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Essays in Financial Economics: Announcement Effects in Fixed Income Markets

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CHAPTER I

INTRODUCTION

This dissertation offers an examination of announcement effects in US Treasury and corporate bond markets. Announcements include both macroeconomic variables, such as GDP growth and consumer price inflation, as well as announcements of supply and demand for Treasury securities at auction. While there is a vast literature that documents the prime importance of macroeconomic announcements in driving US Treasury bond return activity, my research calls into question the empirical methodologies employed in traditional studies and suggests that recent advances in econometric theory offer an improved set of tools for evaluation of announcement effects. The primary tools are the General-to-Specific econometric approach, popularized by Oxford's Sir David F. Hendry, and the recent improvements automated model discovery and indicator saturation methods.

The three main chapters deal with US Treasury returns responses to macroeconomic announcements, US corporate bond returns and trading activity (total trades, institutional trades, and intermediated trades), and US Treasury return responses to Treasury auction announcements, respectively. The findings, elaborated on further, have important implications for market efficiency and market microstructure. However, the main contribution of the collective essays are in the area of econometric modelling. I show that, using a general-to-specific modeling strategy (known as Gets modeling or the LSE econometric approach) and indicator saturation methods we are able to capture the important features of the local data generating process and provide unbiased parameter estimates. I show that the typical modelling approach in the existing bond market macro-announcement effect literature is inadequate and fails to capture salient characteristics of the LGDP. As a result, parameter results in these models are likely to suffer moderate to severe omitted variables bias. I show that the size of the omitted variable bias greatly exceeds unadjusted Gets estimates, based on the correction methods demonstrated by the important work of Hendry and Krolzig (2005).

I shall proceed by further elaborating on the background of the methodological approach, focusing particularly on the history of the GETs approach. Afterward, I will provide detailed descriptions and contributions of the three main essays.

A. <u>Methodological Aspects – Historical Perspective of the LSE Approach</u>

These empirical tools are based on a "Probability Approach" to econometric modelling approach with foundations dating back to the work of Nobel Laureate Haavelmo (1944). The General-to-specific approach – also known as the LSE Approach – grew out of the London School of Economics in the 1960s and 1970s, where rigorous specification testing was a core principal advocated by Professor J. Denis Sargan, one of the leading econometricians of that era. Sargan's contributions to the founding concepts of this approach can be found in Sargan (1961), Sargan (1964), Sargan (1980), Hendry, Pagan and Sargan (1984), and in two posthumously published articles based on earlier work Sargan (2001a), entitled "Model Building and Data Mining," and

Sargan (2001b) "The Choice Between Sets of Regressors." Interested readers should also see his retrospective of econometrics at LSE in Sargan (2003).[1][2]

Hendry, with his coauthors, built an econometric modelling ideology around the core methodological contributions. The methodology is laid out in great detail in Hendry (1993), Hendry (1995), Hendry and Krolzig (2001), and Hendry and Krolzig (2005). Additional recent advances have been developed, including the second-generation automated Gets modelling process called "Autometrics" – which represents an improvement on previous incarnation of the approach, known as PC-Gets. The techniques are adeptly presented in: Hendry, Johansen and Santos (2008), Hendry and Johansen (2011), Castle, Doornik and Hendry (2012), Castle, Clements and Hendry (2013), and Hendry and Doornik (2014).

In harnessing this new technology, I am able to better evaluate a line of research on macroeconomic indicator effects on financial markets that has been applied to various classes of securities. I demonstrate the benefits of employing GETs modelling via Autometrics in a financial setting, whereas these techniques have most-often been applied in macroeconomic studies. Only recently have researchers began to use these models in finance. The results should be interesting both to researchers in finance, macroeconomics and other areas of empirical

[1] Sargan passed away in 1996, however, his later publications were published after his death. Sargan (2001a) was written in March of 1973 and presented at the Association of University Teachers of Economics in Manchester. Sargan (2001b) was originally written in June of 1981 and presented at the LSE MIME Econometrics Workshop. Sargan (2003) is taken from an address given during his visiting appointment at Universidad Carlos III in 1995.

[2] Students of Sargan, including David Hendry (Oxford), Peter Phillips (Yale), Neil Ericsson (Federal Reserve Board) and others have carried the tradition. Key contributions to the core concepts have also been made to the ideology/methodology by other LSE Approach advocates, including but not limited to: Graham Mizon (Southampton and Oxford), Jean-Francois Richard (Pittsburgh), Jurgen Doornik (Oxford), Jennifer Castle (Oxford), and Aris Spanos (Virginia Tech).

academic research, as well as to practitioners who wish to build similar models. However, in the area of finance, the gains in terms of precision and bias reduction are, perhaps, most obviously translated into monetary value. Thus, the contribution can be seen as potentially financial as opposed to strictly pedagogical.

The cornerstone of the General-to-Specific methodology is "testimation" – i.e., as argued by David Hendry:[3]

> "The three golden rules of econometrics are: that all three rules are broken regularity in empirical applications is fortunately easily remedied. Rigorously tested models, which adequately describe the available data, encompass previous findings and were derived from well-based theories would greatly enhance any claim to be scientific. "

While financial markets literature in mainstream finance journals tend to be derived from well-based theories, it does not appear that there is much evidence to support the other aspects cited by Hendry – at least with respect to macro-announcement studies in bond markets. Encompassing testing appears to be virtually non-existent in finance. Researchers often fail to provide rigorous specification testing, instead opting for adjusting standard errors using methods such as the well-known Newey West procedure. However, this would not be acceptable within

[33] See page 406 of Hendry (1980) and page 360 of Spanos (2014). The later represents an outstanding perspective on the LSE tradition from a student of both Hendry and Sargan.

the LSE framework, which look upon such techniques as a sort of “patchwork” incapable of delivering congruence or avoiding omitted variable bias.

B. The Effect of Macroeconomic Announcements on Credit Market

In this chapter, I show that a congruent, parsimonious, encompassing empirical model discovered via Hendry’s Gets modelling approach is able to overcome many inadequacies that are typical of specifications found in financial markets literature – specifically in studies related to macroeconomic announcement effects in bond markets. All too often, studies present empirical results without the accompanying diagnostic tests. These procedures include tests for heteroscedasticity, autocorrelation, nonlinearity, and parameter stability. Within the framework of the “LSE Econometric Approach” – as Hendry’s methodology is often called—a model is not congruent unless it passes all such tests. Failure to achieve congruence means that the data generating process is not adequately captured by the specification and that the model potentially suffers from not only inefficiency but possibly also has biased estimates. While model selection in the Gets paradigm will result in some level of bias, the results are “nearly unbiased” without adjustment and a simple bias adjustment of the parameters can be used to correct for this malady. However, if an empirical model suffers many forms of mis-specification, the results are likely to contain omitted variable bias, which is of an unknown form and cannot be corrected.

In finance, model risk can be translated into financial losses. Biased results could wreak havoc on a portfolio or a risk management strategy. However, only rarely has the Gets procedure been seen in the financial economics literature. I show that a common specification regressing US Treasury bond returns on contemporaneous surprises in macroeconomic announcements fails nearly every specification test. This is rather disturbing, particularly considering the number of studies in the academic literature which employ the very same specification – sometimes with even fewer regressors.

One challenge would be to respecify the model in a more general form. For example, one could easily add additional lags of macro surprises, but it is unlikely to be of much help as the lags are likely insignificant due to the efficiency of markets—i.e., information is reflected in security prices so rapidly that there would be no significant effect the following day. Therefore, one must rely further on theory and intuition to find other sources or parameterization. I use the EGARCH framework of Nelson (1991) to show that asymmetries exist in Treasury bond returns and make that a basis for the inclusion of separate positive and negative surprises in the initial unrestricted model. I further include an autoregressive term and lags of the contemporaneous announcements as well. Additionally, to assure congruence, I employ indicator saturation methods.[4] Finally, I further examine the relative adequacy of the competing models by appealing to the encompassing principle, which states that a good model should be able to explain the results of rival models. In doing so, the results favor the Gets models that incorporate asymmetries and employ indicator saturation. These models formally encompass the rival static models in testing, the static models fail to encompass the Gets models. This further support the use of Hendry's methodology in finance.

[4] See Castle, Doornik, Hendry and Pretis (2015) and Ericsson (2012).

Results indicate that there are significant asymmetric effects associated with macroeconomic announcements. While the asymmetric affects in equity markets can be attributed to "leverage effects" such an explanation would not apply to the US Treasury market. However, one can make a case that the time varying risk premia is a valid explanation. Thus, the results square nicely with existing academic literature on fixed income markets.[5]

Outside of the aforementioned contributions to the existing GARCH and risk premia literature, the study makes a strong case for the use of Gets modelling and indicator saturation methods in finance, as well as the usefulness of the Oxmetrics "Autometrics" procedure for performing the process without human intervention in the model reduction process.[6] It casts doubt on the efficiency, unbiasedness and stability of parameters in prior macroeconomic announcement studies that do not depend on rigorous model testing. General-to-Specific model discovery, therefore, becomes a cornerstone of the following chapter which we discuss next.

[5] Time-Varying Risk Premia articles include: Engle, Lilien and Robins (1987), Evans (1994), Lee (1995), Kryzanowski, Lalancette and To (1997), Campbell, Kazemi and Nanisetty (1999), and Koijen, Nijman and Werker (2010).

[6] Human involvement in the selection of competing models is a long-standing criticism of model selection methods. Autometrics functions without human intervention and avoids this criticism. Note also, users without access to the commercial Oxmetrics product can now perform automated Gets modelling in the manner it was designed to be conducted using the R package "gets" by downloading it at https://cran.r-project.org/package=gets. The package is created and adapted by Pretis, Reade and Sucarrat (2016) with details in the following paper http://www.sucarrat.net/R/gets/gets.pdf. More details are available at http://www.sucarrat.net/R/gets/ and https://cran.r-project.org/web/packages/gets/index.html.

C. A High-Frequency Analysis of Trading Activity in the Corporate Bond Market

In this chapter we explore whether factors that drive trading activity of US corporate bond market are macroeconomic announcements or seasonal. Prior studies have documented a significant response of returns and interest rates to surprises in macroeconomic data in the stock, US Treasury and Treasury futures markets. Likewise, studies document that trading activity changes sharply, based on informational shocks that arrive by way of the release of economic data. We improve on the existing literature by analyzing how both daily and intraday measures of trading activity are impacted by surprises in macro data as well as various measures of seasonality.

Again, we employ the general-to-specific (Gets) modeling approach, also known as the "LSE/Oxford Approach" of Professor David F. Hendry, which commences from a broad unrestricted model and then employs an automated "testing down" procedure which seeks to reduce the model to a statistically valid representation of the data generating process (DGP) based on the characteristics of the local data generating process.[7] Additionally, given that efficient markets does not rule out persistent effects on trading activity (as opposed to returns), we also test for various forms of seasonality in the trading activity regressions.

Our main findings are that corporate bonds is less affected by surprises in individual economic reports and that corporate bond market trading activity is dominated by day-of-week and time-

[7] An extensive review of the Gets modeling literature is provided by Campos and Ericsson (1999).

of-day affects, as opposed to macroeconomic announcements.[8] We find that, unlike daily returns on the S&P 500, corporate bonds are sensitive to surprises in both labor market and inflation data. Trading activity is affected by absolute surprises in core CPI and nonfarm payrolls, but neither core PPI nor jobless claims affect order flow. The trading activity regressions that show statistical significance for macro indicators, however, seem to lack economic significance, as the size of the parameter estimates tend to be very small. Taken together, the results seem to suggest that the significance of returns to macroeconomic surprises of credit spreads and corporate bond returns may be associated simply with Treasury rates. Because corporate bonds trade less frequently, they are often marked to market based on hypothetical prices based on a spread over Treasuries. This "matrix pricing" effect may suggest announcement effects that are, therefore, a mere mirage.

Perhaps most interesting, however, is the presence of "behavioral seasonal" effects associated with the onset and incidence of seasonal affective disorder. This "winter blues" effect has been seen affecting activity in equity markets by Kamstra, Kramer and Levi (2000), Kamstra, Kramer and Levi (2003), and Kamstra, Kramer, Levi and Wermers (2012) with respect to mutual fund asset flows. The effect is also documented in Garrett, Kamstra and Kramer (2005) and, more recently, the theoretical foundations for this empirical regularity are outlined in Kamstra, Kramer, Levi and Wang (2014) . This chapter, however, presents the first study to document such an effect in the trading activity in the corporate bond market. Finally, the "loans-on-sale" seasonal effect, first documented by Murfin & Peterson (Journal Financial Economics, 2014).

[8] Macroeconomic data come from the Action Economics Survey and include Core CPI, Core PPI, Nonfarm Payrolls and Initial Jobless Claims. Future work could and should expand the set of macroeconomic indicators to further verify this finding.

D. The Effect of Treasury Auction Results on Interest Rates: The 1900s Experience

The 1990s presented a change of environment in terms of government budget deficits. As the decade progressed, reductions in spending and increases in tax revenue resulted in considerable improvement on the budgetary front. As a result, budget deficits slowly gave way to budget surpluses and, by the end of the decade, the scarcity of Treasury securities actually became a concern for policymakers.

In this chapter I examine the secondary-market response of U.S. Treasury rates, returns and bid-ask spreads to the release of details from the government's primary-market auctions during the 1990s. I build on prior studies by Two notable papers, Schirm, Sheehan and Ferri (1989) and Wachtel and Young (1987), focus on effect of debt and deficit announcements on interest rates.[9] However, to the author's knowledge, only Wachtel and Young (1987) specifically examined the effect of Treasury auction demand statistics on returns while also controlling for contemporaneous macroeconomic announcements.[10] This set an important precedent for this type of study. Because of the importance of macroeconomic announcement surprises for Treasury returns, failure to incorporate announcements when analyzing auction effects on the market represents a risk to the empirical modeler. Such neglect could have an effect on the efficiency of parameter estimates as well as opening the door to likely omitted variable bias.

[9] As noted in the chapter, Cebula (2013) explores the impact of budget deficits, but on nominal Aaa-rated corporate bond yields.

[10] Again, as the chapter notes, Bahamin, Cebula, Foley and Houmes (2012) provide an analysis of bid dispersion is positively related to bid-to-cover ratio but negatively related to the percentage of noncompetitive bids and percentage on competitive bids accepted at auction during the period of 1998 to 2010.

I provide evidence of how failure to model announcements results in a lack of statistical power when trying to evaluate whether auction day returns behave differently than other days. The contribution of this chapter is that is demonstrates that studies such as the important study of Lou, Yan and Zhang (2013) could be improved upon significantly by incorporating macroeconomic announcement surprises.

Standard t-tests for differences in mean returns between auction and no-auction days show that returns differ significantly only for on-the-run 1-year bills and off-the-run 5-year notes. Longer maturities did not reveal differences in mean returns. Yet it is unclear if there is no difference or if this is just a lack of statistical power.

However, Brown and Forsyth's F-test of homogeneity of variance indicate no significant effects stemming from the existence of Treasury auctions. I am unable to reject the null hypothesis of homogeneous variance, even when partitioning the sample into auction-, announcement-, and "quiet" days.

Again, these results do not account for surprises in contemporaneous macroeconomic announcement effects, nor do they take into account the information content of the auction results. This strongly suggests that a more sophisticated analysis would be required to assess more carefully if Treasury auction operations represent a substantial source of disruption to the market.

I proceed by adopting a GARCH model to control for other important announcements including both macroeconomic reports and Federal Reserve target rate changes. In doing so, we are better-equipped to evaluate the significance of specific auction demand statistics and are able to compare the effects of Treasury fiscal policy funding operations to the Federal Reserve's monetary policy operations and eleven major macroeconomic announcements.[11]

Specifically, I examine how the release of auction details affect US Treasury return movements based on both surprises in auction results (bid-to-cover ratios and volume of noncompetitive bids) and changes in issuance volume.

