for the mortgage holdings. Conditional on holding mortgages, insurers hold an appraised value of $1 billion of mortgages on average. In unreported results, we find that for insurers who hold mortgages, 9.2% of their invested assets are mortgages, on average. As a percentage of appraised value held, insurers have 21.46% of their mortgage holdings in the five states most affected by foreclosures.

Table 2 provides descriptive statistics for the mortgage backed securities holdings. Panel A reports that life insurers hold more MBSs than do property casualty insurers. Conditional on holding MBSs, life insurers hold $777,245,685 on average while property casualty insurers hold $86,921,002 during our sample period. This is consistent with Life insurers holding more fixed income securities than property casualty insurers. Panel B of Table 2 pools life and property casualty insurers and reports the holdings of mortgage backed securities by year. Insurers increased their holdings of mortgage backed securities through 2007 before starting to reduce their holdings in 2008. Increasing holding from 2001 to 2007 provides initial evidence consistent with the Gennaioli et al. model that predicts increased demand for mortgage backed securities prior to the crisis.

## 3.4 Methodology and Results

### *3.4.1 Did insurers learn from mortgage holdings?*

To test our first hypothesis which asserts that insurers who held mortgages were able to skillfully trade around the crisis, we start by splitting our data to consider only the

[33] A Federal Reserve report in 2011 shows that the five states most affected by foreclosure are Arizona, California, Florida, Nevada, and Michigan (Quarterly Report on Household Debt and Credit, 2011).

pre-crisis period. We select the eighteen months prior to the start of the crisis, January 2006 to June 2007, and then test whether or not insurers were net acquirers or net disposers of MBSs in the weeks leading up to the crisis. To find if an insurer was a net acquirer or net disposer, we use the transactions files from Schedule D of the NAIC filings. We aggregate the MBSs that an insurer acquired or disposed of during each week of the pre-crisis period, and then take the difference of the two amounts (measured by actual cost). An indicator variable, $NetDisposerMBS_{j,t}$, is created that is one if firm *j* was a net disposer of MBSs during week *t,* and zero otherwise. The following binary choice model is used, which is estimated using Logistic Regression:

$$\Pr\left(NetDisposerMBS_{j,t} = 1\right) = \beta_0 + \beta_1 MortgageVariable_{i,j} + \beta_2 lnAssets_{j,t} + \beta_3 Turnover_{j,t} + \beta_4 Life_j + \beta_5 Mutual_j + \beta_6 PremToLoss_{j,t} + \beta_7 RBCRatio_{j,t} + \beta_8 lnAmtMBSheld_{j,t} + e$$

where $MortgageVariable_{i,j}$ is one of four mortgage holdings variables (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtHeldMostAff*) that we use in our analysis.[34] *HeldMort* is an indicator variable that is one if the insurer holds mortgages and zero otherwise. *HeldMostAff* is an indicator variable that is one if the insurer holds mortgages in one of the five states (AZ, CA, FL, NV, and MI) most affected by foreclosure. *lnAmtMortHeld* is the natural log of the book value of mortgages the insurer holds. *lnAmtHeldMostAff* is the natural log of the book value of mortgages that the insurer holds in the five states most affected by foreclosures.

[34] The subscript "i" on *MortgageVariable* goes from 1 to 4 and shall denote one of the four mortgage variables (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtHeldMostAff*).

We also include a series of firm specific characteristics to control for the effect of these on the probability of being a net disposer or MBS prior to the crisis. *lnAssets* is natural log of the insurer's assets and controls for the size of the insurer. We argued previously that insurers have relatively long investment horizons compared to other market institutions; however we still capture the heterogeneity within insurers by including a variable (*Turnover*) that measures portfolio turnover in our model specification. We include an indicator variable (*Life*) that is one if the insurer is a Life insurer and zero otherwise. This variable controls for differences between Life and Property Casualty insurers, including but not limited to the different accounting treatments between the firms (see Ellul et al., 2012). Insurance companies can have two forms of ownership, stock or mutual, which have been shown to have different incentive conflicts (Mayers and Smith, 1981). Therefore, we also control for whether the firm is organized as a stock or a mutual (*Mutual*). Insurers are not as sensitive to funding constraints as some other market institutions, but we still include a variable that measures insurer funding liquidity by including the ratio of premiums collected to losses incurred (*premlossratio*). To control for how well the insurer is capitalized we include the Risk-Based Capital Ratio (*RBC*). Finally, the variable *lnAmtMBSheld* is the natural log of the amount of MBSs the insurer holds. We include *lnAmtMBSheld* to control for the possibility that insurers who hold a lot of MBSs are more likely to become net disposers of MBSs in the pre-crisis period. Henceforth, we will use these firm specific control variables in subsequent models as well, but ask the reader to refer back here for definitions of the variable.

Table 3 reports the results of estimating the model. Coefficients are reported as log odds ratios, and standard errors are cluster corrected at the firm-level. The coefficient on

*HeldMort* indicates that insurers who hold mortgages have higher odds to sell MBSs prior to the crisis. Insurers who hold mortgages have higher odds of being a net disposer of MBSs in the pre-crisis period of 1.13 times ($e^{0.126}$ ). Additionally, insurers who hold mortgages in the five states most affected by foreclosure have higher odds of being a net disposer of MBSs of 1.3 times ($e^{0.264}$). Our continuous mortgage holding variables indicate that insurers that hold more mortgages (or more mortgages in states affected by foreclosure) are more likely to be net disposers. Overall, our result is consistent with insurers learning from their mortgage holdings and disposing of MBSs prior to the crisis when many of the MBSs were downgraded.

