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Bell, Peter N

University of British Columbia, Department of Mathematics

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Peter N. Bell [1.]

Department of Mathematics, University of British Columbia, Vancouver BC V6T 1Z1, Canada

Abstract

The new methodology to study the impact of corporate events on bonds is comprised of a sampling technique and regression model. The method is different from standard approaches, motivated by the belief that event impact should be reflected in levels of yield premium. The regression tests for a change in average bond price after an event, statistical inference is made by estimates of a dummy variable. A new sampling method is described to accommodate the irregular spacing of bond trades in time.

Keywords: Event Study, Bonds, TRACE, ANOVA

[1.] Email: pnbell@interchange.ubc.ca

1 Introduction

The information available for bonds of all types is different from that of equities, and the differences are important. The MERGENT Fixed Income Securities Database (FISD) has qualitative information of bonds at issuance and rating changes. The Trade and Reporting Compliance Engine (TRACE) database has records of all individual bond trades that occur in over-the-counter (OTC) markets in the USA. The current milieu of electronic trading makes transaction databases important. By investigating transactions we hope to find patterns of behaviour that betray traders' logic, which refers to the mechanics by which a market appraises value.

Transaction databases pose methodological problems. For example, observation rates are not synchronized in time across assets. This feature is colloquially known as the Epps Effect (Epps, 1979) where correlation, and hence regression coefficients, are generally biased towards zero. This is a challenge for standard event study methods (Bessembinder et al., 2009), which use factor regression models. I propose a new regression model, motivated by insight into bond trader's point of view and analysis of variance (ANOVA) techniques (Crawley, 2005).

To accommodate my regression model, I propose a new sampling technique. Existing techniques to address irregularity in time generally attempt to 'fill in' missing data (Heinkel and Krauss, 1988). The approach I advocate here is a 'coping technique' where I coerce irregularly spaced data to become regularly spaced in a new measure of time. I think the literature on missing data in Social Science (Little and Rubin, 1989) will become important in Finance as transaction databases are increasingly used for research. There is potential for innovation in research of bonds and transaction data.

2 Method

The sampling technique will smooth irregularities in time. The regression model tests for differences in mean, before and after an event. Together these techniques comprise a new event study methodology. Statistical inference can be made with individual bonds, or consolidated by bond attributes.

2.1 Sampling Technique

Some bonds trade every day, others trade once a month. It is recently reported (Bessembinder et al., 2009) that bonds trade once every five trading days, on average; therefore, my sampling technique searches for prices in a window around event dates.

A description of the sampling technique is now presented. Start with events of interest, and restrict attention to bonds issued by companies involved in events. For each event-bond, which are bonds issued by companies involved in events, collect separate pre-event samples and post-event samples of prices. Samples are defined by two parameter assumptions: N, the number of prices in each sample; M, the number of trading days to be searched to find N prices. I use the assumptions N, M for each event-bond in a study. Sort prices by distance to event and collect the N observations closest to the event. This is used for all assets in pre-event and post-event windows, separately. I recommend removing event-bonds that have zero observations in either pre- or post-event windows, and keeping all others.

Based on the frequency of trades mentioned above, (Bessembinder et al., 2009), I take $M>=5N$ as a starting point. This way, I allow five trading days for each price observation from an 'average' event bond. Based on intuition, I recommend $N=5$. This only gives a small number of prices before and after an event, but the choice of M allows me to influence the number of event-bonds that are included. For $N=5$ and M large, say M=250, there is a confounding problem: trades very far from the event date may reflect significant events other than the event of interest. Also, with N large, say N=50, the pervasive skewness in bond prices may influence inference.

2.2 Regression Model

To my dataset, I append a dummy variable to each price observation: D(i,t) where i indicates the event-bond and t indicates the calendar time of the price observation. For all event bonds i, I set D(i,t)=0 if t is before the event date and D(i,t)=1 if t is after the event date. It is important to distinguish whether the event has occurred because of my working assumption: prices for each bond are statistically regular in the pre-event and post-event windows. The regression is meant to determine differences between the pre and post windows for all bonds.

For sake of parsimony, we will use a linear equation that can be estimated by ordinary least squares. However, we will estimate the equation separately for each event-bond. The equation:

$$P(i,t) = a(i) + b(i)\, D(i,t) \qquad \text{for all } i,t$$

where P(i,t) and D(i,t) are vectors, a(i) and b(i) are constants. The parameter a(i) represents the average price for bond i before the event, and b(i) represents the change in average price after the event. We will use the distribution of b(i) to determine event impact.

To conduct inference with the method, create the distribution of estimates of the dummy coefficient estimates, b(i) from Section 2.2. I use the histogram as a guide, and to go further I calculate a t-test against zero mean with the average of all estimates for dummy coefficients. Theoretical properties of this test are not known to me yet.