Consistent with my priors, I find a positive relationship between surprises in bid-to-cover ratios and returns on Treasury notes in three out of four maturities under investigation. The lone exception appears to be more of a function of modeling expectations of the 10-year note which was affected by changes in the auction schedule, as well as having relatively fewer auctions to base estimation on. Also, the effect of these surprises on coverage ratio is roughly of equal order of magnitude to coefficients on standardized surprises of several of our macroeconomic variables and is greater than that of several announcements – notably: unemployment, retail sales and capacity utilization.

[11] Announcements include Core PPI, Core CPI, Nonfarm Payrolls, Durable Goods, Capacity Utilization, Unemployment Rate, Initial Jobless Claims and Retail Sales reports. It should be noted that additional macroeconomic announcements could be added to the study. Future work should increase the sample size and the number of macroeconomic announcements so as to allow for better comparability to Lou, Yan and Zhang (2013). Due to issues regarding data acquisition, I must leave this to future work for the immediate future but plan on revisiting the issue in the near future.

The volume of noncompetitive bids did not provide additional explanatory power. Only the 30-year Treasury bond appears sensitive to surprises in this auction statistic, despite there being fewer auctions at that maturity to use in the estimation. However, that the benchmark 30-year bond coefficient on surprises in noncomps is greater than that of the bid-to cover ratio is notable. Clearly, surprises in auction demand statistics were most important on the long end of the yield curve. The fact that this maturity has the fewest auctions, yet achieves the most significant results underscores the relative importance at this maturity. Again, an expanded study with a longer time series should be used to confirm this finding.

With respect to market volatility, I employ a GARCH model to characterize the effect of auction data on conditional variance. I find interest rate volatility to be largely unaffected by the Treasury auction process. By comparison, Federal Reserve policy announcements and ‘quiet days’ – when no macroeconomic announcement or auction takes place – are shown to have a significant effect on volatility. This is consistent with microstructure literature that links information and trading activity.

The results provide evidence that the U.S. Treasury’s financing operations are conducted in a manner that exerts no more pressure on the market than that of most regularly-scheduled macroeconomic announcement. Further, I find the market to be more sensitive to FOMC policy surprises than Treasury operations.

CHAPTER II

"THE EFFECT OF MACROECONOMIC ANNOUNCEMENTS ON CREDIT MARKETS: AN AUTOMETRIC GENERAL-TO-SPECIFIC ANALYSIS OF THE GREENSPAN ERA"

A. Abstract

I show that a congruent, parsimonious, encompassing model discovered using David Hendry's econometric modelling approach and Autometrics can overcome the many inadequacies of the typical static models of US Treasury returns regressed on macroeconomic announcements. The typical specification tends to fail most, if not all, specification tests. Further, the techniques employed are able to expand our knowledge of time varying risk premia and asymmetric news responses in financial markets. Previously studied within a GARCH framework, such methods offered little evidence as to the precise sources of the asymmetries. Asymmetric effects are shown to be concentrated in a handful of announcements, such as the Employment Cost Index and Core PPI. Results suggest a place for general-to-specific modelling in financial economics, a place where it has only recently begun to be employed. These results underscore the contributions of David F. Hendry and his collaborators in econometric modelling, they also and demonstrate the need for better models in finance that may be alleviated by employing modelling practices advocated by econometricians doing research in the LSE/Oxford tradition.

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B. Introduction

This essay addresses a very general question: How do macroeconomic announcements affect fixed income markets? This question has been asked many times and modeled in a number of different ways, I show that an automated general-to-specific (Gets) dynamic specification and model reduction process can be used to provide consistent and efficient parameter estimates while eliminating unnecessary regressors. The process avoids the major deficiencies of other model specification procedures, such as path dependency. Moreover it delivers a congruent, parsimonious, encompassing final model without requiring any human involvement in the model selection process. Thus it avoids the common criticism of adventitious selection that is often associated with other model selection approaches such specific-to-general. Such approaches are often characterized as a "fishing expedition."

The process that I undertake is the general-to-specific methodology (Gets) of Oxford's David F. Hendry, also known as the LSE/Oxford approach to econometric modelling.[12] The methodology is laid out in great detail in Hendry (1993), Hendry (1995), Hendry and Krolzig (2001), and Hendry and Krolzig (2005). However, a plethora of recent developments have taken place, including the second-generation automated Gets modelling process called "Autometrics" – which represents an improvement on previous incarnations of the approach. These advances

[12] While the General-to-Specific method is traditionally been labelled the 'LSE approach" I will opt to use "LSE/Oxford approach" in this paper for the purpose of recognizing the many talented researchers at Oxford University who have played a role the development and application of Gets modelling and Automated Gets modelling. These include, but are not limited to: Jurgen Doornik, Hans Martin Krolzig, Jennifer Castle and a number of others. See references for a mere partial listing of authors. A more detailed listing of Gets modelling research is found in Campos, Ericsson and Hendry (2005) (https://www.federalreserve.gov/pubs/ifdp/2005/838/default.htm).

have been put forward in: Hendry, Johansen and Santos (2008), Hendry and Johansen (2011), Castle, Doornik and Hendry (2012), Castle, Clements and Hendry (2013), and Hendry and Doornik (2014). By taking advantage of this new methodology, I am able to better evaluate a line of research on macroeconomic indicator effects on financial markets that has been applied to various classes of securities. In doing so, I demonstrate the benefits of employing such a procedure in a financial setting, whereas these techniques have most-often been applied in macroeconomic studies. Only recently have researchers began to use these models in finance. The results should be interesting both to researchers in finance and macroeconomics, as well as to practitioners who wish to build similar models.

In particular, I choose to examine the period of 1990 to 2001 – the heart of the Alan Greenspan era at the Federal Reserve. Greenspan, a macroeconomic forecaster during his career prior to joining the Federal Reserve, he was known for his intense attention to a wide array of macroeconomic indicators.[13]

This study has more to do with the econometric methods of David F. Hendry, none the less, some attention needs to be paid to the lead economic policymaker of the 1990s whose decisions were at the forefront of US Treasury market participants during the period under examination. By the time the 1990s rolled around, Greenspan had several years under his belt as Fed Chairman. He had previously served as Chairman of President Gerald Ford's Council of Economic Advisors from 1974 to 1977. He was the head of the economic forecasting corporation

[13] Details of Greenspan's career can be found in Sicilia and Cruikshank (2000) and in his memoirs Greenspan (2007).

Greenspan & Townsend for over 30 years. Greenspan was well known to financial market economists and traders for both his work in government and in a number of scholarly publications. His contributions were typically in practitioners journals such as *Challenge*, and *Business Economics,* and yet, several articles and comments appeared in main stream economic journals, the *American Economic Review* and *Journal of Finance*.[14] As a result, he was no stranger to Treasury market participants when he took the helm at the Board of Governors.

In addition to his reputation for focusing on esoteric economic indicators, Greenspan was known for his use of what would come to be called "Fedspeak" or "Greenspeak" (the art of answering policy-related questions with relatively incomprehensible stream of consciousness responses that would leave market participants without clear convictions as to the likely policy response that would result.)[15][16] For this reason, the financial press would parse each word for meaning. Eventually tried to infer policy actions from the girth of Greenspan's briefcase (the briefcase indicator) on the morning of Federal Open Market Committee meetings. Such rock star status and media attention put monetary policy on the front page and every economic indicator under intense scrutiny.

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[14] For examples of Greenspan's pre-FRB scholarly works, see: Greenspan, Simpson and Cutler (1958), Greenspan (1964), Greenspan (1971), Hymans, Greenspan, Shiskin and Early (1973), Greenspan (1978), and Greenspan (1980).

[15] Examples of "Greenspeak" can be found at: http://libertystreeteconomics.newyorkfed.org/2013/04/historical-echoes-fedspeak-as-a-second-language.html#.VAkDKpUg_mI and https://web.archive.org/web/20120212132248/http://www.dallasfed.org/news/speeches/greenspeak.html

[16] See also: Hanes (2014) regarding "Open-Mouth Operations" during the 1990s, http://bingweb.binghamton.edu/~chanes/openmouth17.pdf

Given the large number of economic variables being of interest to traders in this period, an empirical methodology capable of handling such a situation is critical. A fair number of studies have included the many macro indicators in recognition of this. However, so far none have employed Hendry's LSE approach to evaluate the effect of macroeconomic announcements on financial markets. Nor have asymmetric responses to macro indicators been evaluated in this manner. By making use of the methodology, this essay provides a basis for determining which indicators were of critical importance to Treasury market participants.

Using a set of 26 macroeconomic announcements, I use Hendry's approach to provide a perspective on how interest rates behave relative to revisions to the macroeconomic information set that occur when macroeconomic data surprises occur. In doing so, we are able to evaluate which indicators actually mattered during the heart of the Greenspan Era. Perhaps more importantly, however, I document sources of time varying risk premia that generate asymmetric volatility can be – at least partially – to asymmetric responses to surprises in key macroeconomic variables. This augments the existing EGARCH literature and demonstrates the value of the LSE/Oxford econometric approach in the area of financial markets.

From a financial economics perspective, a key economic theory being tested is that of market efficiency – i.e. that information is rapidly incorporated into security prices. From a statistical/econometric perspective, I demonstrate the ability of a model selection procedure to handle a reduction of a large set of independent variables and produce sensible results. This allows us to compare these results to previous studies in this area.[17]

The essay will proceed in the following manner. Section II contains a literature review of macroeconomic announcement effects in financial markets. Section III provides a preliminary analysis using EGARCH techniques and news impact curves to provide a basis for investigating asymmetric responses of Treasury returns. Section IV provides a description of the US Treasury return data used in the study and the macroeconomic announcement surprise data. Section V contains model discovery results based on Hendry's general-to-specific modelling techniques using Autometrics, documents extensive model diagnostic and encompassing testing, applies bias correction to the Gets coefficients and shows the relative superiority to the Gets models compared traditional static regression results often seen in academic literature. Section V summarizes results relative to the existing literature and concludes the analysis.

C. Review of Macro-Announcement Effect Literature

Over the years, numerous studies have focused on announcement effects in financial markets. Macroeconomic announcements, in particular, have been a popular point of focus – especially in the cases of interest rates and foreign exchange. While early studies tended to examine daily

[17] In particular, Balduzzi, Elton and Green (2001) is a comparable study in the mainstream finance literature. While they take advantage of intraday data, they fail to provide evidence of rigorous specification testing and use a somewhat shorter time sample. I show that the LSE approach offers a modelling alternative that offers sharper unbiased estimation results compared to the type of estimation presented in this important study.

data, the recent availability of intraday data has opened new doors and have been especially illuminating for researchers in the area of market microstructure.

1. Treasury Markets

Urich and Wachtel (1984) examined the effect of money supply and inflation on interest rates, finding that unanticipated results led to an immediate impact on short-term rates. Money supply was en vogue as the macroeconomic indicator of choice for then Federal Reserve Chairman Paul Volcker, this was reinforced by the 1970s wave of monetarist thinking based on the popularity of Milton Friedman's philosophy given the double digit inflation rates of that era. Under Alan Greenspan, the Federal Reserve would de-emphasize the use of monetary aggregates in forming monetary policy. Instead the focus shifted to a wide array of macroeconomic indicators.

Ederington and Lee (1993) used intraday data to show that macroeconomic announcements are responsible for most of the observed time-of-day and day-of-week volatility in Treasury bond, Eurodollar, and deutsche mark futures markets

Jones, Lamont and Lumsdaine (1998) examined the effect of employment and producer price index data on daily Treasury bond prices. They find that announcement-day volatility does not persist beyond the day of announcement. However, they do uncover day-of-week effects in volatility which deserves further investigation, especially given that they are only controlling for two macroeconomic announcements. It is possible that the day-of-week effects found here are strictly announcement related.

In other studies, Li and Engle (1998) examine the effect of macroeconomic announcements on the volatility of U.S. Treasury futures, while Fleming and Remolona (1999) look at the effect of public information on price formation and liquidity in the Treasury market.

Bollerslev, Cai and Song (2000) find that the employment report, PPI, employment cost index, retail sales, and the national association of purchasing managers survey have the greatest effect on the volatility of Treasury futures.

Similarly, Balduzzi, Elton and Green (2001) studied surprises in 17 public news releases of economic data. They also note and measured the effect on Treasury bond prices, bid-ask spreads, volume, and volatility.

Anderson, Bollerslev, Diebold and Vega (2005) explore the response of global financial markets to the release of U.S. macroeconomic data. They find that markets react differently to the same news depending on the state of the U.S. economy. In the case of equity markets they found that bad news had a positive impact during expansions but a negative impact during recessions.

2. Equity Markets

In one of the earliest high-frequency studies of announcement effects was the Jain (1988) paper which examined money supply, inflation, industrial production and unemployment announcements on equity markets. Jain found that only money supply and CPI significantly affected stock prices, and that the adjustment was complete within an hour (using hourly data).

Connolly and Stivers (2005) examined the effect of macroeconomic announcements on stock turnover and volatility clustering using a sample of daily data for 29 firms over a 15 year time frame. They find volatility clustering tends to be stronger during periods of greater uncertainty as measured by dispersion of beliefs with respect to economic announcements. Increasingly, asymmetries in expectations and responses have become of interest to financial economists both on the theoretical and empirical sides.[18]

Each of the aforementioned studies represent an important contribution to the literature in this area. These studies do not, however, emphasize specification testing and rarely provide evidence that such tests have been performed. The highly dimensional nature of financial markets, the existence of outliers in the data, and the potential for regime shifts may well suggest that a full battery of diagnostic testing should be at the core of the modelling strategy for such a study. I expect to demonstrate herein, why such "testimation" in the "model discovery" process should be considered by researchers performing this type of study, as the financial data environment

[18] For example, see Kazemi (1991), Aktas, de Bodt and Levasseur (2004), Bessembinder, Chan and Seguin (1996), and Brockman, Chung and Pérignon (2009).

often contains the very same modelling challenges that Hendry and LSE approach practitioners focus in the area of macroeconomics.

3. Data Sources

The data for this study comes from several sources, mainly the CRSP US Treasuries database and Standard & Poor's. Survey data from the Standard & Poor's MMS Macroeconomic Indicator Survey are used to capture the effect of revisions to the existing information set at the time of an announcement. Importantly, using "as-reported" data allows us to evaluate the true information signal existing at the time of announcement. The use of revised indictor data would distort the data as revisions are frequent and often translate into a much different signal. For this reason, the MMS data has become the standard for performing this type of analysis.[19]

The survey reports the median expected value from survey participants with the unrevised value reported to the market at the time of announcement. The difference of these two values represents a "surprise" value for the economic indicator. Further, I standardize this variable by dividing by the full-sample standard deviation so that we compared the "standardized surprise" across indictors.

[19] Notable studies using MMS Survey Data include:Urich and Wachtel (1981), Urich (1982), Urich and Wachtel (1984), Jain (1988), Aggarwal, Mohanty and Song (1995), Li and Engle (1998), Almeida, Goodhart and Payne (1998), Balduzzi, Elton and Green (2001), Andersen, Bollerslev, Diebold and Vega (2003), Simpson and Ramchander (2004), Ramchander, Simpson and Chaudhry (2005), Andersen, Bollerslev, Diebold and Vega (2007), and Brenner, Pasquariello and Subrahmanyam (2009). The survey was the main source for such studies for over 25 years.

In table 2.1, we see distributional and descriptive data for standardized surprises in the MMS macroeconomic announcement data. The table provides information about the accuracy of market expectations in macro variables. Certain indicators may tend to give false signals, leading market participants to focus elsewhere.