If insurers are able to learn from their mortgage holdings then they may also trade with more urgency once there is a realization that there is a crisis. To address the second hypothesis that asks if insurers who may be better informed (by holding mortgages) traded with more urgency at the onset of the crisis, we use a Cox Proportional Hazards model. The model is a duration analysis technique that measures time until an event and has been used in the finance literature to model the rate of limit order execution (Lo, Mackinlay, and Zhang, 2002 and Cho and Nelling, 2000) and to study limit orders that are rapidly cancelled (Hasbrouck and Saar, 2009).[35] A proportional hazards model allows us to study which group of insurers sell their MBSs with more urgency at the onset of the crisis, and provides a richer analysis than using a dichotomous dependent variable that indicates if the insurer sells. We specify the following model:

[35] Duration models are also referred to as Survival Analysis and are frequently used in epidemiology and biostatistics where the typical hazard is time until death.

$$
\begin{aligned}
logh_{j,m}(t) = \alpha(t) + \beta_1 MortgageVariable_{i,j} + \beta_2 lnAssets_j(t) + \beta_3 Turnover_j(t) + \beta_4 Life_j \\
+ \beta_5 Mutual_j + \beta_6 PremToLoss_j(t) + \beta_7 RBCRatio_j(t) \\
+ \beta_8 lnAmtMBSheld_j(t) + e
\end{aligned}
$$

where logh(t) is the hazard for insurer j and measures the duration from the start of the crisis to the time of the first sell made by an insurer.[36] We measure time to sell from the start of the crisis period i.e. end of the second quarter 2007 because this is when turmoil in the mortgage market was being realized publicly by investors and rating agencies started downgrading MBSs (Ellul, Jotikasthira, Lundbald, and Wang, 2012). Informed traders should trade with a sense of urgency because as Abreu and Brunnermeier (2003) point out that, "an arbitrageur who waits too long misses the profit opportunity if the price correction occurs in interim …". $MortgageVariable_{i,j}$ is one of our four mortgage variables (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtHeldMostAff*) described earlier. We control for the insurer characteristics described in the previous models.

The results of estimating the model are found in Table 4. The coefficients are reported as hazard ratios. The hazard is defined as the rate at which an event (selling a MBS) occurs measured in units of time (trading days). A hazard ratio is the ratio of the hazard of one group (insurers who hold mortgages) to another (insurers who do not hold mortgages). The hazard ratio for one of our mortgage variables (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtHeldMostAff*) can be interpreted as the rate (or urgency) with which insurers who hold mortgages (or hold more mortgages) sell MBSs as a ratio of the rate at which insurers who do not hold mortgages sell MBSs. Considering all of our

[36] The use of "(t)" following a variable indicates that the variable is a time variant predictor.

mortgage variables, we find no evidence that insurers who hold mortgages are more likely to sell with urgency than insurers who do not hold mortgages (i.e. a hazard ratio greater than 1 which is statistically significant). Where we do find significance (at the 10% level) on the *HeldMort* variable, the result suggests that insurers who hold mortgages do not sell as quickly at the start of the crisis as those who do not hold mortgages. The hazard of insurers who hold mortgages selling their MBSs is 0.788 times that of insurers who do not hold mortgages. Our results are inconsistent with our hypothesis two, perhaps because insurers who hold mortgages were more likely to dispose of MBSs in the pre-crisis period.

*3.4.2 How did insurers trade around the crisis?*

Turning our attention to testing Hypothesis 3, 4, and 5 which test the predictions from GSV (2012), we focus on the asset holdings of insurers. Recall, that GSV model predicts that there is increased demand for MBSs (the new security) in the years leading up to the crisis. Bad news enters the market and the investor then demands the traditional security (the government bond) in a flight to safety episode. Again, we are interested in whether insurers who held mortgages engaged in a more pronounced flight to safety than those who did not hold mortgages.

To address the first prediction from Gennaioli et al. regarding increased demand for MBSs, we look at all insurers and determine whether or not insurers were net acquirers or net disposers of MBSs in the years leading up to the crisis. To find whether or not an insurer was a net acquirer or net disposer, we use the transactions files from the NAIC filings. Similar to our process described earlier, we aggregate the MBSs that an insurer acquired during the course of the year. We then aggregate the MBSs that the insurer disposed of during the year. We then take the difference of the amount (measured by actual cost) of MBSs acquired during the year and the amount of MBSs disposed of during the year. Figure 2 charts the net acquisitions and disposals by year for insurers as a group. Prior to the crisis insurers were net acquirers, i.e. demanders, of MBSs. Therefore, the results of Figure 2 are consistent with the prediction from Gennaioli et al. that investors demanded MBSs prior to the crisis.

To address whether insurer trading behavior is consistent with a flight to safety, and particularly whether or not those insurers who held mortgages did this to a greater extent, we examine the percentage of an insurer's fixed income portfolio that is held in government bonds. Using the transaction files from the NAIC data we recreate each insurer's quarterly fixed income holdings, and calculate the percentage that is government bonds. We then estimate the following fixed effects models;[37]

$$H_{i,j,t} = \beta_0 + \beta_1 Crisis_t + \beta_2 lnAssets_{j,t} + \beta_3 Turnover_{j,t} + \beta_4 Life_j + \beta_5 Mutual_j + \beta_6 PremToLoss_{j,t} + \beta_7 RBCRatio_{j,t} + \beta_8 lnAmtMBSheld_{j,t} + e$$

$$H_{j,t} = \beta_0 + \beta_1 MortgageVariable_{i,j} * Crisis_t + \beta_2 MortgageVariable_{i,j} + \beta_3 Crisis_t + \beta_4 lnAssets_{j,t} + \beta_5 Turnover_{j,t} + \beta_6 Life_j + \beta_7 Mutual_j + \beta_8 PremToLoss_{j,t} + \beta_9 RBCRatio_{j,t} + \beta_{10} lnAmtMBSheld_{j,t} + e$$

