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The Zions Direct Bond Auction Platform and Demand from University Investment Programs

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DEMAND FROM UNIVERSITY INVESTMENT PROGRAMS

by

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ABSTRACT

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The purpose of this paper is to evaluate the niche Zions Direct Auctions fixed income market for the information of the market managers at Zions Direct. The analysis first measures historical data to evaluate market metrics, and the second recommends Vector AutoRegression (VAR) econometric methods to determine if the auction yields within the market are affected by large increases in bidding and buying by the Zion's Bank University Investment Programs(UIPs). In the case that it does, restructuring or at least UIPs.

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INTRODUCTION

The ‘Zion's Direct Auctions’ platform is a secondary market for debt—corporate, municipal, and government—established in 2006 by Zion's Bank, a major holding of Zion's Bancorporation. The platform is relatively unique in that it circumvents the traditional debt market maker as a middle man. This allows individual investors direct involvement in debt bidding and purchasing. Much in the same way that Ebay bypasses retailers, Zion's Direct Auctions bypasses market makers.

The Zion's Direct Auctions platform uses a variation of a second price auction format. In a second price auction the seller offers more than one identical item for sale to allow for more than one winning bidder. Each bidder can bid for all the items, or only some of them, and publicly indicates the price that he/she is willing to pay for each item. However, all winning bidders need to pay only the lowest qualifying (successful) bid. If there are more successful bids than items available, priority goes to the bidders who submitted their bids first (Bagwell 1992). In this case, the items for auction are single $1,000 principal bonds defined as one unit equaling one bond. The U.S. Department of the Treasury employs the second price format when raising funds through bond issuances. Google, Yahoo!, and Facebook also employ a variation of a second price auction in their advertisement pricing programs.

It does not appear that there are many other similar secondary debt auction models implemented, either currently, or when the Zion's Direct Auctions platform was created. Although, there may be one or two holdover attempts from the tech boom of the 90’s (Karchmer 1999). The singular existence of the auction platform and the discontinuation of its predecessors may be explained by the small and apparently niche demand for individual debt purchases.

Zion's Direct Auctions has seen 3.64 billion dollars in transactions since its inception in 2006, or about 455 million each year with recent years seeing a larger share of that volume. This volume is small in comparison to their traditional Bond Store platform which charges a commission fee for each transaction. Most of the auction sizes are between 20 to 80 units for municipal and corporate offerings and 100 to 250 units for certificates of deposit. These auction sizes are ideal for small and individual investors, and may require more effort comparatively (meaning a higher opportunity cost) for large and institutional investors to bid on and win.

The balance of such a small market would, in theory, be particularly susceptible to high capital participants (Oxelheim & Rafferty 2005). In October 2013, Zion's Bank implemented their University Investment Programs(UIPs) that supplied three university teams with 5 million dollars to invest into Zion's Direct fixed income offerings for a period of 6 months including the offerings available on the auction platform (For UIP fund prospectus see Hoffmire 2012). The combined demand shock of 15 million is very significant considering the total volume of auctions in that same month was just over 20 million. One team from Utah State University purchased 1.5 million dollars worth of debt securities from the auction platform in that same month, accounting for 7.4% of the auction volume in October 2013. The other university teams are known to have also used the auction platform, but to a lesser extent.

DATA

The first step to understanding this fairly unique market is to analyze the market metrics and identify any trends of note, particularly in relation to yields . The second step approaches the primary question of interest in this paper— Are yields affected by large demand shocks and if so, by what magnitude? To attempt to address these questions, the data of every auction from January 2012 until March 2014 was collected directly from the auction results reports on the Zion's Direct website and organized into a dataset that includes the name, type of debt, maturity, date of auction, and final auction yield. Additional factors of interest were gathered from publicly available charts from the U.S. Treasury.

A list of the market metrics follows with their descriptions.

Variable of primary interest:

- *Yield* is the price at which an auction ended and its security sold

Other variables include:

- *Day of Week* separated into individual days, Monday through Friday
- *Lagged Treasury Rates* included to provide a base comparison for market yields.

- *Principal* is a measure of individual auction size
- *Bond type* as either Corporate or Municipal
- *Maturity* is the number of months until the security matures.