We observe mild to moderate excess kurtosis across most indicators. Noticeably, core producer price index (PPIXFE), which excludes the volatile food and energy components, stands out with the greatest excess kurtosis at 7.38. Large negative skewness of -1.33 is seen in the GDP price deflator.

Overall, the data fail to reveal any significant abnormalities that would suggest that the market's reaction to any one indicator is due to a systematic inability of economists to forecast indicators. The range of observations for standardized surprises, however, does offer a few interesting outcomes. Leading indicators (LEI) and PPIXFE showed the largest negative standardized surprises at -5.22 and -4.43, respectively. With respect to positive standardized surprises, capacity utilization stands out with the largest positive standardized surprise at 4.19.

US Treasury returns are compiled from the CRSP Daily US Treasury database. I create simple returns for both "on-the-run" and first "off-the-run" 30-year bonds and 10-year notes. The most-recently issued security at a given maturity is considered the "on-the-run" issue (hereafter OTR), while the first "off-the-run" (hereafter, FTR) issue refers to the second-most-recently issued security. Bond market participants have typically shown a marked preference for the OTR issues. This phenomena, called the bond-old bond spread, has been explored in great detail by Krishnamurthy (2002).[20] It has also been well documented as a factor in the famous failure of the hedge fund Long Term Capital Management.[21]

Table 2.1

Properties of Consensus Forecasts

Descriptives for as-reported economic indicators announced from January 1990 to November 2001.

			Central Tendency		Range	
Indicators	Abbreviation	# Obs.	Avg SS	Avg Abs. SS	MIN SS	Max SS
Auto Sales	**AUTOS**	199	0.00	0.78	-2.92	2.47
Business Inventories	**BUSINV**	142	0.19	0.76	-2.30	2.76
Capacity Utilization	**CAPACIT**	141	0.12	0.78	-2.69	4.19
Consumer Confidence	**CONFIDN**	130	0.07	0.76	-2.16	2.71
Construction Spending	**CONSTRC**	142	0.08	0.78	-2.29	2.33
Consumer Price Index	**CPI**	130	-0.15	0.74	-2.48	2.48
Core CPI (excludes food and energy)	**CPIXFE**	141	0.08	0.66	-1.68	3.36
Durable Goods Orders	**DURGDS**	141	-0.01	0.76	-2.60	3.46
Employment Cost Index	**ECI**	30	-0.05	0.83	-2.03	3.04
Gross Domestic Product	**GDP**	138	0.24	0.77	-2.19	3.10
GDP Price Deflator	**GDPPRIC**	117	-0.20	0.63	-3.79	1.89
Goods and Services	**GDSSERV**	142	0.11	0.79	-2.40	3.79
Hourly Earnings	**HREARN**	142	0.10	0.82	-2.22	2.66
Home Sales	**HSLS**	141	0.13	0.81	-2.57	2.33
Housing Starts	**HSTARTS**	142	0.15	0.80	-2.42	3.41
Industrial Production	**INDPROD**	142	0.10	0.77	-2.62	3.37
Index of Leading Economic Indicators	**LEI**	142	0.07	0.72	-4.43	3.16
National Association of Purchasing Managers Index	**NAPM**	142	-0.11	0.80	-2.65	2.25
Nonfarm Payrolls	**NONFARM**	143	-0.16	0.77	-2.53	3.30
Personal Consumption Expenditures	**PCE**	140	0.19	0.77	-3.96	2.48
Personal Income	**PERSINC**	141	0.17	0.69	-3.90	3.47
Producer Price Index	**PPI**	143	-0.16	0.77	-2.88	3.24
Core PPI (excludes food and energy)	**PPIXFE**	143	-0.15	0.71	-5.22	2.61
Retail Sales	**RETSLS**	142	-0.15	0.78	-4.02	2.68
Retail Sales (excluding auto sales)	**RSXAUTO**	142	-0.17	0.72	-3.36	2.52
Unemployment Rate	**UNEMP**	143	-0.22	0.76	-2.72	2.72

Note:
SS indicates standardized surprise based on standard deviation of forecast surprise

D. Preliminary Examination of Asymmetries in Treasury Returns

Owing largely to the work of Nelson (1991) and Glosten, Jagannathan and Runkle (1993), asymmetric forms of the generalized autoregressive conductional heteroscedasticity models have gained popularity over the years. Just as the ARCH model of Engle (1982) and the GARCH extension of Bollerslev (1986) enabled researchers to capture the clustering of volatility in asset returns that previously posed a problem to researchers of financial markets, the asymmetric

[20] See also: Pasquariello and Vega (2007) regarding the "on-the-run *liquidity* phenomenon."
[21] See page 464 of Krishnamurthy (2002).

GARCH extensions have been particularly useful in modelling “leverage effects” in equity market returns. Li and Engle (1998) show evidence of asymmetric volatility in the US Treasury Futures market. Bond market returns asymmetries have also been explored by de Goeij and Marquering (2004), de Goeij and Marquering (2006), and Cappiello, Engle and Sheppard (2006). Although the leverage effect interpretation of asymmetric volatility does not apply in the case of US Treasury bonds, the existence of a time varying risk premium is typically seen as an explanation.[22]

Table 2.2 presents asymmetric volatility models of US Treasury returns for both OTR and FTR bonds and notes in the form of Nelson’s EGARCH model.[23] Here, the asymmetry term is γ. The impact is asymmetric if $\gamma \neq 0$. We can see in the estimation results that the asymmetry term is highly significant in all four cases.

To the best of my knowledge, this is the first study to show that the OTR issues demonstrate a greater degree of asymmetry associated with “bad news.” We should also note that, in the world of US Treasuries, good economic news is bad news for market participant. This is because positive economic news is considered as contributing to inflation risk. Negative economic news would be preferred by bond holders because a decreased inflation risk premia translates into higher bond prices and a greater return.

[22] Relevant Time-Varying Risk Premia articles include: Engle, Lilien and Robins (1987), Evans (1994), Lee (1995), Kryzanowski, Lalancette and To (1997), Campbell, Kazemi and Nanisetty (1999), and Koijen, Nijman and Werker (2010).
[23] Nelson (1991) assumes generalized error distribution, whereas the models in the table are based on a Student’s t-distribution with degrees of freedom estimated.

Equation 2.1

$$\Delta Y_t = \mu + \phi_1 Y_{t-1} \qquad 1.A$$

$$\ln(\sigma_t^2) = \omega + \alpha \left| \frac{\epsilon_{t-1}^2}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\epsilon_{t-1}^2}{\sigma_{t-1}} \qquad 1.B$$

Table 2.2 - EGARCH Estimation Results

AR(1) - EGARCH(1,1,1)

	30-Year		10-Year	
	OTR	FTR	OTR	FTR
Mean Equation	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
Constant	0.043 **	0.046 **	0.040 **	0.041 **
AR(1)	0.019	0.014	0.057 *	0.054 *
Variance Equation				
ω	-0.103 **	-0.097 **	-0.150 **	-0.144 **
α	0.088 **	0.083 **	0.105 **	0.099 **
β	-0.027 *	-0.028 *	-0.014 *	-0.013
γ	0.961 **	0.965 **	0.960 **	0.963 **
T-Dist. DOF	7.51 **	7.81 **	6.09 **	6.19 **
Log Liklihood	-2748.93	-2706.68	-1469.64	-1358.89
SIC	1.90	1.87	1.02	0.95
Included observations:	2927	2927	2927	2927

Sample: 1/02/1990 to 9/10/2001

**,* indicate significance at 0.05 and 0.01, respectively.

Optimization Algorithm: BFGS

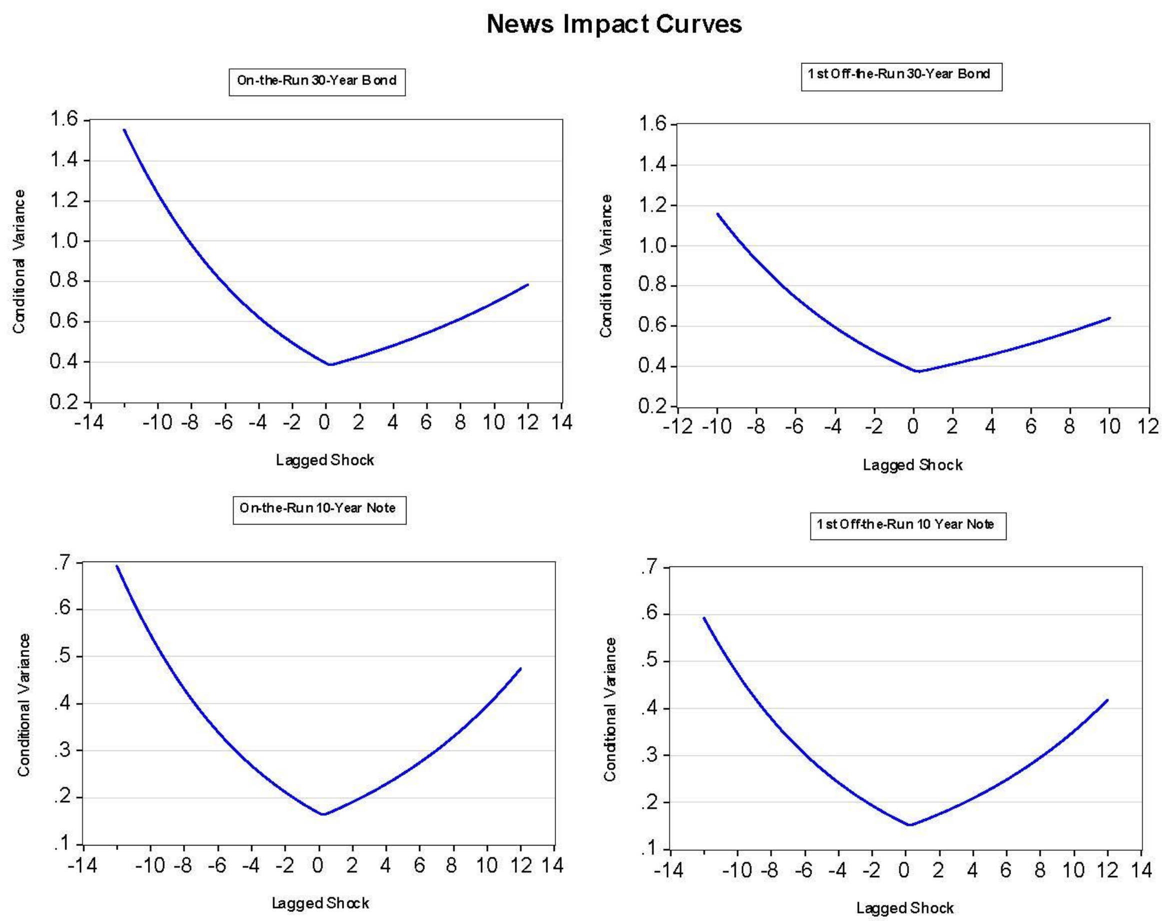
OTR = On-the-Run

FTR = 1st Off-the-Run

While the regression results are interesting, using the estimation results to plot out so-called "news impact curves" is additionally informative. The curves visually convey the extent of the asymmetry between the value of the conditional variance with respect to the value of the lagged shock.

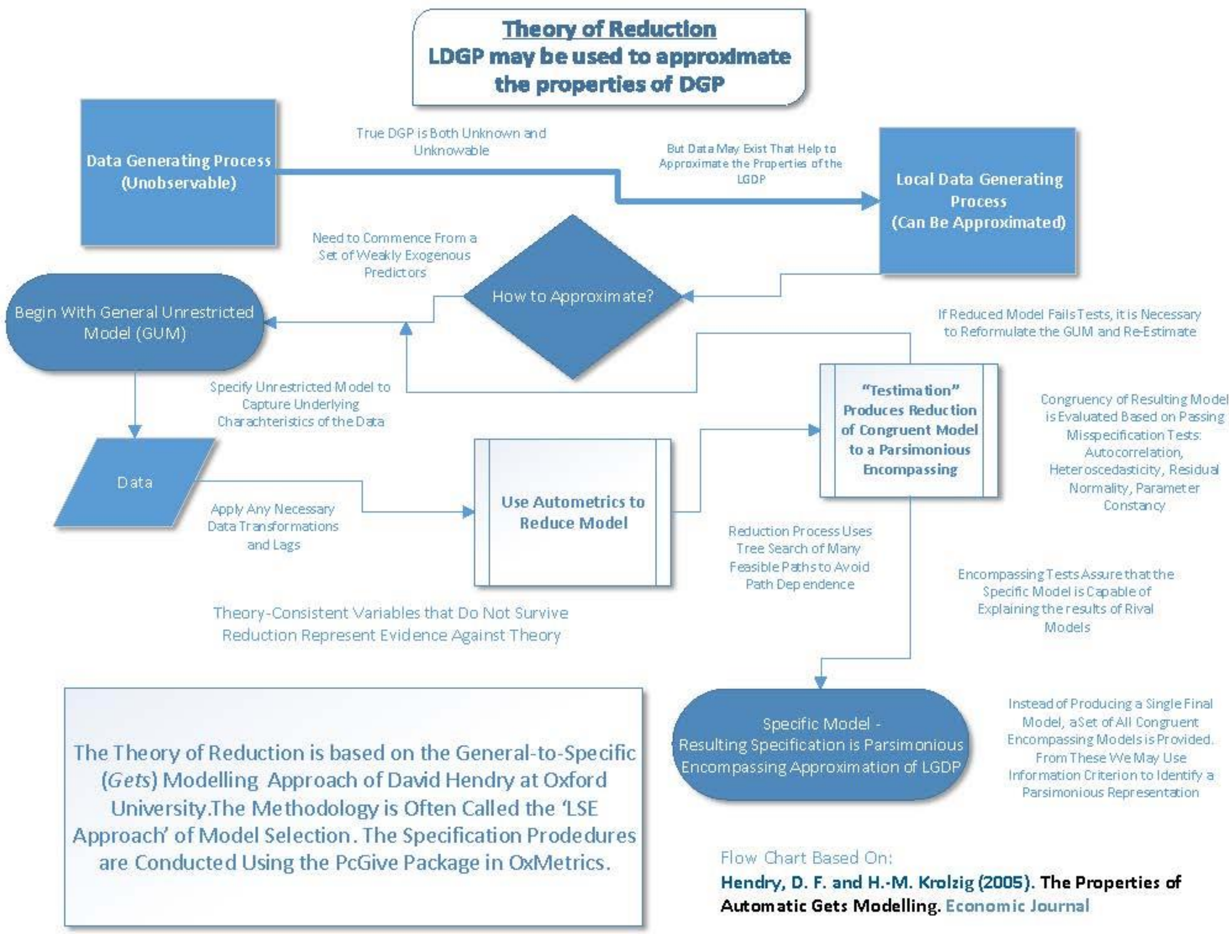
In figure 2.1, we see that the OTR news curves in the left column are markedly steeper for negative shocks when compared to the FTR curves. The benchmark 30-year Treasury bond shows the greatest degree of asymmetry. The reason for the greater asymmetry is unclear. The OTR and FTR securities are typically nearly identical, other than a slightly shorter maturity and a possible change in the coupon. But the preference for OTR is well documented. To this we can add an apparent greater increase in asymmetry for OTR, compared to FTR.

Figure 2.1



What remains unexplored is how surprises in macroeconomic variables can induce such behavior. To answer this, we will need to look at many economic variables in the context of a well specified econometric model. Such a situation allows us an opportunity to employ general-to-specific modelling in a macro-finance setting. The process of Gets modelling is outlined in figure 2.2 to provide a visual representation.