[37] Results of a Hausman test indicate that a fixed effects approach is appropriate.

where the dependent variable $H_{j,t}$ is the percentage of insurer j's fixed income portfolio held in government bonds, in quarter *t*. In the first model, we seek to test hypothesis 4, which asserts that insurers trading behavior is consistent with a flight to safety. With the second model, we are testing Hypothesis 5, which asserts that insurers who hold mortgages exhibit trading behavior more consistent with a flight to safety. In the models above, $MortgageVariable_{i,j}$ represents one of our four measures for holding mortgages (HeldMort, HeldMostAff, lnAmtMortHeld, or lnAmtHeldMostAff) that we have defined previously. The variable *MortgageVariable*Crisis* is an interaction term of the mortgage variable and *Crisis*. The variable *Crisis* is an indicator variable that is one if the date is within the crisis period (July 1, 2007 to December 31, 2009) and zero otherwise. The other control variables in the model are the same as described previously. In both specifications, we include firm fixed effects (not shown) and report firm cluster corrected standard errors.

Table 5 reports the results of estimating the models. The results in column [1] indicate that insurers did exhibit a flight to safety. Insurers increased their percentage holdings of government bonds by 7% during the crisis period. In columns [2] through [4] we consider insurers who hold mortgages. The results in column [2] indicate that insurers who hold mortgages during the crisis do not exhibit a flight to safety. Insurers who held mortgages during the crisis reduced their government bond holdings by 3.2%, a result inconsistent with hypothesis 5. The effect appears to be larger for insurers who hold mortgages in the five states most affected by foreclosures, reducing their holdings by 4.3% during the crisis period. Our continuous measures of mortgage holdings result in similar results. The more mortgages insurers hold during the crisis period is associated with reducing government bond holdings.

## 3.5 Conclusion

In this paper we examine how insurers trade around the 2007-2008 financial crisis and contribute to a growing literature regarding institutional trading during crisis periods. Specifically, we ask whether or not insurers who hold mortgages trade differently than those insurers who do not hold mortgages and infer learning from holding mortgages. We also examine if insurers exhibit a flight to safety during the crisis.

We find that insurers who hold mortgages are more likely to dispose of their MBS holdings in the eighteen months leading up to the financial crisis. This result is consistent with insurers learning from their experience in their mortgage holdings. We then examine the period following the onset of the crisis, and find no evidence that insurers who hold mortgages sell with more urgency than those who do not hold mortgages. Instead we find slight evidence that insurers who hold mortgages do not sell as quickly as those who do not hold mortgages. This result is contrary to our prior expectation, but may be a result of insurers who hold mortgages and disposing of MBSs with higher likelihood in the pre-crisis period. Insurers who hold mortgages may have needed fewer reductions to their MBS portfolio at the onset of the crisis.

We also test the Gennaioli et al. model that predicts increased demand for MBSs in the pre-crisis period and a flight to safety at the onset of the crisis. Consistent with their model, we document that insurers are net acquirers (net demanders) of MBSs in the pre-crisis period. We then examine whether or not insurers exhibit a flight to safety at the onset of the crisis. We document that insurers do exhibit a flight to safety, increasing the percentage of their fixed income portfolio that they hold in government bonds. However, we also hypothesized that insurers who hold mortgages would exhibit behavior that is more consistent with a flight to safety. We document that the opposite is true, finding that insurers who hold mortgages reduce the percentage of their fixed income portfolios held in government bonds in the crisis period.

**Figure 1: MBS and Mortgage Holdings**
This figure reports the average amount (measured as book value) of MBSs and mortgages for all insurers