METHODS

Market Metrics

The summary statistics of the market metrics are shown in Figure 1. Some interesting suppositions can be taken from the summary about day trade patterns in this market. In Figure 1, The distribution of trades over the period by day of week shows that Friday has a dip in offerings and Monday offers far fewer auctions than any other day of the week. Specifically, Friday's account for 18.5% of all auctions and Monday's account for 16.34% of all auctions, and the remaining 65.16% are distributed through the core of the week. Given current information, it is unclear whether the lower number of auctions on those days is controlled by Zion's Direct or organic market demand pattern, but it could be conjectured to be a combination of both assuming prior knowledge of both parties.

It is also interesting to note that the average maturity of auctions is grouped around 6 months with a tail toward longer maturities (Figure 1). Recall that the UIPs' demand structures put particular weight on 6 month and shorter maturities (Note the trends and dips for short maturities seen in Figure 2, including a large dip during October 2013). Figure 1 does not give a concrete idea of how yields vary, so Figure 2 is useful to see where yields were at various maturities. It is worthwhile to note the downward trend of those short and middle maturity auction yields through 2013 and the large dip of short maturity auction yields in the 9th and 10th months of that year.

Determining Yield Sensitivity to Demand Volume

To discern the effect that UIP volume demand shocks have on the yield in Zion's Direct Auctions, the econometric process known as VAR(Vector AutoRegression) combined with impulse response analysis can be used to estimate the effects on yields of the trades made by UIPs each day. The data required for a VAR analysis of trade volume and prices is a series of consecutive price estimates, preferably daily, for the securities purchased by UIPs throughout the month for which they are capitalizing their portfolios. Application of VARs in financial research has historically been applied to equities markets as the data for the analysis exists and is publicly available(Hasbrouck 1991a). Because of the nature of fixed income markets, the depth of VAR framework applications in fixed income has had limitations (Diebold, Piazzesi, and Rudebusch 2005). For instance, lack of publicly available data prohibits application of VAR modeling on the data gathered from Zion's Direct for this paper, but the actual framework is applicable for the relatively simple question at hand. Even though the data is not public, Zion's Direct does have internal access to sufficient data for all the securities they handle including securities sold through the auctions platform and thus should have no issue performing VAR modeling. As such, this section of the paper is most useful to persons with access to the Zions Direct Auctions data.

Vector autoregression is a form of regression analysis comprising two variables of interest and their endogenous lagged values whose estimates can be interpreted similarly to standard OLS regression output. Hasbrouck has used VARs extensively to analyze financial data and estimate the effects of shocks. In his 1991a paper he utilizes a form of VAR modeling called a SVAR(Structural Vector Auto Regression) model to attempt to increase the fit of his model. As previously mentioned, management at Zion's Direct could employ the data they have on hand into a mirror model of the Hasbrouck's 1991b model by swapping NYSE stock price for Zions Direct auction bond yields and NYSE daily stock trade volume for Zions Direct auction volume won by UIP's each day. The construction of this SVAR model can be seen below where: '**A**' is a 2x2 matrix imposing the structure from a contemporaneous auction volume term in the returns half of the VAR, ' **y**' is a vector of the variables returns and trade volume at the specified relative time period, '**B**' are matrices of coefficient estimates for each lag vector, and '$\boldsymbol{\varepsilon}$' is the noise of the process.

$$\boldsymbol{A}\boldsymbol{y}_t = \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{B}_2\boldsymbol{y}_{t-2} + \boldsymbol{B}_3\boldsymbol{y}_{t-3} + \boldsymbol{\varepsilon}_t$$

Given current data constraints, the application of this model must be run using simulated data. Using the financial estimates from Hasbrouck 1991b, and assuming a Gaussian random walk, financial data can be generated that will respond similarly to the actual data. The form of the simulated data follows directly below where *r* is the simulated returns at indicated time periods, *x* is the simulated trade volume at the indicated period, and the noise $v \sim N(0,1)$.

$$r_t = -.1333r_{t-1} - .0216r_{t-2} -.012r_{t-3} + .000912x_t + .000437x_{t-1} + .000045x_{t-2} + .000094x_{t-3} + v_{1,t}$$

$$x_t = -63.73r_{t-1} - 31.79r_{t-2} - 8.107r_{t-3} + .172x_{t-1} + .135x_{t-2} + .091x_{t-3} + v_{2,t}$$

The code for the full implementation of the simulation and its resultant analysis is given in annotated form in Figure 5.

The newly simulated data satisfies the conditions to run a SVAR model. The statistical package R is used to estimate SVAR using the method of direct optimization of the negative log-likelihood(Step-by-Step examples of the code for this analysis can be found in chapter 2 of Pfaff 2008). Once the SVAR has been estimated, impulse response analysis can be run to estimate the effects of shocks to trade volume on prices and consequently determine if UIPs are effecting yield prices.