Figure 2.2 – The Gets Model Reduction Process



E. Gets Modelling of Macroeconomic Announcement Effects

In this section I use the Gets approach to econometric modelling to estimate asymmetric effects of daily US Treasury bonds and notes. Models currently in the literature tend to be in the static form of equation 2.2, and results are often presented with little or no regression diagnostics – although standard errors are often adjusted using Newey-West or some other method to deal with heteroscedasticity and/or autocorrelation. While this is common practice, it is not necessarily the best way of performing empirical research – particularly when other forms of misspecification may be present. The Gets method of Hendry, requires meticulous testing when conducting econometric estimation, via a battery of specification tests. I will proceed by using the standard static model as representative of the "straw man" erected by Gilbert (1986), which we will refer to as the "Average Economic Regression"(hereafter, AvER) – a long-standing target of LSE econometricians.[24]

Equation 2.2

$$R_t = \mu + \sum_{i=1}^{26} \beta_i x_{i,t} + u_t$$

Where:
$R_t = (r_t - r_{t-1})/r_{t-1}$ is the simple daily return of the US Treasury security at time t
$x_{i,t}$ = standardized surprise
$u_t \sim NIID(0,1)$ gaussian i.i.d. error term

In performing estimation of equation 2.2 on US Treasury returns, one will quickly find that the resulting estimates suffer (badly) from numerous forms of test failures. Estimates will typically

[24] See also: Phillips (1988), Gilbert (1989), Phillips (2003), Sargan (2003), and Hendry and Phillips (2017)

fail in terms of autocorrelation, heteroscedasticity, nonlinearity, and parameter constancy. What I find, is that it's not uncommon to fail 4 (or even all 5) tests. Yet, somehow, studies have been conducted (and published) using the very same Treasury returns and same macroeconomic announcements as predictors without providing specification testing results. Clearly, the problem is bigger than one requiring a "patchwork" approach of applying HAC standard errors. Such a strategy would probably leave us with a model likely to be plagued by omitted variables bias, with other issues still not addressed—namely, parameter constancy and nonlinearity. Fortunately, the Gets approach offers us the opportunity to build a better model. Moreover, recent advances, such as indicator saturation methods, make even the difficult case at hand workable.

What the static AvER models like equation 2.2 suffer from is a lack of "congruence" with the local data generating process – i.e., the model is insufficiently general to capture the key attributes of the data under examination. A congruent model should have all the following properties;[25]

1.) homoscedastic, independent errors;

2.) weak- or strong-form exogeneity of conditioning variables for the parameters of interest;

3.) constant invariant parameters of interest;

4.) theory-consistent identifiable structures;

[25] Based on Hendry and Nielsen (2007), pages 166-169, Hendry (1980), Hendry and Richard (1983), and Hendry (1995), and Hendry (2001). Note, however, the literature tends to require only weak form exogeneity. Therefore, the second property of congruence lists "weak or strong" exogeneity, instead of strong form exogeneity, as in Hendry and Nielsen (2007). Note also, I turn off pre-search lag reduction for this study as I wanted to assess the ability of Automated Gets to test the Efficient Market Hypothesis, not to bypass it. Leaving pre-search lag reduction on is likely to result in significantly shorter computation times.

5.) data-admissible formulations on accurate observations; and

6.) encompassing rival models.

We can evaluate the congruence of our models via specification testing. While the true data generating process is unknowable, we can assess model congruence with the local data generating process by performing the requisite battery to tests prescribed by Professor Hendry and advocates LSE/Oxford approach. Using the Oxmetrics platform, I used the Autometrics functions in PC-GIVE, which automate the Gets procedures.[26] The tests included by default are;

1.) AR 1-2 test – a Lagrange Multiplier test for *r*th order autocorrelation;

2.) ARCH 1-1 test – a standard ARCH test based on Engle (1982) and Engle, Hendry and Trumbell (1985);

3.) Normality Test – is of the form of Doornik and Hansen (2008);

4.) Hetero test is a general test for heteroscedastic errors, based on White (1980);

5.) The RESET test (Regression Specification Test) based on Ramsey (1969), to test nonlinearity.

The general-to-specific modelling strategy commences from a general unrestricted model, called the GUM, which is reduced based on the autometrics procedure. The estimation of equation 2.2 already fails, thus any reduction will also fail as the model lacks sufficient generality. Thus, we

[26] See www.doornik.com for additional details on the software. I used the 64 bit version 7.1 of the Oxmetrics Enterprise Edition on a dual quad core processor IBM computer with CPU processing speed of 2.2 GHz to perform model reductions. Windows Server 2008 R2 is the operating system. Given the large amount of data and regressors, the computation can take several hours. However, the cost of computation time in menial compared to the cost of model misspecification. Given advances in processing speed, potential gains from GPU processing and the likelihood of further gains from additional parallel processing and chip architecture advances, a newer machine would likely perform much more favorably compared to my computation times.

need to re-specify the model in a more general form. This can be done in a number of ways, but the objective is to go from general to specific, not specific to general.[27] Further, the model should be consistent with theory.

That the Treasury market is affected by macroeconomic data and that the surprise component of announcements that moves markets is obvious to all. Introducing lags of the independent variables pose only a minor problem. Namely, it would represent a violation of the Efficient Market Hypothesis that says financial markets adjust rapidly and fully to new information. Given that the Treasury markets are considered the most liquid financial market on the planet, adding lags is unlikely to be of any help achieve congruence, although it does allow us the opportunity to test EMH using Gets. This is one way of incorporating theory into a model within the LSE/Oxford modelling paradigm, to model a violation of theory and test down to see if the variable survives the model reduction.

In order to commence from a sufficiently general specification, we allow for violations of the EMH to occur, we will, however, likely need more than that to achieve a congruent, parsimonious, encompassing specification. However, based on the notion of time varying risk premia and asymmetric volatility, I allow for additional marginal affects associated with positive and negative surprises in macroeconomic announcements. This aspect has yet to be examined in this manner and represents a significant improvement over many poorly specified models in the

[27] For a comparison of RETINA and Gets modelling with PcGets (which preceded Autometrics), see Perez-Amaral, Gallo and White (2005). A comparison with LASSO can be found in Camila Epprecht, Dominique Guegan, Álvaro Veiga and Rosa (2013). See also: Castle, Doornik and Hendry (2013).

existing financial markets literature.[28] Additionally, I allow for inclusion of a lagged dependent variable by adding an autoregressive term to the GUM.

Yet, arriving at a congruent model specification can sometimes still require greater generality than data availability would *easily* provide. Such is the case when there are structural breaks, such as level shifts, or the presence of outliers in the data. Fortunately, recent advances in indicator saturation methods have offer us an additional set of tools for producing congruent empirical models when such complications exist. By adding indicator saturation methods to be used in the modelling process, we arrive at the specification of the GUM that is in equation 3. The equation takes the typical autoregressive distributed lag model, built with the dynamic model typology of dynamic models in Hendry, Pagan and Sargan (1984).[29]

1. Indicator Saturation Results

Knowing that the highly stochastic nature of fixed income markets is a difficult environment, I proceed first by running Autometrics reductions with each of the Autometrics indicator saturation methods individually to see which, if any, are able to provide a congruent model. The methods are large residual saturation (LRS), impulse indicator saturation (IIS), step indicator saturation (SIS), differenced impulse indicator saturation (DIIS) and combinations of IIS+SIS and SSI+DIIS. The results are provided in tables 2.3 and 2.4.[30]

[28] However, two interesting and important studies that adopt a different empirical framework on the subject are found in studies by de Goeij and Marquering (2006) and Brenner, Pasquariello and Subrahmanyam (2009).
[29] See also: Fisher (1925), Koyck (1954), Almon (1965), Dhrymes (1971), Forest and Turner (2013).
[30] IIS is discussed in Santos, Hendry and Johansen (2008), Castle, Doornik and Hendry (2013),Castle and Hendry (2013), Hendry and Doornik (2014). SIS is discussed in Doornik, Hendry and Pretis (2013) and Castle, Doornik, Hendry and Pretis (2015). A wider range of saturation methods are examined by Ericsson (2012), which include IIS,

Equation 2.3

$$R_t = \mu + \alpha_j y_{t-1} + \sum_{i=1}^{26} \beta_i x_t + \sum_{i=1}^{26} \delta_i x_{t-1} + \sum_{i=1}^{26} \varphi_i x_t^+ + \sum_{i=1}^{26} \eta_i x_t^- + \sum_{i=1}^{N+} \theta z_t + u_t$$

Where:

$R_t = (r_t - r_{t-1})/r_{t-1} = R_{i,t}$ Simple daily return of bond at time t

x_t^+ = positive standardized surprise

x_t^- = negative standardized surprise

z_t = indicator saturation dummy variables (IIS, SIS, IIS+SIS, DIIS, IIS+DIIS)

$u_t \sim NIID(0,1)$ gaussian i.i.d. error term

Table 2.3 contains results for the OTR and FTR 30-year bonds, while table 2.4 contains results for 10-year notes. What is clear from the results, is that the combined indicator saturation methods appear to do the best job at achieving a congruent model specification in this particular application. Given there is a greater body of literature on single saturation methods, and given a preference for parsimonious models being a cornerstone of the methods advocated by David Hendry, I chose to opt for either IIS or SIS when either passed the full battery of tests. If a single test failed, even at 0.01 significance, I opted for the combined IIS+SIS (if congruent). Based on the success of the IIS and SIS methods, it appears that saturation methods have much to offer for the financial econometrician.[31]

Certainly, additional regressors could have been included in the general unrestricted model that could have lessened the degree of saturation required to achieve a congruent representation of the

SIS, DIIS among others. See also: Johansen and Nielsen (2009), Marczak and Proietti (2014), Johansen and Nielsen (2016) and Doornik (2016) .

[31] It should be noted, also, that the use of DIIS appears to actually introduce nonlinearity issues in this particular application as a failure of the RESET test is found in all four securities when using DIIS. However, the combined IIS+DIIS clearly rectifies the problem.

local data generating process. For example, we could have added additional regressors and/or dummy variables for the following: 1.) key speeches, such as Greenspan's Humphrey Hawkins testimonies before Congress, 2.) additional macroeconomic announcements such as Johnson Redbook Retail Sales and the Philly Fed Manufacturing Index, 3.) announcements of Treasury auction volumes and auction results[32], 4.) lead dummy variables to account for "set-up effects" ahead of key macro announcements and auctions[33], 5.) some quantification of the Federal Reserve's "Beige Book" release of regional economic activity and/or FOMC meeting minutes,[34] 6.) dummy variables for known market predicaments that affected Treasury rates, such as the failure of Long-Term Capital Management, the Orange County CA bankruptcy, the failure of Barings bank, the Russian sovereign debt default and the Asian currency crisis.

Due to the unavailability of date or difficulties in compiling such data, some of the above are not attempted simply due to a cost benefit analysis on the part of the researcher.[35] However, Treasury auctions, set-up effects, and particularly FOMC meetings (3, 4, 5, and 6 above) are relatively manageable. Nevertheless, for the purpose of evaluating the ability of saturation methods in capturing unmodelled effects, I leave the task up to the indicator saturation algorithms to capture these effects.[36]

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[32] See Wachtel and Young (1987), Lou, Yan and Zhang (2013) and Forest (2017a)
[33] See van Dijk, Lumsdaine and van der Wel (2016) and Forest and Berry (2017b)
[34] See Ericsson (2016)
[35] For example, Johnson Redbook retail sales are proprietary reports not frequently forecast by economists, nor are they considered to be market movers in the Treasury market. The cost associated with finding forecasts of this series might be significant, while the benefits are likely to be negligible.
[36] See Appendix A for a table of 15 days of large moves in fixed income markets when there were no macroeconomic announcements. The table provides evidence supporting the ability of indicator saturation methods to pick up unmodelled effects such as the LTCM crisis and FOMC meetings. But, specific to FOMC meetings, Appendix B shows that most of the 99 FOMC meetings in the 1990s were not associated with an indicator saturation variable being retained. This could simply be because expectations were usually "baked in" to the market.

Table 2.3–Alternative Indicator Saturation Methods, 30-Year Bond

	On-the-Run Bonds				1st Off-the-Run Bonds		
Static No Saturation							
AR 1-2 test:	F(2,2898) =	4.9146 [0.0074]	**	AR 1-2 test:	F(2,2897) =	0.37984 [0.6840]	
ARCH 1-1 test:	F(1,2925) =	34.129 [0.0000]	**	ARCH 1-1 test:	F(1,2925) =	26.925 [0.0000]	**
Normality test:	Chi^2(2) =	450.27 [0.0000]	**	Normality test:	Chi^2(2) =	474.57 [0.0000]	**
Hetero test:	F(52,2874)=	1.8332 [0.0003]	**	Hetero test:	F(54,2872)=	2.026 [0.0000]	**
RESET23 test:	F(2,2898) =	2.3131 [0.0991]		RESET23 test:	F(2,2897) =	1.9772 [0.1386]	
Large Residual Saturation							
AR 1-2 test:	F(2,2884) =	0.40261 [0.6686]		AR 1-2 test:	F(2,2883) =	0.22184 [0.8011]	
ARCH 1-1 test:	F(1,2925) =	0.13277 [0.7156]		ARCH 1-1 test:	F(1,2925) =	1.0499 [0.3056]	
Normality test:	Chi^2(2) =	2.5398 [0.2809]		Normality test:	Chi^2(2) =	1.9546 [0.3763]	
Hetero test:	F(23,2875)=	1.9387 [0.0047]	**	Hetero test:	F(27,2872)=	1.8861 [0.0038]	**
RESET23 test:	F(2,2884) =	1.1726 [0.3097]		RESET23 test:	F(2,2883) =	3.1519 [0.0429]	*
Impulse Indication Saturation							
AR 1-2 test:	F(2,2808) =	0.56198 [0.5701]		AR 1-2 test:	F(2,2815) =	1.2327 [0.2917]	
ARCH 1-1 test:	F(1,2925) =	0.53201 [0.4658]		ARCH 1-1 test:	F(1,2925) =	1.1711 [0.2793]	
Normality test:	Chi^2(2) =	4.32590 [0.1150]		Normality test:	Chi^2(2) =	1.9221 [0.3825]	
Hetero test:	F(20,2800)=	1.83460 [0.0132]	*	Hetero test:	F(18,2808)=	1.8625 [0.0148]	*
RESET23 test:	F(2,2808) =	0.46745 [0.6266]		RESET23 test:	F(2,2815) =	0.40963 [0.6639]	
Step Indicator Saturation							
AR 1-2 test:	F(2,2760) =	3.4536 [0.0318]	*	AR 1-2 test:	F(2,2751) =	1.70890 [0.1813]	
ARCH 1-1 test:	F(1,2925) =	2.7299 [0.0986]		ARCH 1-1 test:	F(1,2925) =	1.25510 [0.2627]	
Normality test:	Chi^2(2) =	2.5819 [0.2750]		Normality test:	Chi^2(2) =	0.60785 [0.7379]	
Hetero test:	F(133,2752)=	1.0596 [0.3075]		Hetero test:	F(151,2739)=	1.18810 [0.0629]	
RESET23 test:	F(2,2760) =	2.9626 [0.0518]		RESET23 test:	F(2,2751) =	1.28880 [0.2758]	
IIS and SIS							
AR 1-2 test:	F(2,2764) =	1.6495 [0.1923]		AR 1-2 test:	F(2,2784) =	0.7803 [0.4584]	
ARCH 1-1 test:	F(1,2925) =	2.4525 [0.1174]		ARCH 1-1 test:	F(1,2925) =	0.41604 [0.5190]	
Normality test:	Chi^2(2) =	2.6591 [0.2646]		Normality test:	Chi^2(2) =	0.70898 [0.7015]	
Hetero test:	F(98,2756)=	1.1454 [0.1591]		Hetero test:	F(86,2777)=	1.1656 [0.1442]	
RESET23 test:	F(2,2764) =	1.4723 [0.2296]		RESET23 test:	F(2,2784) =	2.4078 [0.0902]	
Differenced IIS							
AR 1-2 test:	F(2,2817) =	3.0847 [0.0459]	*	AR 1-2 test:	F(2,2806) =	2.9772 [0.0511]	
ARCH 1-1 test:	F(1,2925) =	1.9619 [0.1614]		ARCH 1-1 test:	F(1,2925) =	2.6195 [0.1057]	
Normality test:	Chi^2(2) =	2.3248 [0.3127]		Normality test:	Chi^2(2) =	1.8608 [0.3944]	
Hetero test:	F(192,2734)=	0.6189 [1.0000]		Hetero test:	F(210,2716)=	0.59851 [1.0000]	
RESET23 test:	F(2,2817) =	6.3752 [0.0017]	**	RESET23 test:	F(2,2806) =	10.254 [0.0000]	**
IIS and DIIS							
AR 1-2 test:	F(2,2805) =	0.99931 [0.3683]		AR 1-2 test:	F(2,2823) =	0.82454 [0.4385]	
ARCH 1-1 test:	F(1,2925) =	3.3756 [0.0663]		ARCH 1-1 test:	F(1,2925) =	3.1551 [0.0758]	
Normality test:	Chi^2(2) =	0.87191 [0.6466]		Normality test:	Chi^2(2) =	2.196 [0.3335]	
Hetero test:	F(124,2749)=	0.65844 [0.9986]		Hetero test:	F(94,2779)=	0.70666 [0.9851]	
RESET23 test:	F(2,2805) =	1.3507 [0.2592]		RESET23 test:	F(2,2823) =	0.87421 [0.4173]	

Notes on the tests above based on descriptions provided in the PCGIVE documentation.