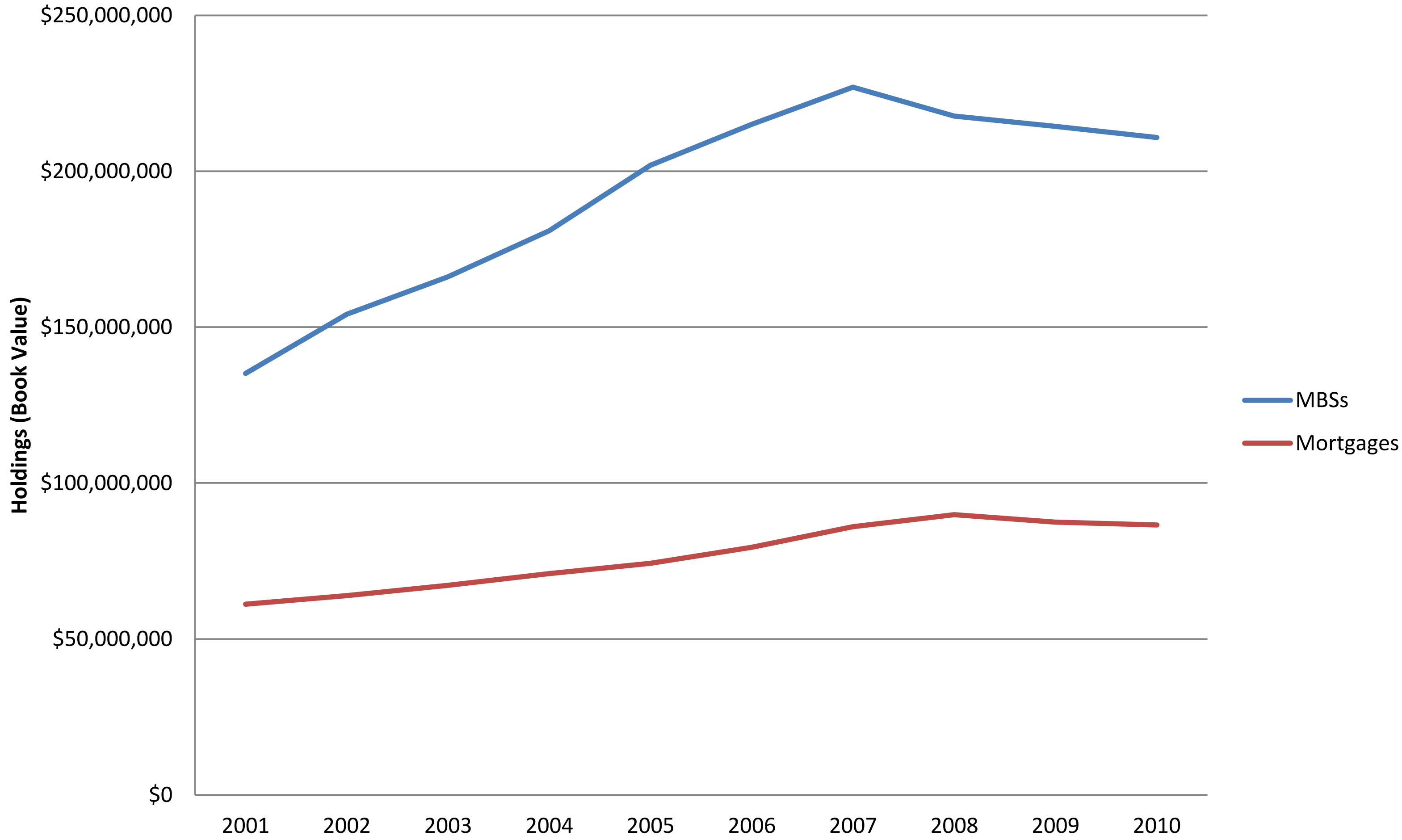

**Figure 2: Net Aquisitions and Disposals of MBSs**

This figure presents net acquisitions and disposals of MBSs (in $billions) for insurers over the period 2001 to 2010. The data is taken from the transaction files found in Schedule D of the NAIC statutory

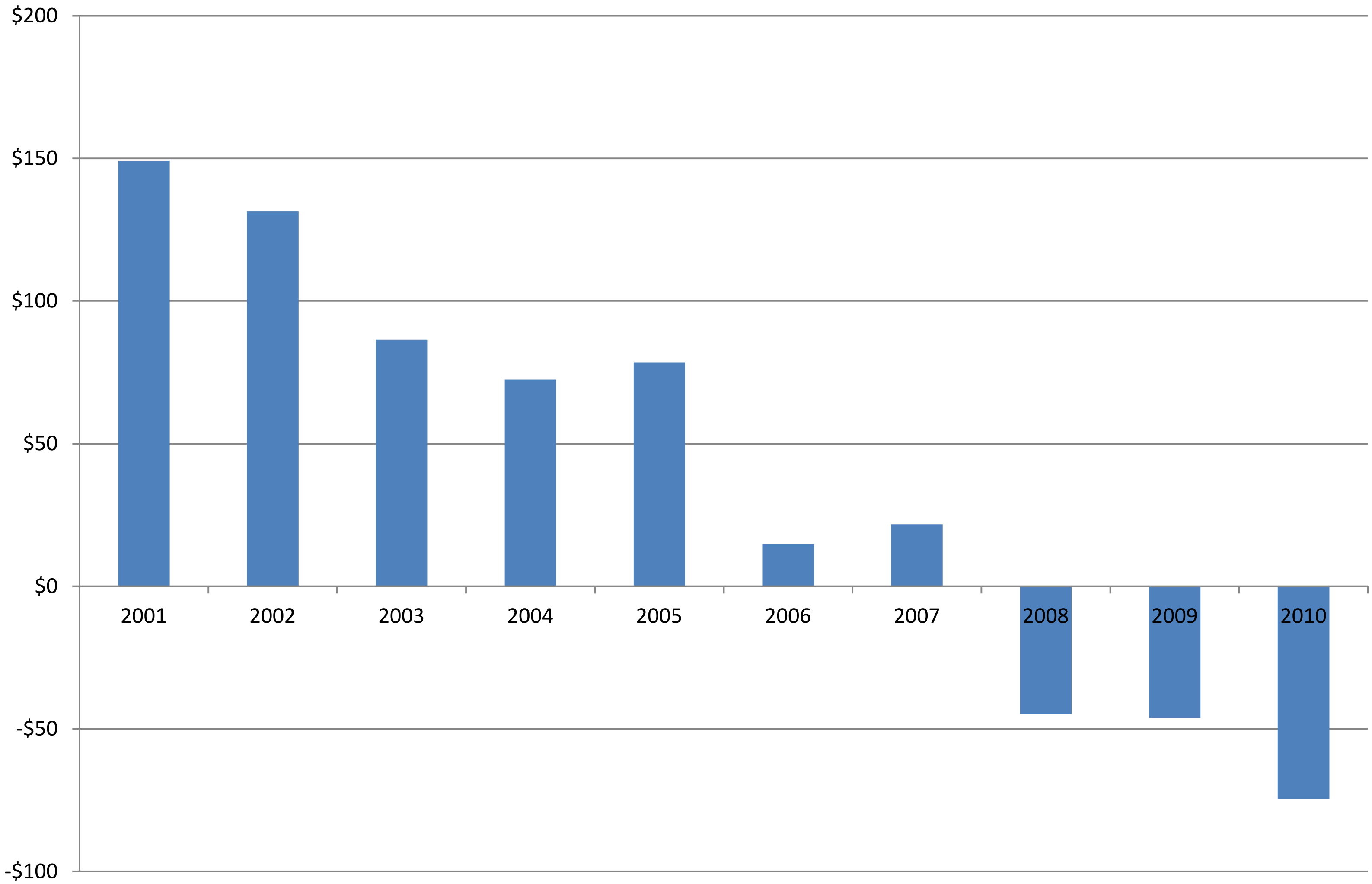

**Table 1: Descriptive Statistics**

This table presents descriptive statistics for our sample period of 2001 to 2010. Panel A holds counts of various descriptive statistics of our data set. Panel B holds descriptive statistics for the mortgage data found in Schedule B on the NAIC filing. Values in Panel B are conditional on the insurer holding mortgages.