3 Discussion

The bond event study literature suffers because it misuses models designed for equities; I believe the concept of 'abnormal returns' is misapplied to bonds. Bond event studies would benefit from using levels of yield premium rather than price differences.

3.1 Standard Approaches

There are many approaches to test the significance of a corporate event on asset prices. Some (Barber and Lyon, 1997) use the 'cumulative abnormal return' metric, which is an average of model residuals. The model is typically first difference of log-prices, with a Fama French factor (Fama and French, 1993). The factors are deservedly popular, with free web access, and important. The factors are crucial for the standard approaches to bond event studies, see (Bessembinder et al., 2009) for a survey.

The 'mean adjusted model' for daily data is bond price change minus a matched treasury index price change. Corporate bonds do not trade every day, then we do not have prices; I recommend matching treasury levels to bond levels, and then calculating intermittent returns. The model uses a window of data before the event to determine the distribution of price changes, as I understand it, then the price changes are calculated around the event to determine event impact on price. It is a bootstrap approach. The Fama French industry provides us with data and theory, (Fama and French, 1993), to guide creation of 'matching portfolios'. Such a portfolio is substituted for a treasury bill to remove supposed risk premium.

The use of bond price differences and factor models is made difficult by the irregularity of price observations in time; some bonds trade every day, others trade once a month. The Epps Effect was formulated with high frequency transaction data (Epps, 1979), but something similar occurs when transaction rates are very low. Also, the principle of parsimony is important for researchers; standard factor models are popular and successful, but there may be more simple ways to proceed.

3.2 New Approach

There is skewness in series of bond price differences. This is a problem with standard approaches, and it appears in my method with large sampling windows. When using my method for coursework, I used N = 5, M = 150. Heuristically, I claim sample size is increasing in M while accuracy is decreasing in N. This is because of negative skewness, for N as small as 30. The skewness can disrupt inference in the model. This skewness is pervasive and simply understood with price equal to duration multiplied by yield; bonds at premium prices have negative skewness, and bonds with discount prices have positive skew. Most skewness in TRACE is negative because of the historic low-rate environment.

In my mind, bond traders profit focus is interest income rather than capital gains. This is intuitive and familiar, but not universal. When quoting bond trades in yield premium, traders show what is important to them. I would like to use bond yield premium to asses event impact, but it is not possible to test for changes in yield premium around events because the TRACE yield information is not reliable (FINRA 2008). I advocate price levels as a proxy for yield premiums and this leads to the test for the change in price levels after event dates. The method is meant to resemble the difference in means test from the ANOVA toolbox (Crawley, 2005). The qualitative information on bonds (at issuance and rating changes) is important and different from equities; to exploit this, I recommend analysis of variance or covariance (ANOVA or ANCOVA) techniques (Crawley, 2005). And though we have transaction data, we often resort to daily prices for statistical research. There is great potential for new research with bond attributes.

3.3 Full Implementation

Please note that full implementation of the method described here had root directory 10.4 Gigabytes in 21 Files. Full implementation used six separate programs: Clean MERGENT; Clean TRACE; Cross Event List, Acceptable Issue List; Cross Event Bonds, Trading Records; Collect Event Windows; Estimate Regression. The code was written in SAS, for which I can share code. Much thanks to Dr William Maxwell from University of Arizona for sharing code (Bessembinder et al., 2009), this code was used for the 'Clean TRACE' program and I encourage the use of Maxwell's code as literature standard.

I have explored the entire universe of events from the Center for Research in Securities Prices (CRSP) file Daily Stock Events. Stock splits and routine dividend payments have the same null effect as random dates, while stock dividends have a clear effect (but very small sample size). I intend for this paper to describe the methodology, rather than the results. And in future work, I intend to exploit differences between event declaration dates and dates of occurrence.

4 Conclusion

There is potential for much innovation in research with corporate bonds and transaction data. It is possible that a bond does not trade for several days, even months. Transaction records are irregularly spaced in time, and we need to adapt methods to deal with these objects in Finance. In Section 2.1 I present such a method.

I encourage research that uses transaction data, for example compare trade frequency around an ex-post significant event to a control period for several assets. However, I use consolidated daily prices in this study. The regression is supposed to be a simplification of standard factor models. I revise the concept of the abnormal returns for bonds and suggest it is misapplied to bonds. My regression is modeled after the difference in means test from ANOVA (Crawley 2005).

I name the six programs I wrote to achieve full implementation of the method for coursework, but I do not present results of the method in action. There is potential for innovation in financial research by using transaction data. Particularly in event studies, the rate of trading in an asset trade can inspire new test of event impact. Also, I believe that ANOVA and analysis of covariance (ANCOVA) techniques can be used to exploit important qualitative information about bonds to further event studies.

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