Greater detail is available at https://www.doornik.com/pcgive/index.html

1) Autocorrelation test (AR 1-2 test) is the Lagrange-multiplier test for rth order residual autocorrelation.

The F- form of the test is used. Under the null hypothesis that there is no autocorrelation (that is, that the errors are white noise).

2) ARCH 1-1 test is the standard Autoregressive Conditional Heteroscedastity test H0: $\gamma=0$. The F-form is reported.

Both first-order and higher-order lag forms are easily calculated (see Engle, 1982, and Engle, Hendry, and Trumbull, 1985)

3) Normality Test is of the form of Doornik and Hansen (1994) with the null being that of normality.

4) Hetero test is a general test for heteroscedastic errors: H0 is that the errors are homoscedastic. Test is based on White (1980).

5) The RESET test (Regression Specification Test) due to Ramsey (1969) tests the null of correct specification of the original model against the alternative that powers of $\hat{y}_t$ have been omitted.

Autometrics procedure also involves parameter stability testing based on the approach in Hansen (1992).

Table 2.4 – Indicator Saturation Methods, 10-Year Note

	On-the-Run Notes				**1st Off-the-Run Notes**		
Static No Saturation							
AR 1-2 test:	F(2,2897) =	0.37984 [0.6840]		AR 1-2 test:	F(2,2898) =	4.347 [0.0130]	*
ARCH 1-1 test:	F(1,2925) =	26.925 [0.0000]	**	ARCH 1-1 test:	F(1,2925) =	24.823 [0.0000]	**
Normality test:	Chi^2(2) =	474.57 [0.0000]	**	Normality test:	Chi^2(2) =	479.71 [0.0000]	**
Hetero test:	F(54,2872)=	2.026 [0.0000]	**	Hetero test:	F(52,2874)=	1.599 [0.0043]	**
RESET23 test:	F(2,2897) =	1.9772 [0.1386]		RESET23 test:	F(2,2898) =	2.0078 [0.1345]	
Large Residual Saturation							
AR 1-2 test:	F(2,2871) =	0.63503 [0.5300]		AR 1-2 test:	F(2,2875) =	0.56044 [0.5710]	
ARCH 1-1 test:	F(1,2925) =	0.040235 [0.8410]		ARCH 1-1 test:	F(1,2925) =	0.093487 [0.7598]	
Normality test:	Chi^2(2) =	7.7743 [0.0205]	*	Normality test:	Chi^2(2) =	13.294 [0.0013]	**
Hetero test:	F(36,2855)=	1.622 [0.0111]	*	Hetero test:	F(37,2859)=	1.5888 [0.0135]	*
RESET23 test:	F(2,2871) =	3.899 [0.0204]	*	RESET23 test:	F(2,2875) =	4.9986 [0.0068]	**
Impulse Indication Saturation							
AR 1-2 test:	F(2,2819) =	1.2836 [0.2772]		AR 1-2 test:	F(2,2796) =	2.6703 [0.0694]	
ARCH 1-1 test:	F(1,2925) =	0.91307 [0.3394]		ARCH 1-1 test:	F(1,2925) =	0.21052 [0.6464]	
Normality test:	Chi^2(2) =	2.2006 [0.3328]		Normality test:	Chi^2(2) =	2.9671 [0.2268]	
Hetero test:	F(20,2811)=	1.7026 [0.0264]	*	Hetero test:	F(20,2788)=	1.3793 [0.1208]	
RESET23 test:	F(2,2819) =	0.53229 [0.5873]		RESET23 test:	F(2,2796) =	0.12934 [0.8787]	
Step Indicator Saturation							
AR 1-2 test:	F(2,2757) =	1.9565 [0.1415]		AR 1-2 test:	F(2,2771) =	1.47890 [0.2281]	
ARCH 1-1 test:	F(1,2925) =	0.62871 [0.4279]		ARCH 1-1 test:	F(1,2925) =	0.37855 [0.5384]	
Normality test:	Chi^2(2) =	2.3116 [0.3148]		Normality test:	Chi^2(2) =	1.00720 [0.6044]	
Hetero test:	F(134,2747)=	0.95983 [0.6132]		Hetero test:	F(123,2761)=	0.93475 [0.6817]	
RESET23 test:	F(2,2757) =	2.1907 [0.1120]		RESET23 test:	F(2,2771) =	2.82890 [0.0592]	
IIS and SIS							
AR 1-2 test:	F(2,2727) =	0.92569 [0.3964]		AR 1-2 test:	F(2,2726) =	2.80810 [0.0605]	
ARCH 1-1 test:	F(1,2925) =	0.17571 [0.6751]		ARCH 1-1 test:	F(1,2925) =	0.05769 [0.8102]	
Normality test:	Chi^2(2) =	4.5265 [0.1040]		Normality test:	Chi^2(2) =	1.57020 [0.4561]	
Hetero test:	F(112,2719)=	1.3208 [0.0149]	*	Hetero test:	F(121,2716)=	1.01850 [0.4286]	
RESET23 test:	F(2,2727) =	2.58 [0.0760]		RESET23 test:	F(2,2726) =	1.90110 [0.1496]	
Differenced IIS							
AR 1-2 test:	F(2,2814) =	0.61483 [0.5408]		AR 1-2 test:	F(2,2796) =	0.5749 [0.5628]	
ARCH 1-1 test:	F(1,2925) =	3.8205 [0.0507]		ARCH 1-1 test:	F(1,2925) =	2.4689 [0.1162]	
Normality test:	Chi^2(2) =	2.0524 [0.3584]		Normality test:	Chi^2(2) =	0.69013 [0.7082]	
Hetero test:	F(194,2732)=	0.5 [1.0000]		Hetero test:	F(225,2701)=	0.59947 [1.0000]	
RESET23 test:	F(2,2814) =	14.498 [0.0000]	**	RESET23 test:	F(2,2796) =	10.724 [0.0000]	**
IIS and DIIS							
AR 1-2 test:	F(2,2798) =	0.15254 [0.8585]		AR 1-2 test:	F(2,2781) =	0.074857 [0.9279]	
ARCH 1-1 test:	F(1,2925) =	4.0607 [0.0440]	*	ARCH 1-1 test:	F(1,2925) =	0.43975 [0.5073]	
Normality test:	Chi^2(2) =	1.9943 [0.3689]		Normality test:	Chi^2(2) =	1.6227 [0.4443]	
Hetero test:	F(133,2739)=	0.56899 [1.0000]		Hetero test:	F(118,2730)=	0.54746 [1.0000]	
RESET23 test:	F(2,2798) =	5.5684 [0.0039]	**	RESET23 test:	F(2,2781) =	5.9552 [0.0026]	**

Notes on the tests above based on descriptions provided in the PCGIVE documentation.

Greater detail is available at https://www.doornik.com/pcgive/index.html

1) Autocorrelation test (AR 1-2 test) is the Lagrange-multiplier test for rth order residual autocorrelation.

The F- form of the test is used. Under the null hypothesis that there is no autocorrelation (that is, that the errors are white noise).

2) ARCH 1-1 test is the standard Autoregressive Conditional Heteroscedastity test H0: γ=0. The F-form is reported.

Both first-order and higher-order lag forms are easily calculated (see Engle, 1982, and Engle, Hendry, and Trumbull, 1985)

3) Normality Test is of the form of Doornik and Hansen (1994) with the null being that of normality.

4) Hetero test is a general test for heteroscedastic errors: H0 is that the errors are homoscedastic. Test is based on White (1980).

5) The RESET test (Regression Specification Test) due to Ramsey (1969) tests the null of correct specification of the original model against the alternative that powers of $\hat{y}_t$ ha

Automatrics procedure also involves parameter stability testing based on the approach in Hansen (1992).

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The Autometrics software does additional testing in the model reduction process that is not reported in the table. However, this is not to suggest that these tests are of lesser importance. Nothing could be further from the truth. Encompassing testing and parameter constancy tests are an integral part of the model reduction process.[37]

Table 2.5—Parameter Stability AvER Models

Model and Parameter Instability Tests

Static Modes with no Selection/Saturation

	OTR 30-Year	FTR 30-Year	OTR 10-Year	FTR 10-Year
Hansen Instability tests:				
variance	1.764 **	2.185 **	0.769 *	0.815 **
joint	7.030 **	7.641 **	6.333 *	6.393 *
Individual instability tests:				
Constant	0.037	0.038	0.045	0.050
ss_autos	0.114	0.106	0.176	0.142
ss_businv	0.103	0.085	0.184	0.138
ss_capacit	0.461	0.381	0.471 *	0.486 *
ss_confidn	0.080	0.076	0.087	0.083
ss_constrc	0.173	0.218	0.248	0.278
ss_cpi	0.054	0.054	0.054	0.054
ss_cpixfe	0.063	0.060	0.079	0.082
ss_durgds	0.123	0.144	0.090	0.162
ss_eci	0.072	0.078	0.105	0.104
ss_gdp	0.041	0.049	0.046	0.048
ss_gdppric	0.122	0.114	0.232	0.210
ss_gdsserv	0.147	0.156	0.157	0.168
ss_hrearn	0.127	0.128	0.085	0.090
ss_hsls	0.211	0.264	0.188	0.211
ss_hstarts	0.577 *	0.577 *	0.751 *	0.673 *
ss_indprod	0.328	0.175	0.311	0.292
ss_lei	0.104	0.111	0.098	0.102
ss_napm	0.253	0.306	0.142	0.160
ss_nonfarm	0.157	0.146	0.123	0.134
ss_pce	0.477 *	0.566 *	0.544 *	0.558 *
ss_persinc	0.172	0.192	0.116	0.110
ss_ppi	0.175	0.164	0.226	0.189
ss_ppixfe	0.488 *	0.400	0.581 *	0.533 *
ss_retsls	0.455	0.382	0.547 *	0.478 *
ss_rsxauto	0.052	0.046	0.061	0.063
ss_unemp	0.082	0.104	0.053	0.075

Instability based on Hansen (1992)

Larger values indicate parameter/model non-constancy (marked by * or **).

[37] See Hendry and Doornik (2014), Chapter 13, regarding the role of encompassing in the model discovery process.

2. Parameter Stability

In this section, I provide evidence for the effectiveness of Autometrics in achieving parameter constancy in the Gets models relative to the AvER models. Table 2.5 contains model and parameter stability tests for the static AvER models, based on Hansen (1992). Models of all four securities under investigation fail in terms of parameter constancy. The offending predictors are: capacity utilization, housing starts, personal consumption expenditures, core producer prices (PPI excluding food and energy), and retail sales.

We can contrast these results with those of table 2.6, which contains test results for the Gets models. Because Hansen's test in not appropriate for models with dummy variables, the individual parameter stability results are from the same specification as the Gets model, but having dropped the dummy variables. This is just to give a sense of the level of improvement. The model constancy tests are the standard Chow tests that are a default test in the Autometrics procedure.

The result provided in table 2.6 clearly underscores the value of Gets modelling with Autometrics. All four models pass the parameter constancy tests. While retail sales are indicated as potentially unstable, again, this is based on a reduced model that excludes the indicator saturation dummy variables. What we can say is that parameter constancy appears to have come partially by way of indicator saturation and partially by way of model reduction.

Clearly, we have done a tremendous amount of testing thus far without yet focusing on the estimation results. This is because our primary concern is achieving an admissible representation of the local data generating process. Having achieved improved results in testing down to a satisfactory model, we may now shift our attention to the regression results.

Table 2.6 – Parameter Stability of Gets Models

Model and Parameter Instability Tests

Gets Models with Indicator Saturation

	OTR 30-Year	FTR 30-Year	OTR 10-Year	FTR 10-Year
Chow Breakpoint Tests (H_0: Break at 70% of sample):				
P-Value	0.723	0.353	0.675	0.800
Cut-Off	0.010	0.010	0.010	0.010
Individual instability tests based on Hansen (1992):				
Dependent Variable(-1)		0.259		
Constant				0.065
ss_confidn	0.091	0.091	0.099	0.084
ss_cpixfe	0.065	0.063	0.100	0.082
ss_durgds	0.157	0.184	0.107	0.209
ss_eci				
ss_gdp				
ss_hrearn	0.141	0.142	0.100	0.105
ss_napm	0.239	0.295	0.141	0.156
ss_nonfarm	0.165	0.153	0.127	0.141
ss_ppixfe		0.250		
ss_ppixfe_1		0.270		
ss_retsls	0.509 *	0.404	0.623 *	
neg_ss_eci	0.112	0.118	0.123	0.131
neg_ss_persinc				0.027
neg_ss_ppixfe	0.085		0.119	
pos_ss_cpi				0.050
pos_ss_eci		0.075	0.154	
pos_ss_hsls				0.038
pos_ss_ppi		0.191		

Parameter Instability based on Hansen(1992).
Due to presence of indicator saturation dummies in these models,
Model tests are given by standard Chow Breakpoint Tests with
break occurring at 70% of the sample. This is the PC-Give software default in Autometrics.
Individual parameter instability based on Hansen (1992), with indicator saturation dummies removed.
Larger values in indicate parameter non-constancy (marked by * or **).

3. Estimation Results

In this section we analyze and interpret the regression results to better assess the underlying question of the sources of asymmetric risk premia in the US Treasury market. Thus far, we have gained an appreciation for the benefits of Gets modelling in financial econometrics. Poorly specified AvER models attempting to relate fixed income returns to contemporaneous surprises in macroeconomic variables failed to represent the local data generating process adequately. Those models failed (or nearly failed) virtually every specification test. Such models would prove far too inadequate to be repaired with a duct tape and bubble gum solution of HAC standard errors. General-to-specific modelling via Autometrics was employed to solve the problem and we were able to achieve a congruent, parsimonious, encompassing, model alternative.

Tables 2.7 and 2.8 contain the regression results for the 30-year and 10-year securities, respectively. The results suggest that fewer economic variables were market movers than originally expected. However, the big headline macro variables that were watched closely during the Greenspan era at the Fed are retained in the model reductions—i.e., nonfarm payrolls, the Employment Cost Index (ECI), durable goods orders, consumer confidence, etc..