| **Panel A -NAIC Data** | | | | | |
|---|---|---|---|---|---|
| Number of insurers in the NAIC database | 5,093 | | | | |
| Number of insurers who held mortgages | 893 | | | | |
| Number of insurers who held mortgages in the 5 states most affected by foreclosure | 508 | | | | |
| Number of insurers who held MBSs | 3,394 | | | | |
| Number of Agency MBS identified | 207,059 | | | | |
| Number of Private-Label MBS identified | 95,775 | | | | |
| Average Maturity of MBS (years) | 23.20 | | | | |
| **Panel B - Mortgage Data** | Mean | St Dev | Min | Median | Max |
| Average Amount Held (Book Value) | $506,769,258 | $2,255,410,339 | $0 | $8,700,000 | $40,695,906,405 |
| Average Amount Held (Appraisal Value) | $1,020,885,911 | $4,466,363,553 | $0 | $17,450,000 | $84,389,422,842 |
| Average Percent Held in 5 most affected states (measured in Book Value) | 21.5659% | 27.3571% | 0.000% | 14.8816% | 100.0000% |
| Average Percent Held in 5 most affected states (measured in Appraisal Value) | 21.4573% | 27.1044% | 0.000% | 14.1308% | 100.0000% |

**Table 2: Descriptive Statistics for MBSs**

This table presents results for the amount of mortgage backed securities held conditional on holding mortgage backed securities. Panel A reports the results by insurer type. Fair_Val is the Fair Value reported in the NAIC database. The Fair Value represents the value marked to market at the end of a reporting period. Actl_Cost is the sum of the Actual Cost reported in the NAIC filings. Actual Cost represents the cost of the asset plus transaction costs. Panel B presents the amount of holdings by year. Our sample period is 2001 to 2010.

**Panel A - MBS holdings by Insurer Type**

| Insurer Type | Variable | N | Mean | Min | 25th Pctl | Median | 75th Pctl | Max | Std Dev |
|---|---|---|---|---|---|---|---|---|---|
| Life | Fair_Val | 7,409 | $754,333,056 | $0 | $3,641,355 | $35,907,485 | $254,243,071 | $72,234,022,403 | $3,242,289,629 |
| | Actl_Cost | 7,409 | $777,245,685 | $0 | $3,660,581 | $36,242,990 | $257,071,123 | $71,938,793,208 | $3,351,242,896 |
| Property/ Casualty | Fair_Val | 16,802 | $85,469,441 | $0 | $1,813,463 | $8,961,787 | $41,622,255 | $11,203,381,299 | $382,600,071 |
| | Actl_Cost | 16,802 | $86,921,002 | $0 | $1,814,000 | $9,025,091 | $41,871,685 | $11,315,837,133 | $391,498,427 |

**Panel B - MBS holdings by Year**

| year | N | Mean | Min | 25th Pctl | Median | 75th Pctl | Max | Std Dev |
|---|---|---|---|---|---|---|---|---|
| **2001** | 2,504 | $211,883,892 | $0 | $1,916,881 | $9,294,530 | $56,980,305 | $41,308,320,468 | $1,234,620,231 |
| **2002** | 2,498 | $237,851,512 | $0 | $1,979,313 | $10,374,216 | $60,595,436 | $46,140,455,497 | $1,429,744,278 |
| **2003** | 2,451 | $259,073,692 | $0 | $1,816,587 | $10,227,389 | $64,035,677 | $51,688,636,209 | $1,640,890,477 |
| **2004** | 2,463 | $279,039,475 | $0 | $1,733,297 | $10,619,636 | $68,308,152 | $54,455,696,121 | $1,758,606,193 |
| **2005** | 2,435 | $312,749,516 | $0 | $2,198,574 | $12,075,808 | $73,974,362 | $58,299,382,925 | $1,935,812,353 |
| **2006** | 2,406 | $335,412,950 | $0 | $2,343,873 | $13,446,183 | $78,515,747 | $59,577,277,422 | $2,102,750,286 |
| **2007** | 2,377 | $355,658,109 | $0 | $2,445,957 | $15,276,434 | $82,925,337 | $63,443,943,916 | $2,166,297,011 |
| **2008** | 2,361 | $342,348,032 | $0 | $2,725,911 | $16,066,905 | $81,215,530 | $68,675,046,553 | $2,134,850,664 |
| **2009** | 2,355 | $334,695,035 | $0 | $2,633,543 | $14,545,658 | $80,113,811 | $70,726,820,167 | $2,246,318,944 |
| **2010** | 2,361 | $322,595,212 | $0 | $2,349,962 | $13,130,536 | $71,855,083 | $71,938,793,208 | $2,207,501,501 |

**Table 3: Probability of Disposing in Pre-Crisis Period**

This table presents the results of estimating the following Logistic Regression model for the pre-crisis period (January 1,2006 to June 30, 2007):

$$\Pr\left(NetDisposerMBS_{j,t} = 1\right) = \beta_0 + \beta_1 MortgageVariable_{i,j} + \beta_2 lnAssets_{j,t} + \beta_3 Turnover_{j,t} + \beta_4 Life_j + \beta_5 Mutual_j + \beta_6 PremToLoss_{j,t} + \beta_7 RBCRatio_{j,t} + \beta_8 lnAmtMBSheld_{j,t} + e$$