RESULTS

An example of the impulse response function(IRF) analysis for a single iteration of the simulation can be found in Figure 3. The cumulative IRF is the summation of the yield response to shocks to trade volume over 30 lagged periods. As economic theory and empirical experience suggest, the largest effects are from closer periods to an event with a right-skewed tail of less significant residual effects from farther periods. The full simulation data can be seen graphed in Figure 4 and its summary statistics are given immediately below. The results of numerous iterations of the data simulation appear normal which is expected given the error assumptions in the simulation process. As an example, the minimum IRF simulation result can be interpreted as follows: yield levels are estimated to be .3299 lower as a result of UIP trade volume.

Summary Statistics of Simulated IRF Results

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.3299000	-0.0681800	0.0000665	0.0000128	0.0722800	0.3751000

Upon implementation, Zions Direct, in accordance with theory and observed evidences, should look for a significant negative value from impulse response analysis, which would indicate the existence and magnitude of yield lowering pressure from UIP activity.

CONCLUSION

The Zions Direct Auctions platform is a small market engineered with attributes that differentiate and insulate it from larger financial markets. Zion's Bank UIPs add a combined large market player with defined investment preferences at predictable times during the year which may affect yields in a disruptive manner for both buyers and sellers. The oversight of this small markets' health is valuable to those interested in its success and continuance. Analysis of historical auction data has identified notable characteristics in auction yield results across days and maturities. Additionally, using internal data, Zions Direct can utilize vector autoregression as presented in this paper to implement impulse response analysis to confirm the direction and magnitude of market yield response to UIP trading volume. With this information in hand, market controllers and policy makers have the information to further ensure the stability, reliability and predictability of Zions Direct Auctions.

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Figure 1. Summary Statistics for Market Variables

This table contains the summary statistics for the entire dataset which spans from January 2012 until March 2014. The statistics can be interpreted as market metrics specific to Zion's Direct Auctions in the case of: Yield, (Day of Week), Principal, (Type of Bond), Maturity, and Monthly Principal. Treasury Rate is exogenous to the market. Yield, Principal, Treasury Rate and Maturity are on a per transaction level.

Variable	*Mean*	*Std Dev*	*Minimum*	*Maximum*
Yield	0.90313	0.28969	0.16	2.46
Monday	0.16341	0.36977	0	1
Tuesday	0.21053	0.40771	0	1
Wednesday	0.21852	0.41327	0	1
Thursday	0.22244	0.41591	0	1
Friday	0.18507	0.38838	0	1
Treasury Rate	0.09375	0.05067	0	0.45
Principal (# of bonds)	52.42472	77.95447	4	500
Corporate	0.34402	0.47508	0	1
Municipal	0.29704	0.45698	0	1
Maturity (in months)	6.15312	4.12584	1	24

Figure 2. Average Monthly Yields for Auctions of Various Maturities

The average yields combine to present a general feel for the cycle and trends within the auction platform. The year 2012, saw generally increasing yields, while 2013 and 2014 saw a reversal in trend direction and saw decreasing yields corresponding to a generally positive economic sentiment as a whole in American markets. October 2013 is a global minimum for very short maturity bond auctions.