We also see yet another benefit of the Gets procedure, that being the ability to discern between competing variable definitions such as CPI and Core CPI, which excludes food and energy prices. The popular press tended to, and perhaps still does, report more on the overall index. However, policymakers tend to pay closer attention to the core rate of inflation. The results appear to confirm the wisdom of this approach, with the core rates for CPI and PPI tending to survive, while the headline number is reduced out.

With respect to market efficiency, the EMH holds as expected as only one single lagged macro variable failed to be reduced in the model reduction process – that being Core PPI in the FTR 30-year bond regression model. Given the target "size" of 1%, we would expect to see an occasional retention of a variable that does not belong in the model. But the benefits clearly outweigh the costs and I would not consider this a violation of the EMH. If a case were to be made for Core PPI representing a market anomaly, we would have expected to see the variable retained at other maturities or in the OTR bond as well.[38]

With respect to one of the main points of the paper, a small number of variables that appear to generate the asymmetric response effects suggested by the estimation results from our EGARCH models. Interestingly, the Employment Cost Index (ECI) appears only to affect Treasury returns significantly when the surprise is negative. This result is seen in all four securities, with the same sign on the coefficient and similar order of magnitude. Other indicators that appear to elicit asymmetric responses include: Core PPI, PPI, CPI, home sales, personal income, and capacity utilization. From this, I would draw the conclusion that these variables contribute to the asymmetric time varying risk premia. To some, it may be surprising that that nonfarm payrolls,

[38] This is because the on-the –run and off-the-run issues at each maturity are near perfect substitutes for one another. Likewise, the 10-year note and 30-year bond are at the long end of the Treasury yield curve and the behavior of the returns for these securities are affected by common risk factors. The US government has never defaulted on its obligations and market participants consider these securities to be free of default risk. The main risk component for long-term Treasuries is the inflation risk premia.

the most widely followed macro variable of the Greenspan era, does not appear to be a source of asymmetry.

Table 2.7 – 30-Year Bond Estimation

	30-Year On-the-Run			30-Year 1st Off-the-Run		
	A.	B.	C.	A.	B.	C.
	Coefficient	Uncorrected Coefficient	2-Step Corrected Coefficient	Coefficient	Uncorrected Coefficient	2-Step Corrected Coefficient
bond_30_ftr_1_rt(-1)					-0.086	-0.085 **
Constant	0.031 **			0.035 **		
ss_autos	-0.073			-0.070		
ss_businv	0.014			0.021		
ss_capacit	-0.130			-0.137		
ss_confidn	-0.225 **	-0.243	-0.242 **	-0.216 **	-0.247	-0.246 **
ss_constrc	-0.015			-0.010		
ss_cpi	-0.068			-0.070		
ss_cpixfe	-0.182 **	-0.248	-0.248 **	-0.180 **	-0.185	-0.176 **
ss_durgds	-0.189 **	-0.137	-0.098 **	-0.188 **	-0.171	-0.157 **
ss_eci	-0.316 **			-0.311 **		
ss_gdp	-0.023			-0.018		
ss_gdppric	-0.104			-0.090		
ss_gdsserv	0.008			0.014		
ss_hrearn	-0.243 **	-0.139	-0.102 **	-0.237 **	-0.122	-0.065 **
ss_hsls	0.069			0.129		
ss_hstarts	-0.015			-0.008		
ss_indprod	-0.006			0.024		
ss_lei	-0.043			-0.049		
ss_napm	-0.312 **	-0.363	-0.363 **	-0.297 **	-0.329	-0.329 **
ss_nonfarm	-0.394 **	-0.317	-0.317 **	-0.402 **	-0.355	-0.355 **
ss_pce	-0.007			-0.013		
ss_persinc	-0.090			-0.091		
ss_ppi	0.063			0.062		
ss_ppixfe	-0.160 **			-0.170 **	-0.231	-0.229 **
ss_ppixfe(-1)					-0.122	-0.064 **
ss_retsls	-0.191 **	-0.133	-0.081 **	-0.194 **	-0.117	0.000 **
ss_rsxauto	0.023			0.025		
ss_unemp	0.066			0.071		
neg_ss_eci		-0.785	-0.785 **		-0.915	-0.915 **
neg_ss_ppixfe		-0.229	-0.219 **			
pos_ss_ppi					0.227	0.161 **
sigma	0.62	0.52		0.61	0.52	
log-likelihood	-2738.69	-2157.68		-2685.54	-2139.80	
no. of observations	2927	2927		2927	2927	
mean(Y)	0.033	0.033		0.036	0.036	
RSS	1113.411	748.585		1073.699	739.498	
no. of parameters	27	161		27	174	
se(Y)	0.639	0.639		0.628	0.628	
Saturation	None	IIS+SIS		None	SIS	
Congruent @ 1%	No	Yes		No	Yes	
Diagnostic Test	**P-Value**	**P-Value**		**P-Value**	**P-Value**	
AR 1-2 test:	0.5259	0.1923		0.8202	0.1813	
ARCH 1-1 test:	0.0000 **	0.1174		0.0000 **	0.2627	
Normality test:	0.0000 **	0.2646		0.0000 **	0.7379	
Hetero test:	0.0075 **	0.1591		0.0005 **	0.0629	
RESET23 test:	0.3359	0.2296		0.1877	0.2758	

ss = standardized surprise

**,* indicate significance at .05 and .01, respectively

Table 2.8 – 10-Year Note Estimation Results

	10-Year On-the-Run			10-Year 1st Off-the-Run		
	A.	B.	C.	A.	B.	C.
	Coefficient	Uncorrected Coefficient	2-Step Corrected Coefficient	Coefficient	Uncorrected Coefficient	2-Step Corrected Coefficient
Constant	0.030 **			0.032 **	0.040	0.040 **
ss_autos	-0.039			-0.041		
ss_businv	0.004			0.006		
ss_capacit	-0.105 *			-0.108 *		
ss_confidn	-0.174 **	-0.167	-0.166 **	-0.169 **	-0.170	-0.169 **
ss_constrc	-0.011			-0.009		
ss_cpi	-0.037			-0.042		
ss_cpixfe	-0.117 **	-0.143	-0.142 **	-0.108 **	-0.122	-0.112 **
ss_durgds	-0.117 **	-0.111	-0.102 **	-0.114 **	-0.100	-0.087 **
ss_eci	-0.210 **			-0.196 **		
ss_gdp	-0.031			-0.018		
ss_gdppric	-0.051			-0.056		
ss_gdsserv	0.009			0.011		
ss_hrearn	-0.162 **	-0.180	-0.180 **	-0.153 **	-0.173	-0.173 **
ss_hsls	-0.187			-0.267		
ss_hstarts	-0.012			-0.014		
ss_indprod	0.016			0.022		
ss_lei	-0.022			-0.022		
ss_napm	-0.225 **	-0.238	-0.238 **	-0.210 **	-0.228	-0.228 **
ss_nonfarm	-0.303 **	-0.208	-0.208 **	-0.282 **	-0.174	-0.174 **
ss_pce	-0.013			-0.011		
ss_persinc	-0.051			-0.055		
ss_ppi	0.076			0.075		
ss_ppixfe	-0.094 *			-0.081 *		
ss_retsls	-0.136 **	-0.083	-0.042 **	-0.138 **		
ss_rsxauto	0.007			0.008		
ss_unemp	0.063			0.074 *		
neg_ss_eci		-0.426	-0.424 **		-0.382	-0.378 **
neg_ss_persinc					-0.126	-0.068 **
neg_ss_ppixfe		-0.109	-0.076 **			
pos_ss_capacit		-0.111	-0.076 **			
pos_ss_cpi					-0.148	0.000 *
pos_ss_hsls					-2.894	-2.299 **
sigma	0.405	0.340		0.389	0.322	
no. of observations	2927	2927		2927	2927	
mean(Y)	0.030	0.030		0.033	0.033	
RSS	474.878	318.420		438.820	289.954	
log-likelihood	-1491.600	-906.658		-1376.030	-769.603	
no. of parameters	27	168		27	129	
se(Y)	0.420	0.420		0.403	0.403	
Saturation	None	SIS		None	IIS	
Congruent @ 1%	No	Yes		No	Yes	
Diagnostic Test	**P-Value**	**P-Value**		**P-Value**	**P-Value**	
AR 1-2 test:	0.0074 **	0.1415		0.0130 *	0.0694	
ARCH 1-1 test:	0.0000 **	0.4279		0.0000 **	0.6464	
Normality test:	0.0000 **	0.3148		0.0000 **	0.2268	
Hetero test:	0.0003 **	0.6132		0.0043 **	0.1208	
RESET23 test:	0.0991	0.1120		0.1345	0.8787	

ss = standardized surprise

**,* indicate significance at .05 and .01, respectively

Bias Correction Based on Code Courtesy of Hendry, Doornik and Castle

4. Dealing with Bias – The Known vs. the Unknown

A point of contention for critics of Gets model discovery methods, is that the parameter estimates are not perfectly unbiased. Admittedly, this is a verifiable fact. Notwithstanding, Professor Hendry and LSE approach advocates will argue that the estimates are, in fact, nearly unbiased.[39] Further, the form of the bias is well understood and easily corrected via a routine bias adjustment procedure.[40]

Because of sampling, some relevant variables will likely have $t^2 < C_\alpha^2$ in a particular sample. Conditional estimates will be biased away from the origin as variables are based on the condition $t^2 > C_\alpha^2$. By chance, approximately α(N-n) irrelevant variables will be retained due to adventitiously significant $t^2 > C_\alpha^2$.[41] However, as shown in Hendry and Krolzig (2005), bias correction will achieve approximate unbiasedness of the relevant variables while also driving coefficients on the irrelevant variables to zero. The two-step bias correction procedure can be applied to parameter estimates, and requires only the estimated parameters, t-stats, sample size and significance level from the Gets estimation.

When compared to the "phantom menace" of omitted-variables-bias, which is likely to plague an empirical model that does not adequately represent the local data generating process, the small

[39] See chapter 10 of Hendry and Doornik (2014).
[40] The bias correction process is described in great detail in Hendry and Krolzig (2005).
[41] Hendry and Doornik (2014) page 133.

and manageable bias of the Gets estimator poses little risk to the empirical modeler.[42] But when models fail specification tests at the degree we see in this study, omitted-variable bias is likely to be present. Clearly, the downside of Gets modeling – i.e., computation time and bias correction – are pale in comparison to the upside – efficient, consistent, and unbiased parameter estimates. In tables 2.10 and 2.11, I attempt to provide a sense of the degree of Gets estimator bias vs omitted-variable bias. The analysis draws heavily from Hendry and Krolzig (2005) and Hendry and Doornik (2014).[43] The results are favorable to the Gets modeler but AvER models are shown to suffer badly in terms of bias relative to the un-corrected Gets model coefficients. Gets bias is low in absolute terms, often producing estimates with no bias at all. When bias exists in the uncorrected coefficients, the size of the bias tends to be less than half that of the omitted variable bias in the uncorrected AvER regressions.

For example, looking at the results for the 30-year on-the-run bond, the bias in the AvER model coefficient on hourly earnings surprises is 138.2% of the bias corrected Gets coefficient. By comparison, the bias in the uncorrected Gets coefficient is only 36.7% of the bias corrected Gets coefficient. All of the common coefficients in the AvER model suffer from bias, while the uncorrected Gets model has bias in only 3 of 7 coefficients. Also, with respect to the 30-year off-the-run bond, we see the retail sales coefficient is driven down to zero. While the percent bias is undefined due to division by zero, in absolute terms the AvER parameter estimate is -.194 instead of zero. In finance, nineteen basis points can amount to a lot of money – particularly

[42] This ghostly characterization in quotes is based on the imaginative description in the title of Clarke (2005).
[43] I would like to thank David Hendry, Jurgen Doornik and Jennifer Castle for making their Ox code for the bias adjustment available to me.

when moving lots of Treasury bonds between large institutions. So the losses associated with poor parameter estimation in finance stand to be costly on more than just an analytical level.

Uncorrected Gets parameter estimates for the 10-year on-the-run note achieve even lower levels of relative bias. The troublesome retail sales series, which we had warning signs on earlier in the study when it was revealed that the presence of stability issues, has the greatest bias. Uncorrected Gets bias is 95% compared to the corrected counterpart. However, the AvER model bias is 220.0% greater than the corrected Gets estimate. Having 4 models, with 29 common coefficients estimated, only one uncorrected Gets coefficient showed larger bias relative to the corrected Gets coefficient than did its AvER model counterpart – that being the case of core CPI which had positive 8.4% bias relative to the corrected Gets, while the AvER had a -4.1 percent relative bias estimate. While uncorrected Gets failed to pitch a shutout against AvER, a 28 to 1 score looks pretty convincing. Given the ease of applying the bias correction, the general to specific methodology looks even more attractive for the financial econometrician.

Table 2.9 – Analysis of Bias in Common Coefficients - 30-Year Bond

	30-Year On-the-Run					30-Year 1st Off-the-Run				
	AvER Without Correction	Gets Without Correction	Gets 2 Step Bias Corrected	Gets Bias %	AvER Est. OV Bias %	AvER Without Correction	Gets Without Correction	Gets 2 Step Bias Corrected	Gets Bias %	AvER Est. OV Bias %
Constant										
ss_autos										
ss_businv										
ss_capacit										
ss_confidn	-0.225	-0.243	-0.242	0.6	-6.9	-0.216	-0.247	-0.246	0.5	-12.1
ss_constrc										
ss_cpi										
ss_cpixfe	-0.182	-0.248	-0.248	0.2	-26.7	-0.180	-0.185	-0.176	5.3	2.0
ss_durgds	-0.189	-0.137	-0.098	40.7	93.1	-0.188	-0.171	-0.157	9.0	19.3
ss_eci										
ss_gdp										
ss_gdppric										
ss_gdsserv										
ss_hrearn	-0.243	-0.139	-0.102	36.7	138.2	-0.237	-0.122	-0.065	88.1	266.2
ss_hsls										
ss_hstarts										
ss_indprod										
ss_lei										
ss_napm	-0.312	-0.363	-0.363	0.0	-14.2	-0.297	-0.329	-0.329	0.0	-9.7
ss_nonfarm	-0.394	-0.317	-0.317	0.0	24.3	-0.402	-0.355	-0.355	0.0	13.4
ss_pce										
ss_persinc										
ss_ppi										
ss_ppixfe						-0.170	-0.231	-0.229	0.6	-25.7
ss_retsls	-0.191	-0.133	-0.081	64.4	136.1	-0.194	-0.117	0.000	Undefined	Undefined
ss_rsxauto										
ss_unemp										

ss = standardized surprise

Bias Correction Based on Code Courtesy of Hendry, Doornik and Castle

P-Value =0.01

OV Bias %=(AER Coefficient -Gets 2 Step Bias Corrected Coefficient)/Gets 2 Step Bias Corrected Coefficient

Gets Bias %=(Unadjusted Gets Coefficient -Gets 2 Step Bias Corrected Coefficient)/Gets 2 Step Bias Corrected Coefficient

Table 2.10 – Analysis of Bias in Common Coefficients - 10-Year Note

	10-Year On-the-Run					10-Year 1st Off-the-Run				
	AvER Without Correction	Gets Without Correction	Gets 2 Step Bias Corrected	Gets Bias %	AvER Est. OV Bias %	AvER Without Correction	Gets Without Correction	Gets 2 Step Bias Corrected	Gets Bias %	AvER Est. OV Bias %
Constant						0.032	0.040	0.040	0.0	-19.1
ss_autos										
ss_businv										
ss_capacit										
ss_confidn	-0.174	-0.167	-0.166	0.3	5.0	-0.169	-0.170	-0.169	0.1	-0.5
ss_constrc										
ss_cpi										
ss_cpixfe	-0.117	-0.143	-0.142	1.1	-17.5	-0.108	-0.122	-0.112	8.4	-4.1
ss_durgds	-0.117	-0.111	-0.102	9.3	14.7	-0.114	-0.100	-0.087	14.4	30.4
ss_eci										
ss_gdp										
ss_gdppric										
ss_gdsserv										
ss_hrearn	-0.162	-0.180	-0.180	0.0	-9.5	-0.153	-0.173	-0.173	0.0	-11.5
ss_hsls										
ss_hstarts										
ss_indprod										
ss_lei										
ss_napm	-0.225	-0.238	-0.238	0.0	-5.4	-0.210	-0.228	-0.228	0.0	-7.8
ss_nonfarm	-0.303	-0.208	-0.208	0.0	46.1	-0.282	-0.174	-0.174	0.0	62.1
ss_pce										
ss_persinc										
ss_ppi										
ss_ppixfe										
ss_retsls	-0.136	-0.083	-0.042	95.2	220.0					
ss_rsxauto										
ss_unemp										

ss = standardized surprise
Bias Correction Based on Code Courtesy of Hendry, Doornik and Castle
P-Value =0.01
OV Bias %=(AER Coefficient -Gets 2 Step Bias Corrected Coefficient)/Gets 2 Step Bias Corrected Coefficient
Gets Bias %=(Unadjusted Gets Coefficient -Gets 2 Step Bias Corrected Coefficient)/Gets 2 Step Bias Corrected Coefficient

F. Encompassing Tests

A cornerstone of the LSE approach to econometric modelling is the idea and encompassing and the advocacy of a progressive research strategy. The concept of encompassing is rather simple, it is basically the notion that a model should be able to explain the results of a competing model. The concept is discussed in great detail in chapter 14 of Hendry (1995).