The dependent variable is 1 if the insurer was a net disposer of mortgage backed securities for a particular week and zero otherwise. MortgageVariable is one of our four variables for holding mortgages (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtMostAffHeld*). *HeldMort* is an indicator variable that is one if the insurer holds mortgages and zero otherwise. *HeldMostAff* is an indicator variable that is one if the insurer holds mortgages in one of the five states most affected by foreclosures (AZ, CA, FL, NV, and MI) and zero otherwise. *lnAmtMortHeld* is the natural log of the amount of mortgages an insurer holds. *lnAmtMostAffHeld* is the natural log of the amount of mortgages held in the five state most affected by foreclosures. *lnAssets* in the natural log of the insurer's assets. The variable *Turnover* measures the turnover of the insurer's portfolio. *Life* is an indicator variable that is 1 if the insurer is a Life insurer and zero otherwise. *Mutual* is an indicator variable that is one if the insurer is organized as a mutual insurer and zero otherwise. *PremToLoss* is a ratio of the insurer's premiums to losses. *RBC ratio* is the risk-based capital ratio for the insurer. *lnAmtMBSheld* is the natural log of the amount of mortgage backed securities that the insurer holds. Standard errors are firm cluster corrected and are reported in parentheses. Statistical significance is noted by asterisks. * is significant at 10% level. ** is significant at 5% level. *** is significant at 1% level.

| | iNetDisposer | iNetDisposer | iNetDisposer | iNetDisposer |
|---|---|---|---|---|
| Intercept | -6.134*** | -5.924*** | -6.050*** | -5.895*** |
| | (0.173) | (0.180) | (0.180) | (0.186) |
| HeldMort | 0.126*** | | | |
| | (0.044) | | | |
| HeldMostAff | | 0.264*** | | |
| | | (0.048) | | |
| lnAmtMortHeld | | | 0.009*** | |
| | | | (0.003) | |
| lnAmtMostAffHeld | | | | 0.014*** |
| | | | | (0.003) |
| lnAssets | 0.158*** | 0.147*** | 0.153*** | 0.145*** |
| | (0.010) | (0.011) | (0.011) | (0.011) |
| Turnover | 0.023** | 0.023** | 0.023** | 0.022** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Life | 0.141*** | 0.104*** | 0.129*** | 0.110*** |
| | (0.039) | (0.037) | (0.039) | (0.037) |
| Mutual | 0.008 | 0.004 | 0.006 | 0.005 |
| | (0.042) | (0.042) | (0.042) | (0.042) |
| PremToLoss | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| RBC Ratio | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| lnAmtMBSheld | 0.089*** | 0.089*** | 0.089*** | 0.089*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Obs | 216,548 | 216,548 | 216,548 | 216,548 |

**Table 4: Selling After the Onset of Crisis**

This table presents the results of estimating the following proportional hazard model:

$$logh_{j,m}(t) = \alpha(t) + \beta_1 MortgageVariable_{i,j} + \beta_2 lnAssets_j(t) + \beta_3 Turnover_j(t) + \beta_4 Life_j + \beta_5 Mutual_j + \beta_6 PremToLoss_j(t) + \beta_7 RBCRatio_j(t) + \beta_8 lnAmtMBSheld_j(t) + e$$

The dependent variable is the log hazard time for insurer j and asset m, where hazard time is the duration from the start of the crisis (start of third quarter 2007) to the first sell. MortgageVariable is one of our four variables for holding mortgages (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtMostAffHeld*). *HeldMort* is an indicator variable that is one if the insurer holds mortgages and zero otherwise. *HeldMostAff* is an indicator variable that is one if the insurer holds mortgages in one of the five states most affected by foreclosures (AZ, CA, FL, NV, and MI) and zero otherwise. *lnAmtMortHeld* is the natural log of the amount of mortgages an insurer holds. *lnAmtMostAffHeld* is the natural log of the amount of mortgages held in the five state most affected by foreclosures. *lnAssets* in the natural log of the insurer's assets. The variable *Turnover* measures the turnover of the insurer's portfolio. *Life* is an indicator variable that is 1 if the insurer is a Life insurer and zero otherwise. *Mutual* is an indicator variable that is one if the insurer is organized as a mutual insurer and zero otherwise. *PremToLoss* is a ratio of the insurer's premiums to losses. *RBC ratio* is the risk-based capital ratio for the insurer. Coefficients are reported as hazard ratios. Chi-Square statistics based on robust standard errors are reported in parentheses. Statistical significance is noted by asterisks. * is significant at 10% level. ** is significant at 5% level. *** is significant at 1% level.

| | | | | |
|---|---|---|---|---|
| Heldmort | 0.788* | | | |
| | (3.833) | | | |
| HeldMostAff | | 0.856 | | |
| | | (1.413) | | |
| lnAmtMortheld | | | 0.990 | |
| | | | (2.013) | |
| lnAmtHeldMostAff | | | | 0.993 |
| | | | | (0.746) |
| lnAssets | 0.928*** | 0.924*** | 0.930*** | 0.923*** |
| | (14.338) | (14.907) | (10.984) | (12.838) |
| Turnover | 1.000 | 1.000 | 1.000 | 1.000 |
| | (0.0169) | (0.025) | (0.020) | (0.027) |
| Life | 1.151 | 1.106 | 1.136 | 1.096 |
| | (1.737) | (0.923) | (1.267) | (0.707) |
| Mutual | 0.821** | 0.820** | 0.823** | 0.820** |
| | (4.053) | (4.119) | (4.016) | (4.127) |
| PremToLoss | 1.000*** | 1.000*** | 1.000*** | 1.000*** |
| | (11.577) | (12.735) | (11.976) | (12.921) |
| RBC Ratio | 1.000 | 1.000 | 1.00 | 1.000 |
| | (0.029) | (0.003) | (0.009) | (0.001) |
| lnAmtMBSheld | 1.003 | 1.003 | 1.002 | 1.002 |
| | (0.193) | (0.160) | (0.129) | (0.139) |
| Obs | 825,313 | 825,313 | 825,313 | 825,313 |