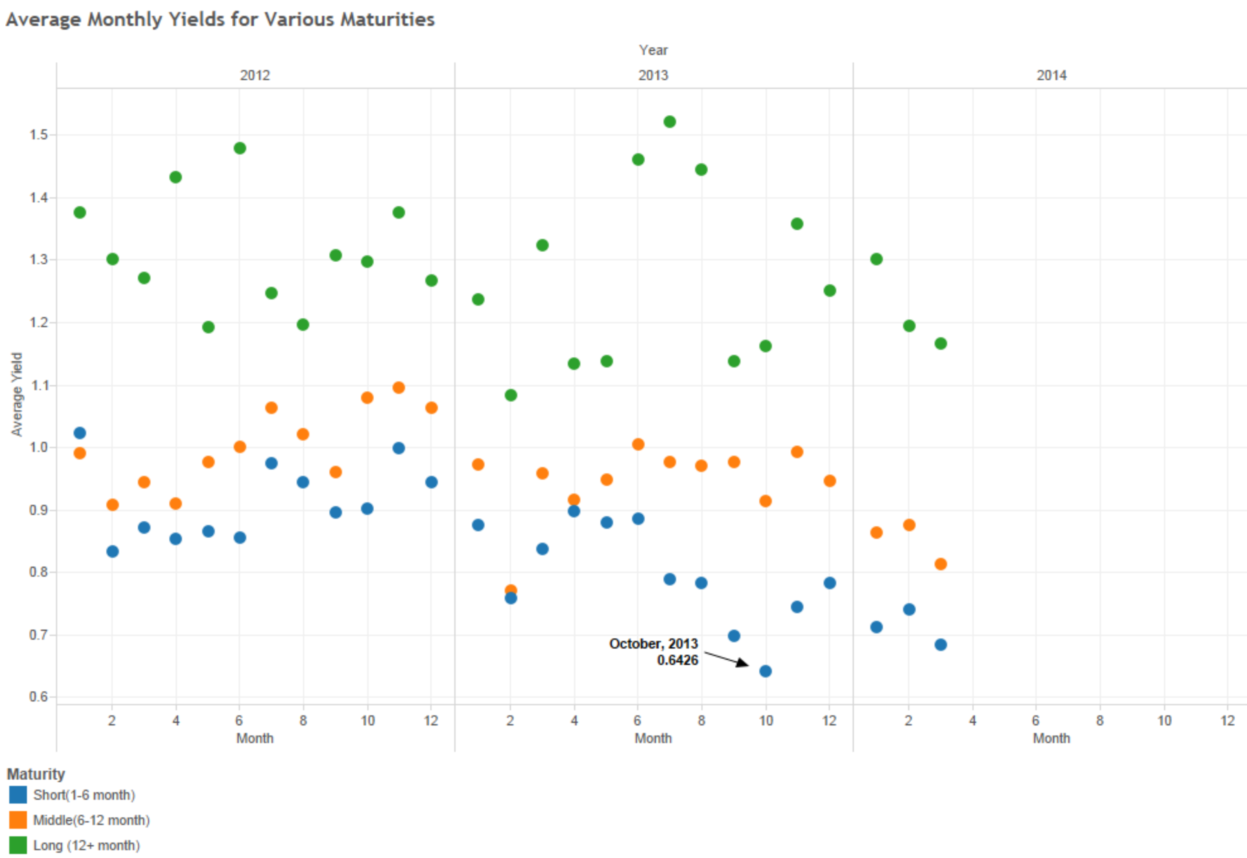

Figure 3. A Single Impulse Response Run From Simulated Data

This chart tracks the response returns to impulses(shocks) from volume over time, with the x-axis being number of periods beyond the original impulse. The cumulative modifier is not directly observe in this graphic, as each period is not cumulative to the others, but indicated that further in the calculation a cumulative value is returned.

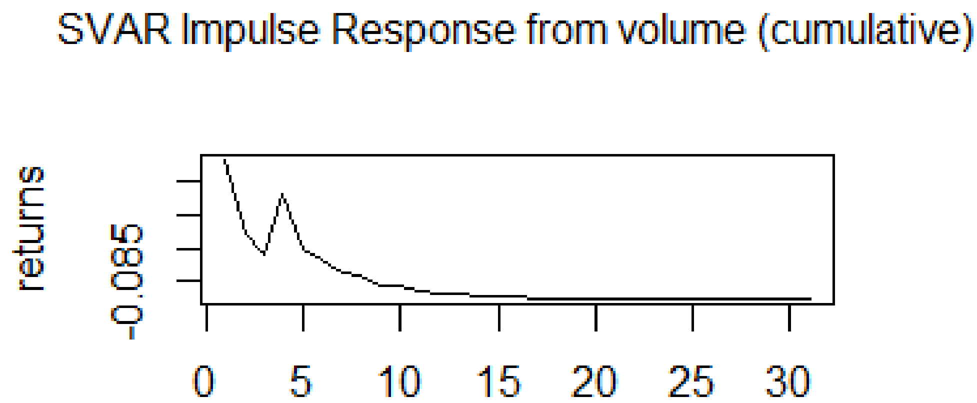

Figure 4. Histogram of 300 Cumulative Impulse Response Results

The results of the repetition of the cumulative IRF 300 times. It is steered by the Gaussian noise assumption, but exhibits a correct range for the final results given our simulated data.