Therein, Hendry states that when two or more explanations compete in describing a phenomenon, one or more of them must be incorrect. He states that, because models are simply just reduction of the data generating process, they are reduced re-combinations of the data. If a model, $M_{1,}$ purports to explain the data, then it should be able to explain re-combinations of the data that the rival models of other investigators purport to explain. In this section, I treat the AvER model as M_1 and the Gets model as M_2 and perform formal encompassing tests of whether M_1 encompasses M_2 and whether M_2 encompasses M_1. In terms of notation, the varepsilon is used for encompassing – i.e., we test $M_1 \varepsilon M_2$ and $M_2 \varepsilon M_1$, respectively.[44]

While I have already demonstrated that the traditional static AvER model often found in the academic literature on macroeconomic announcement effects is inadequate for reliable estimation and that automated Gets models offer a statistically admissible alternative (especially when applying bias correction), it can also be shown that the Gets models are capable of explaining the results of the typical AvER model. Furthermore, it can be shown that the AvER models fail to encompass the Gets models. This is yet another example of the inadequacy of the AvER models—i.e., that they fail to explain the models of their rivals.

Gets modeling employs extensive use encompassing in the model reduction process, in that case the test is a test against the nesting general unrestricted model. However, encompassing testing of non-nested models is also a valuable tool for the applied econometrician. In the case of the

[44] Hendry (1995) page 502

AvER and Gets models, M_1 and M_2 are mutually non-nested. There are four tests for each model. The first two tests are for variance encompassing – i.e., whether the adjusted likelihoods of the rival models are compatible. The tests are based on Cox (1961) and Ericsson (1983), respective. We find that, only in the case of the on-the-run 30-year bond, $M_2 \varepsilon M_1$. This somewhat favors Gets over AvER, albeit at a loose significance of 5%. Yet there is mutual failure to encompass at 1% significance in the three other models.

Table 2.11

Encompassing Tests

30-Year On-the-Run Bonds

Test	Model 1 vs. Model 2	Model 2 vs. Model 1
Cox	N(0,1) = -266.5 [0.0000]**	N(0,1) = -2.517 [0.0118]*
Ericsson IV	N(0,1) = 218.0 [0.0000]**	N(0,1) = 2.441 [0.0147]*
Sargan	Chi^2(154)= 968.13 [0.0000]**	Chi^2(20) = 25.390 [0.1869]
Joint Model	F(154,2746)= 8.9358 [0.0000]**	F(20,2746)= 1.2720 [0.1864]
sigma[M1] = 0.619625	**sigma[M2]** = 0.520229	**sigma[Joint]** = 0.519718

30-Year 1st Off-the-Run Bonds

Test	Model 1 vs. Model 2	Model 2 vs. Model 1
Cox	N(0,1) = -282.8 [0.0000]**	N(0,1) = -2.924 [0.0035]**
Ericsson IV	N(0,1) = 234.1 [0.0000]**	N(0,1) = 2.828 [0.0047]**
Sargan	Chi^2(166)= 919.00 [0.0000]**	Chi^2(19) = 22.525 [0.2589]
Joint Model	F(166,2734)= 7.6405 [0.0000]**	F(19,2734)= 1.1871 [0.2586]
sigma[M1] = 0.608474	**sigma[M2]** = 0.518281	**sigma[Joint]** = 0.517947

10-Year On-the-Run Notes

Test	Model 1 vs. Model 2	Model 2 vs. Model 1
Cox	N(0,1) = -251.8 [0.0000]**	N(0,1) = -3.024 [0.0025]**
Ericsson IV	N(0,1) = 205.9 [0.0000]**	N(0,1) = 2.927 [0.0034]**
Sargan	Chi^2(161)= 968.03 [0.0000]**	Chi^2(20) = 17.828 [0.5987]
Joint Model	F(161,2739)= 8.5242 [0.0000]**	F(20,2739)= 0.89072 [0.5996]
sigma[M1] = 0.404662	**sigma[M2]** = 0.339722	**sigma[Joint]** = 0.339857

10-Year 1st Off-the-Run Notes

Test	Model 1 vs. Model 2	Model 2 vs. Model 1
Cox	N(0,1) = -241.4 [0.0000]**	N(0,1) = -5.283 [0.0000]**
Ericsson IV	N(0,1) = 195.4 [0.0000]**	N(0,1) = 5.134 [0.0000]**
Sargan	Chi^2(122)= 1001.2 [0.0000]**	Chi^2(21) = 33.428 [0.0417]*
Joint Model	F(122,2777)= 12.008 [0.0000]**	F(21,2777)= 1.5989 [0.0411]*
sigma[M1] = 0.388534	**sigma[M2]** = 0.321914	**sigma[Joint]** = 0.321193

Notes:

1. The Cox non-nested hypotheses test (Cox, 1961)

This tests whether the adjusted likelihoods of two rival models are compatible. It is equivalent to checking variance encompassing.

2. The Ericsson Instrumental Variables test (Ericsson, 1983) - This is an IV equivalent to the Cox test.

3. The Sargan restricted/unrestricted reduced form test (Sargan, 1964)

This checks if the restricted reduced form of a structural model encompasses the unrestricted reduced form including exogenous regressors from rival models.

4. The joint model F-test - checks if each model parsimoniously encompasses the linear nesting model.

Note: Shading indicate tests reflecting models where encompassing in not rejected

* Significant at 5%, ** Significant at 1%

We focus our attention on the bottom two tests in the output, the results more convincingly favor the Gets models. The test of Sargan (1964) checks if the restricted reduced form of a structural model encompasses the unrestricted reduced form including exogenous regressors from rival models. The fourth test is a Joint Model F-test which checks whether each model parsimoniously encompasses the linear nesting model. Both the Sargan Test and the Joint Model F-test suggest that M_2 ε M_1—i.e., the Gets models encompass their AvER model rivals.[45] In three of the four cases, we fail to reject encompassing at both 5% and 1%. In the case of the 10-year off-the-run note, we would reject the null at 5% but fail to reject the null at 1%. With respect to the hypothesis that M_1 ε M_2, we can reject AvER models encompassing the Gets model rivals at 1% in all four cases. There is no evidence that the AvER models of macroeconomic announcement effects are able to explain the results of the Autometrics Gets models with indicator saturation.

G. Conclusion

Herein, I have shown that a congruent, parsimonious, encompassing model discovered using Hendry's LSE/Oxford econometric modelling approach with Autometrics and indicator saturation can overcome the many inadequacies of the typical static models of US Treasury return behavior and macroeconomic announcements that tend to fail virtually every specification test imaginable. Further, such modelling techniques are able to expand our knowledge of time varying risk premia and asymmetric news responses in financial markets that were previously studied within a GARCH framework that offered little or no evidence as to the precise sources of the asymmetries. Despite a wide array of macroeconomic indicators covered by the financial press during the Greenspan Era at the Federal Reserve, only a handful of 7 or 8 key indicators were consistent driving factors in US Treasury market returns. However, other indicators like the Employment Cost Index demonstrated one-sided asymmetric effects which appears to be likely contributor to the asymmetric volatility and time varying risk premia in this market.

[45] Other related studies include: Govaerts, Hendry and Richard (1994), Hendry and Richard (1982), Hendry and Richard (1983), Mizon and Richard (1986), Hendry (1988a), Hendry (1988b), Ericsson, Hendry and Mizon (1998), Ericsson and Hendry (1999), Manera (1995), Florens, Hendry and Richard (1996), Mizon (1995), Bontemps and Mizon (2001), Bontemps and Mizon (2008), Ermini and Hendry (2008), Spanos, Hendry and James Reade (2008), and Ericsson (2008) and Doornik, Hendry and Cook (2015)

Results strongly suggest a place for Gets modelling in financial economics, a place where it has only recently begun to be employed. The use of non-nested encompassing tests further underscore the relative strength of the Gets models vs. the AvER model alternatives that are common in the existing literature. These results underscore the contributions of David F. Hendry and his collaborators in the “LSE approach” to econometric modelling school of thought and demonstrate the need for better models in finance that may be alleviated by employing modelling practices advocated by econometricians doing research in the LSE/Oxford tradition.

CHAPTER III.

A HIGH-FREQUENCY ANALYSIS OF TRADING ACTIVITY IN THE CORPORATE BOND MARKET: MACRO ANNOUNCEMENTS OR SEASONALITY?

A. Abstract

We explore the factors that drive trading activity of US corporate bond market. Prior studies have documented a significant response of returns and interest rates to surprises in macroeconomic data in the stock, US Treasury and Treasury futures markets. Likewise, studies have also documented that trading activity changes sharply, based on informational shocks provided by the release of economic data. We contribute to the existing literature by examining how both daily and intraday measures of trading activity are impacted by surprises in macro data as well as various measures of seasonality. Our main findings are that the thinly-traded market for corporate bonds is less affected by surprises in individual economic reports and that the market is dominated by day-of-week and time-of-day affects. We find that, unlike daily returns on the S&P 500, corporate bonds are sensitive to surprises in both labor market and inflation data. Trading activity is affected by absolute surprises in core CPI and nonfarm payrolls, but neither core PPI nor jobless claims affect order flow. Perhaps most interesting, however, is the presence of "behavioral seasonal" effects associated with the onset and incidence of seasonal affective disorder. This "winter blues" effect has been seen affecting activity in equity markets by Kamstra, M. J., L. A. Kramer and M. D. Levi (American Economic Review; 2000, 2003) and with respect to mutual fund asset flows in Garrett, I., M. J. Kamstra and L. A. Kramer (Journal of Empirical Finance, 2005). This is the first study to document such an effect in the trading activity in the bond market. Finally, the "loans-on-sale" seasonal effect, first documented by Murfin & Peterson (Journal Financial Economics, 2014).

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B. Introduction

In this study, we examine a market that shares attributes of *both* fixed-income *and* equity markets. We address the determinants of daily and intraday trading activity in the US corporate bond market with respect to macroeconomic announcements, seasonality, and aggregate credit ratings activity. Thus far, few academic research studies has addressed factors determining the dynamics of high-frequency trading activity in the US corporate bond market. Our results extend the existing body of knowledge on the mechanics of fixed-income markets. We show that recent advancements in the literature that suggest relatively unexplored forms of seasonality exert significant effects in the corporate debt market and demonstrate the usefulness of econometric techniques typically employed in the macroeconomic literature as being particularly useful in this type of financial markets research setting.

We employ the econometric methodology of Hendry, also known as the "LSE/Oxford approach" or general-to-specific (Gets) methodology. We show that trading activity in this market is affected by macroeconomic announcements, but only to a lesser degree when compared to other factors and only when compared to the effects seen to be exerted in other markets.

Various measurements of trading activity prove to be dominated by seasonality of various forms – both in the typical form as well as with respect to newer behavioral and structural forms suggested in recent literature. We show that the daily and intraday reaction of total trades, institutional trades and dealer-intermediated trades are all dominated by seasonality. These findings have implications for researchers investigating return/order-flow and volatility/order-flow relationships in financial markets.

Perhaps most interesting in the results is the consistency with the "winter blues" human-behavior based seasonal factors of Kamstra, Kramer and Levi (2000), Kamstra, Kramer and Levi (2003), Garrett, Kamstra and Kramer (2005), and Kamstra, Kramer, Levi and Wang (2014) are seen to affect trading activity across each of our trading activity measures. The seasonal factors associated with daylight savings time and the onset and incidence of seasonal affective disorder (SAD) are shown to be prevalent for both investment grade (IG) and high-yield (HY) issues, as well as within the Aaa rated IG subgrouping. Likewise, we also consistently see the recent "Loans-on-Sale" effect documented by Murfin and Petersen (2016) to be statistically significant in the corporate bond marketplace, both in "actively-traded" IG and HY bonds.

Numerous studies have also documented significant effects of macroeconomic data surprises on returns in US Treasury markets and foreign exchange rates, including Fleming and Remolona (1999), Bollerslev, Cai and Song (2000), Balduzzi, Elton and Green (2001), Andersen, Bollerslev, Diebold and Vega (2003), and Brenner, Pasquariello and Subrahmanyam (2009). While equity market returns have also been shown to been shown to be sensitive to these announcements by Jain (1988), Fair (2002).

However, macroeconomic influences are not as prevalent as has been seen in prior literature from the stock, bond, FX and futures markets. The corporate bond market has relatively lower liquidity, slower turnover, and slower information dissemination in the corporate bond market. Therefore, it is not overly surprising to see a muted response to macro announcements in the corporate debt market, compared to that of corporate equity and US Treasury marketplaces. To the best of our knowledge, this is the first study to examine the impact of macroeconomic announcements on corporate bond *trading*. The relative lack of importance in driving trading activity places this study in direct contrast to results seen in other related markets.

We assess the effects of announcements on both returns and trading, using the empirical approach of Hendry (1995) and Hendry and Doornik (2014), This general-to-specific (Gets) modeling approach is often referred to as the LSE approach or Hendry's approach.[46] We reconcile the findings between corporate and government securities and provide an important distinction between the behavior of securities in the corporate market – which can be thought of as a *hybrid market* sharing both equity and bond market attributes.

Additionally, as we wish to draw inferences on the parameters of interest, our empirical investigation is built on a methodology that requires rigorous model testing to assure a specification that is congruent with the local data generating process.[47] While the empirical approach has been regularly used in the area of macroeconomics, it has just recently been employed in a number of financial studies. These include: Bauwens and Sucarrat (2010), Sucarrat and Escribano (2012), Fratzscher, Rime, Sarno and Zinna (2015). To the best of the

[46] The connection to the London School of Economics is based on David Hendry, Denis Sargan and other researchers that were affiliated with the university. Foundations of the modeling technique may be found in Sargan (1961), Sargan (1964), Hendry (1974), Davidson, Hendry, Srba and Yeo (1978), Sargan (1980), Hendry (1980), Engle, Hendry and Richard (1983), Chong and Hendry (1986), Hendry and Ericsson (1991), Mizon (1995), Florens, Hendry and Richard (1996), Ericsson, Hendry and Mizon (1998), Sargan (2001a), Sargan (2001b), Hendry (2003), Sargan (2003)

[47] A congruent empirical model is one that is consistent with the local data generating process. Formal mis-specification testing can be employed to evaluate model congruence. General-to-specific modeling requires a model be free of heteroscedasticity, non-normality, serial correlation, parameter instability, non-linearity and possibly other forms of mis-specification. See Bontemps and Mizon (2001) for a formal explanation.

authors' knowledge, this study represents the first application of Gets modeling to corporate bond markets, trading activity, and macroeconomic indicators.