**Table 5: Flight to Safety during Crisis**

This table presents the results of estimating the following fixed effects models for the entire sample period (2001 to 2010):

$$H_{i,j,t} = \beta_0 + \beta_1 Crisis_t + \beta_2 lnAssets_{j,t} + \beta_3 Turnover_{j,t} + \beta_4 Life_j + \beta_5 Mutual_j + \beta_6 PremToLoss_{j,t} + \beta_7 RBCRatio_{j,t} + \beta_8 lnAmtMBSheld_{j,t} + e$$

$$H_{j,t} = \beta_0 + \beta_1 MortgageVariable_{i,j} * Crisis_t + \beta_2 MortgageVariable_{i,j} + \beta_3 Crisis_t + \beta_4 lnAssets_{j,t} + \beta_5 Turnover_{j,t} + \beta_6 Life_j + \beta_7 Mutual_j + \beta_8 PremToLoss_{j,t} + \beta_9 RBCRatio_{j,t} + \beta_{10} lnAmtMBSheld_{j,t} + e$$

The dependent variable is the quarterly percentage of the insurer's fixed income portfolio that is held in government bonds. *MortgageVariable* represents one of the four measures for mortgages (*HeldMort*, *HeldMostAff*, *lnAmtMortHeld*, or *lnAmtHeldMostAff*). *HeldMort* is an indicator variable that is one if the insurer held mortgages and zero otherwise. *HeldMostAff* is an indicator variable that is one if the insurer held mortgages in one of the five states most affected by foreclosures (AZ, CA, FL, NV, and MI) and zero otherwise. *lnAmtMortHeld* is the natural log of the amount of mortgages an insurer holds. *lnAmtMostAffHeld* is the natural log of the amount of mortgages held in the five state most affected by foreclosures. *MortgageVariable**iCrisis is an interaction term between one of the four mortgage holdings measures and *Crisis* where *Crisis* is an indicator variable if the date is between July 1, 2007 and December 31, 2009. *lnAssets* in the natural log of the insurer's assets. The variable *Turnover* measures the turnover of the insurer's portfolio. *Life* is an indicator variable that is 1 if the insurer is a Life insurer and zero otherwise. *Mutual* is an indicator variable that is one if the insurer is organized as a mutual insurer and zero otherwise. *PremToLoss* is a ratio of the insurer's premiums to losses. *RBC ratio* is the risk-based capital ratio for the insurer. *lnAmtMBSheld* is the natural log of the amount of mortgage backed securitites the insurer holds. We also include firm fixed effects (not shown). In column [1] we report the results of estimating the first model. In column [2] through [5] we estimate the second model that includes one of the four measures of mortgage holdings. Standard errors are firm cluster corrected and are reported in parentheses. Statistical significance is noted by asterisks. * is significant at 10% level. ** is significant at 5% level. *** is significant at 1% level.

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| | %Govn Bonds | %Govn Bonds | %Govn Bonds | %Govn Bonds | %Govn Bonds |
| Intercept | 1.518*** | 1.517*** | 1.516*** | 1.516*** | 1.516*** |
| | (0.083) | (0.083) | (0.083) | (0.083) | (0.083) |
| HeldMort*Crisis | | -0.032*** | | | |
| | | (0.006) | | | |
| HeldMort | | -0.006 | | | |
| | | (0.006) | | | |
| Heldmostaff*Crisis | | | -0.043*** | | |
| | | | (0.006) | | |
| Heldmostaff | | | -0.005 | | |
| | | | (0.008) | | |
| lnAmtMortHeld*Crisis | | | | -0.002*** | |
| | | | | (0.000) | |
| lnAmtMortHeld | | | | -0.000 | |
| | | | | (0.000) | |
| lnAmtHeldMostAff*Crisis | | | | | -0.003*** |
| | | | | | (0.000) |

| | | | | | |
|---|---|---|---|---|---|
| lnAmtHeldMostAff | | | | | -0.000 |
| | | | | | (0.001) |
| Crisis | 0.070*** | 0.075*** | 0.074*** | 0.076*** | 0.075*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| lnAssets | -0.063*** | -0.063*** | -0.063*** | -0.063*** | -0.063*** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| Turnover | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Life | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Mutual | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) |
| PremToLoss | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| RBC ratio | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| lnAmtMBSHeld | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| | | | | | |
| Obs | 100,833 | 100,833 | 100,833 | 100,833 | 100,833 |
| $R^2$ | 0.057 | 0.057 | 0.057 | 0.057 | 0.057 |

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APPENDIX

## Appendix A: Data Description

The National Association of Insurance Commissioners (NAIC) data set reports that we use in our study is a comprehensive data set of all licensed insurers in the United States. All licensed insurers are required to complete the statutory filings each year. Schedule D of the statutory filings reports all fixed income, preferred equity, and common equity investments of insurers. Several prior studies use the NAIC Schedule D data mainly to study the corporate bond market (see for example Schultz, 2001; Campbell and Taksler, 2003; Krishnan, Ritchken, and Thomson, 2005; Bessembinder, Maxwell, and Venkataraman, 2006, Ellul, Jotikasthira, and Lundbald, 2011). Prior to the TRACE database, the NAIC data was one of the only sources of bond transactions data.[38]

The NAIC data is a unique institutional data set. Unlike other institutional data sets such as holdings based on 13F, the NAIC data provides both the year-end holdings as well as the transactions that occur throughout the year. The holdings and transactions data are for all asset types (e.g. fixed income, preffered equity, common equity) in which an insurer invests. The insurer is identified by a unique company code and the assets are identified by a Cusip number.