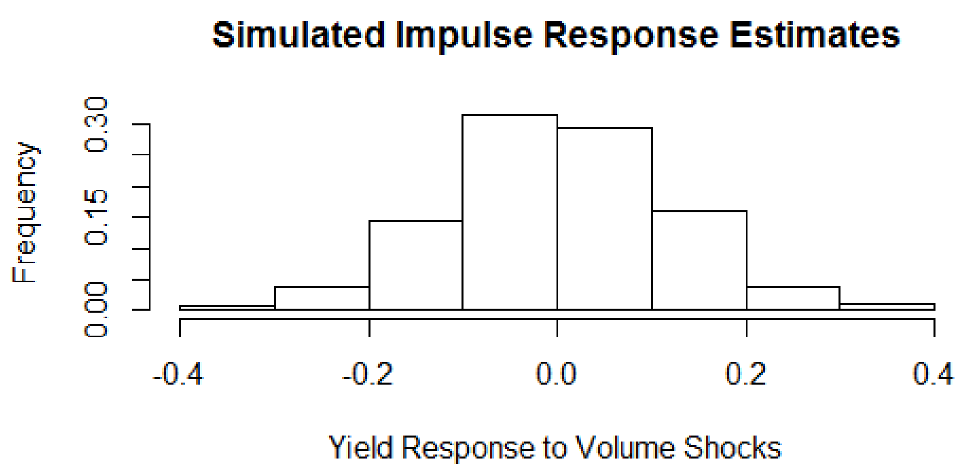

Figure 5. R Code for Data Simulation and SVAR and IRF Implementation

Beyond the data simulation, this code draws heavily from Pfaff 2008, so explanations for small steps can be found in chapter two of his book. Annotations are in blue and code is in black.

```
library(dse1)
library(vars)
#define functions that will simulate returns/volume for a single period using Holbrook's estimates
Returnsimulator <- function(r1,r2,r3,x0,x1,x2,x3,v1)
{
 y<- (-.1333*r1)-(.0216*r2)-(.0120*r3)+(.000912*x0)+(.000437*x1)+(.000045*x2)+(.000094*x3)+v1
 return (y)
}
Volumesimulator <- function(r1,r2,r3,x1,x2,x3,v2)
{
 y<- (-63.73*r1)-(31.79*r2)-(8.107*r3)+(.172*x1)+(.135*x2)+(.091*x3)+v2
 return(y)
}
#setting up loop
j<-1
irfs<- rep(0, 300)
#loop to get 300 cumulative impulse response function values
for(j in 1:length(irfs))
{
 #create return and volume shocks
 r<-rnorm(300)
 x<-rnorm(300)
 shocks<-cbind(r,x)
 #create empty vectors to store simulated data for both returns and volume
 returns <- rep(0, 300)
 volume <- rep(0,300)
 #Run each function 297 times
 #The code below feeds previous values from the simulated returns/volume vectors
 #and the appropriate concurrent shocks into the simulation function
 i<-4
 for(i in 4:length(x))
 {
  volume[i]<-Volumesimulator(returns[i-1],returns[i-2],returns[i-3],volume[i-1],volume[i-2],volume[i-3],shocks[i-3,2])
  returns[i]<-Returnsimulator(returns[i-1],returns[i-2],returns[i-3],volume[i],volume[i-1],volume[i-2],volume[i-3],shocks[i-3,1])
 }
  #drop the first 10 values to allow for burn-in
 returns <- returns[11:length(returns)]
 volume <- volume[11:length(volume)]
  #begin creating dataset in order to estimate parameters
 dataforestimation<-data.frame(returns,volume)
 #Run VAR on returns and volume
 varest <- VAR(dataforestimation, p=3, type ="none")
 #Run SVAR
 Amat <- diag(2)
 Amat[2,1] <- NA
 Amat[1,2] <- NA
 svar.A <- SVAR(varest, estmethod = "direct", Amat = Amat, hessian = TRUE)
 #Run IRF to determine effect of shocks to volume
 irf.svara <- irf(svar.A, impulse = "volume", response = "returns", boot = FALSE, cumulative=TRUE, n.ahead=30)
 #plot(irf.svara)
 #Pulls the final value from the cumulative IRF list where n.ahead = 30
 cum.impulse <- irf.svara$irf$volume[31]
 #stores that value to the vector of simulated IRFs
 irfs[j]<- cum.impulse
}
#summary of vector of 300 IRF estimations of the effects of volume shocks on returns
summary(irfs)
#histogram of IRF estimations
h<-hist(irfs,plot=FALSE, freq=FALSE)
h$counts=h$counts/sum(h$counts)
plot(h, main="Simulated Impulse Response Estimates", xlab="Yield Response to Volume Shocks" )
```