In addition to the company and asset identifiers, the holdings data provides the amount of holdings in par value (for fixed income) or number of shares held (for equity), fair value and actual cost. The fair value represents the marked to market value of the asset

[38] Several researchers argue that the NAIC data is a good source for bond transaction data, as insurers make up a substantial portion of the corporate bond market. For example, Schultz (2001) reports that insurance companies hold up to 40% of investment grade bonds. Similarly, Cambell and Taskler (2003) report that insurance companies hold about one third of the outstanding corporate bonds. Additionaly, Bessembinder, Maxwell, and Venkataraman (2006) report that insurance companies accounted for 12.5% of dollar trading volume in the last six months of 2002.

at the time of the statutory filing.  The actual cost represents the amount paid (including transactions cost) for the asset.  The data also contain the date the asset was acquired.

The NAIC transaction data also provides company and asset identifiers as well as the date of the transaction, the direction of the trade (buy or sell), par value (or number of shares sold), the name of the vendor or dealer, and the actual cost (including transactions costs).  Having both the holdings and the transactions data provides a couple of advantages for our study.  First, by combining transactions and holdings we are able to identify exact holding periods of private placements.

We are also able to identify the public equity trades that take place during a period where the insurer holds the private placement in the same firm.  Being able to identify the date that a trade takes place in the public equity gives us an advantage over other studies that use quarterly holdings and must infer the date the trade takes place.  This allows us to be more precise in our return calculations.

We identify holdings of private placements by the presence of a #,*, or @ in the Cusip number of the asset.  While the majority of private placement holdings are in non-public firms, there are still substantial investments in privately placed assets of public firms.  For this study, we focus only on the privately placed assets issued by public firms, and from here on any references to privately placed assets shall refer to only those privately placed assets issued by public firms.  If the privately placed security is issued by a publicly traded firm, then the #,*, or @ occurs in the 7$^{th}$ or 8$^{th}$ position of the Cusip number, where the first 6 digits identifies the issuing firm.

VITA

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## PUBLICATIONS

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## DISSERTATION

**Cancelling Liquidity**
With Bonnie Van Ness and Robert Van Ness

We document a two-fold increase in limit order cancellation activity over the last decade, and study the determinants of cancellations and their evolution through time. We also examine the impact of order cancellation on market quality. We use an instrumental variable approach and estimate a simultaneous equations model to overcome simultaneity in the trading process. We find significant differences in the behavior of cancellation activity in the post Reg NMS environment, and differences in cancellation activity between exchanges. However, we fail to find evidence that the increase in cancellations has had deleterious effects on market quality, despite concerns from regulators and traders.

**Information Generation and Learning by Holding Privately Placed Securities**
With Andre Liebenberg and Andy Puckett

We examine whether or not tradable private information is generated in the market for privately placed securities. Further, we contribute to the literature that investigates how relationships influence trading behavior. Specifically, we examine if insurers generate information via relationships with publicly traded firms through investing in privately placed securities (privately placed debt, preferred stock, or common stock) of the public firm. We investigate in which type of private placement information generation is the strongest. Additionally, we study if information is generated via the origination and/or the monitoring process, testing theories of information reusability.

**Information Generation, Learning and the Skill of Institutional Investors during the Crisis of 2007-2008**
With Andre Liebenberg and Andy Puckett

We study if institutional traders acquire information from the assets that they hold and how this impacts trading decisions around the 2007-2008 financial crisis. Specifically, we test if insurance companies who hold mortgages exhibit different trading behavior in their mortgage backed securities portfolio than insurers who do not hold mortgages. We examine insurers' trading behavior in light of several theories of how institutions trade during crisis periods. We document that insurers who hold mortgages are more likely to be net disposers of MBSs prior to the crisis, than are other insurers. We also find that, on average, insurers exhibited a flight to safety during the crisis.

## WORKS IN PROGRESS

Factors that Determine Market Share of Designated Market Makers, with Jared Egginton

## PRESENTATIONS

**Cancelling Liquidity**

University of Mississippi and University of Memphis Spring 2012 joint Ph.D. research seminar (February 10th)

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Manager - Children's Healthcare of Atlanta
January 2006 to October 2006

Administrative Fellow - Medical College of Georgia Health System, Inc
July 2004 to January 2006

## ACADEMIC SERVICE

- 2012 Southern Finance Association Program Committee

## HONORS, ASSOCIATIONS, AND LEADERSHIP ACTIVITIES

- Selected for the Financial Management Association's Doctoral Consortium, 2012.
- Nominated for Graduate Student of the Year, 2011-2012, University of Mississippi.
- Graduate Student Member, Financial Management Association
- Student Senator, Graduate Student Association University of Alabama at Birmingham, 2002-2004.
- Student Senator, Student Association, Mississippi State University, Starkville, MS, 1998-1999.
- Inductee, Mortar Board, Mississippi State University, Starkville, MS, 1999-2000.
- Inductee, Elder Statesman (academic and leadership honorary), Mississippi State University, Starkville, MS, 1999.
- Recognized National Dean's List, 1997 and 1998.
- Lifetime Member, Golden Key National Honor Society, Mississippi State University, Starkville, MS.

- Lifetime Member, Phi Kappa Phi National Honor Society, Mississippi State University, Starkville, MS.