We proceed with some insight on the market structure of the corporate bond, providing the reader with an enhanced understanding of the setting in which corporate bond trading takes place, and by surveying recent research on corporate bond trading.

C. Corporate Bond Market Structure and Literature Review

To understand trading in the corporate bond market, one should begin with market structure. This is because the buy-and-hold nature of the market and the institutional trading arrangements that facilitate trading in the market distinguish it from other types of financial markets. Unlike the organized equity markets, such as New York Stock Exchange (NYSE), the vast majority of corporate bond trades occur based on verbal quotations between traders and dealers in an "over-the-counter" (OTC) market. Historically, this market has been opaque as no mandatory reporting of transactions was required. In this particular market, improved data availability is intimately intertwined with the evolution of empirical research.

In an opaque dealer market, traders actively seek quotes from various dealers to discover the best price available. Market participants may be able to purchase the same bond for appreciably different prices from different dealers. Investors were essentially blind in this market as they could only receive quotes through direct contact with dealers. The environment, where information dissemination was historically a word-of-mouth process, is adeptly described by Saunders, Srinivasanb and Walter (2002).[48]

Although the New York Stock Exchange does list corporate bonds, the vast majority of the market was still "behind the curtain" of the dealer market.[49] Researchers were usually left to analyze a much-smaller subset of bond data. These included: credit spread aggregates, NYSE-traded bonds, and several other sources.[50] However, the market has slowly evolved and become more transparent to investors and researchers.

As dealer market data slowly became more accessible to researchers, new paths of discovery were paved. For example, the Capital Access International (CAI) bond database is a significant catalyst for the following two studies.

From a market-microstructure perspective, Hong and Warga (2000) undertake a comparative empirical analysis of liquidity in the OTC dealer-market vs. NYSE-traded corporate bonds. They find that effective bid-ask spreads are similar in their sample. They also find that the magnitude of price differences appear to be associated with risk and liquidity proxies.

48 For example, see pgs. 96-97 for greater detail.
49 This characterization comes from the title of the article by Schultz (2001), discussed later.
50 For example, corporate bond market indices from credit ratings firms Moody's and Standard & Poor's

In a related study, Schultz (2001) examines trading costs in the OTC market and finds that trading costs are lower for large trades. Smaller institutions pay higher trading costs relative to large institutions. Further, smaller bond dealers charge more than large dealers. Across bond ratings, however, trading costs do not appear to vary.

Elton, Gruber, Agrawal and Mann (2001) find that expected default accounts for a "surprisingly low" percentage of credit spread, while state taxes play a significant role. Risk factors commonly associated with equity risk premia are also found to affect credit spreads. We take this factor into account in our analyses.

Using the FIPS data set, Hotchkiss and Ronen (2002) pave the way for future high-frequency research on corporate bond market trading activity. In a sample of 50 actively-traded bonds, they find that stocks do *not* lead bonds in reflecting firm-specific information. They also find that earnings news is rapidly incorporated into bond prices, as is the case in equity markets. Importantly, the article highlights the connection between corporate bonds and stocks and provides an early examination of intraday corporate bond activity on an hourly basis. Like this study, we will also examine intraday activity.[51]

Campbell and Taksler (2003) also build on the prior literature examining the connection between equity market volatility and corporate bond yields. Using panel data from the late 1990s, they

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[51] Hotchkiss and Ronen (2002) use hourly data, while we aggregate to a half-hourly frequency.

show that idiosyncratic firm-level volatility explains as much cross-sectional variation in yields as do credit ratings.

Criticism of the OTC market's opacity eventually took root and in 2002 regulations took effect aimed at increasing bond market transparency. The regulatory response was a new trade reporting system, the "Trade Reporting and Compliance Engine" (TRACE), launched in July 2002 by the Financial Industry Regulatory Authority (FINRA).[52]

TRACE was designed to improve the flow of information between market participants, create a transaction database that allows regulators to supervise the market, and improve investor confidence in the market. TRACE has evolved continuously since its introduction. Initially, only 500 investment-grade bonds and 50 high-yield issues reported trades on the system. But by 2005, information on approximately 99% of all public bond transactions were disseminated via TRACE.[53] As the data history has grown, so has the associated research stream.

Perhaps the most obvious target for research, given the availability of the new data, was in investigating the effect of transparency on the market. After all, TRACE data are merely a byproduct of a system designed to improve information flow between agents participating in the

52 FINRA was previously known as the National Association of Securities Dealers or NASD TRACE database.

53 Source: TRACE Fact Book 2007 – The current version is available at the following url: http://www.finra.org/Industry/ContentLicensing/TRACE/P085342

corporate bond market. Given the newly available data, that initial studies focus on transparency was not surprising.

Two other path-breaking studies examine this effect of increased transparency in trading costs and pricing. Bessembinder, Maxwell and Venkataraman (2006) study show a 50% reduction in trade execution cost on TRACE-eligible insurance bonds. They also find evidence of a "liquidity externality" in the reduction of trade execution cost by 20% versus bonds ineligible for reporting to TRACE. Likewise, Edwards, Harris and Piowar (2007) also find lower costs for bonds which publicly disseminated trade information via TRACE, and that overall trading costs also dropped when TRACE reporting began.

Additionally, Goldstein, Hotchkiss and Sirri (2007) examine the effect of transparency on both volume and liquidity. They found that the effect of greater transparency on market liquidity may be either neutral or positive. With respect to trading activity, transactions per day did not increase during their sample period. In all but one category, spreads declined on newly-transparent bonds by a greater amount than declines for non-disseminated control bonds. However, it is notable that transparency had no effect on bonds which trade very infrequently.[54]

[54] Unlike this study, we do not look at infrequently traded bonds and focus strictly on the actively traded bonds reporting to TRACE. However, we encourage future work to see if the effects found in this study do, in fact, carry over to bonds that are not actively exchanged in the marketplace.

In a related study, Hotchkiss and Jostova (2007) examine the determinants of corporate bond trading volume and liquidity based on a large transaction database from the National Association of Insurance Commissioners. They find that the most important determinants of trading volume are the bond's issue size and age. Also, they find that companies with actively-traded stocks tend to have more actively-traded bonds.[55] The authors focus on the relationship between bond characteristics and trading volume, as opposed to time-varying order flow and informational effects that we study herein in a time series context.

Pasquariello and Vega (2007) demonstrate the importance of order flow in fixed income markets, within the contest of US Treasury securities. But the role of macroeconomic announcements in determining order flow of corporate bond markets remain a stone that is largely left unturned. One need look no further than Savor and Wilson (2013), who study effects of macroeconomic announcements on equity and Treasury securities, to find an impetus for examining the effects on corporate bonds. Given that corporate bonds share characteristics of both markets, it would not be surprising to find that announcements, shown to be important for both stocks and Treasuries, would also be important for participants in the corporate debt market.

We build on both the early literature on macroeconomic announcement effects and the more-recent TRACE literature by investigating the impacts of macroeconomic announcements, information surprises, end-of-year, holiday and other seasonal effects. In the next section we will elaborate with a description of the data used in this study, followed by a preliminary analysis

[55] The data covered the period of January 1995 to December 1999, which preceded the TRACE platform.

with some descriptive statistics. Afterward, we describe the empirical modeling approach and the model structure.

D. Description of Data

1. Dependent Variables: Corporate Bond Performance Data & Trading Activity

Bond market performance data includes daily simple returns on the Bank of America/Merrill Lynch Investment-Grade and High-Yield Corporate Bond Market Indexes. These data are downloaded from the St. Louis Federal Reserve's Fred database.[56] For comparison to corporate equity securities, we use returns and volume data from the Standard & Poor's 500 Index.[57] The return data are used as dependent variables in preliminary regressions to provide for comparison to previous studies and to add context to the trading activity regressions that follow. These regressions provide for a basis of comparison to prior literature on market efficiency and macroeconomic announcement effects that have been performed in stock, bond, futures and foreign exchange markets. They will also allow us to contrast results from trading activity regressions and enable us to characterize more effectively the return/order-flow relationship in the vast and relatively-unexplored corporate debt market.

Trading activity data were extracted from the FINRA TRACE database.[58] The TRACE database contains transaction data details over a vast set of corporate debt issues. We focus only on bonds identified as being "frequently traded" based on their inclusion in the FINRA-Bloomberg

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[56] Specifically, for corporate bond market returns, we use Bank of America Merrill Lynch US Corp Master Total Return Index and US High Yield Master II Total Return Index to compute simple returns for investment-grade and high-yield. These are downloadable from the Federal Reserve Bank of St. Louis FRED Database series: bamlcc0a0cmtriv and bamlhyh0a0hym2triv, respectively.

[57] This data can be downloaded at no cost from Yahoo! Finance

[58] http://www.finra.org/industry/trace

corporate bond indexes. We use this set of (relatively) active corporate bonds as a representation of the 'top bonds' that, according to Ronen and Zhou (2013), help facilitate the price discovery process.[59]

We believe this dichotomy is a useful characterization of a market that has long been segmented into a small group of actively-traded bonds and a larger set of bonds that are largely bought and held to maturity. To be sure, Biais and Green (2007) trace back to the early 1900s the existence of an "active crowd" of exchange traded corporate bonds and a "cabinet crowd" of inactive bonds on the NYSE.[60]

Approximately 750 investment-grade bonds and 300 high-yield bonds were in the Investment-Grade and High-Yield indices, respectively. We extracted 441 investment-grade bonds and 38 high-yield bonds from the indices.[61] Bonds were excluded based on the following criteria; Bonds that matured during our sample period were dropped so that trading activity data would not be biased by securities that matured during our sample period.[62] Likewise, we excluded bonds that

[59] Ronen and Zhou (2013) define a top bond as an issue that attracts most of the institutional trades following the release of firm-specific information and facilitates the price discovery process.

[60] See also, Meeker (1922) and Shultz (1946).

[61] FINRA incrementally increased in the number of bonds reporting to the system during our sample period. Therefore, we chose a subset of securities from this universe as described in the following paragraphs.
On October 1, 2004, TRACE phase IIIa implementation started requiring reporting of all bonds not qualified for delayed dissemination. Due to the limited number of speculative-grade bonds reporting prior to this date, we use this as the beginning of the sample period. For investment-grade bond, however, there were a sufficient number of bonds reporting. Therefore, we use June 1, 2004 as the beginning date for the investment-grade sample.

[62] This also enables us to test the hypothesis that bonds trade less actively as they age – a phenomena often referred to as the "seasoning" effect. We discuss this more completely, later in the study.

changed in terms of credit quality between investment-grade and speculative-grade categories in order to hold this factor constant.[63]

2. Independent Variables: Economic Survey, Ratings & Seasonal Data

Macroeconomic survey data were acquired from Action Economics, a San Francisco firm specializing in capital market analysis and economic forecasting. Action Economics (hereafter AE) surveys market participants weekly on expectations for the following week's economic data releases. We choose to examine labor market data in the form of weekly initial jobless claims and monthly nonfarm payrolls and inflation in the form of Consumer Price Index (CPI) and the Producer Price Index (PPI) core rates.[64]

Importantly, AE survey data represents consensus expectations for these economic variables at the time of the announcement and retains the actual "as-reported" results for the announcement date. This is consistent with prior academic studies of macroeconomic announcements, which have typically used the now-defunct S&P Money Market Services (MMS) data. This real-time capture of changes in expectation is critical in evaluating the information set available to the

[63] Another aspect of particular interest is whether trading activity differs across industry categorization. Therefore, we also partition sub-samples of bonds in the financial and industrial sectors for both the investment-grade and speculative-grade credit ratings.

[64] "Core rates" exclude food and energy prices which tend to be volatile and have the propensity to deviate from the underlying level of price pressures in the broader consumer and producer markets. Economists and market participants tend to focus on the core rates as they tend to provide a better representation of the underlying inflation pressures. This preference is documented by Forest (2018) and seen in Forest (2017a).

market as frequent revisions to economic data would otherwise render use of revised historical data ineffective.[65]

As seen in prior studies, we follow the convention of standardizing the surprise component (reported value minus expected value) by dividing by the sample standard deviation of the surprise. Thus, the regression coefficients on an economic variable can be interpreted as expected change in the dependent variable associated with a one standard deviation surprise in that particular macroeconomic factor.

In order to avoid omitted variables bias, we include dependent variables that are likely to be of importance to market participants. For example, we control for changes in credit ratings by aggregating historical US corporate bond ratings changes. The Senior Ratings Table (SRT) data of Moody's Default Risk Service were acquired for this purpose. The Moody's Senior Ratings Algorithm (SRA) is used to generate the SRT.[66] The data are split into two series, one that aggregates the number of "notches up" of and another of "notches down" for Moody's rated debt issues. A notch represents a level change – e.g., from A1 up to Aa3 or A3 down to Baa1—in the

[65] The data were acquired directly from the company. The Action Economics website is: http://www.actioneconomics.com/.

[66] The SRT's data are recorded as estimated equivalent unsecured senior debt ratings and associated historical up/down rating notch changes. While Moody's discloses that the SRT consists of SRA-based estimates and may not precisely reflect the published Moody's ratings (which are based on further analysis by Moody's), the SRT is still useful in our regression as a proxy for changes in credit quality.

bond rating hierarchy.[67] Again, to facilitate meaningful interpretations of estimated coefficients, we standardize this series by dividing by the sample standard deviation.[68]

E. Preliminary Analysis

Table 3.1 contains descriptive statistics for data within our sample separated into sub-samples and based on credit quality.[69] We find that the investment-grade financial bonds tend to trade more frequently than non-financial bonds – about 9 times per day per bond versus 7.35 times per day per bond, respectively. In the smaller high-yield sample, however, bonds traded 4.72 times per day, compared to 8.01 times for non-financials. Our data sample spans the period from June 1, 2004 to July 31, 2006.[70]

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[67] Details are provided by Moody's in the February 2009 Moody's Global Credit Policy Special Comment, entitled "Moody's Senior Ratings Algorithm & Estimated Senior Ratings." The report is available for download at the following link: https://www.moodys.com/sites/products/DefaultResearch/2007300000572017.pdf. Details of "notching" procedures are depicted on page 4 (see Table 1.).

[68] It should also be noted that the notches down series retains its negativity for non-zero record – i.e., it is not in absolute value form.

[69] We break the data down further, into financial, non-financial subsets. Also, we filter our trade sample based on recent research in Zitzewitz (2011) which shows a relatively active inter-dealer market that supports dealer-client transactions. The study shows that nearly 40 percent of dealer-client trades are accompanied by an inter-dealer trade for the exact amount and often at nearly the exact same second. The filtered trades will serve as a benchmark for the degree of dealer intermediated trades, which we will investigate further in the regression analyses.

[70] The HY sample begins on October 1, 2004. The reason for the shorter sample is because we needed to hold the number of bonds constant during the full sample, so as not to distort volume and trade data being reduced due to bonds maturing.

Table 3.1 – Independent Variables for Regression Analysis

Factor	Lag Structure	Description	Selected Citations
Macro Announcement Surprises	Contemporaneous, Lag	Standardized Surprises and Absolute Standardized Surprises for Nonfarm Payrolls, Initial Jobless Claims, Core-CPI, Core-PPI	Hardouvelis (1988), Jain (1988), Engle and Ng (1993), McQueen and Roley (1993), Almeida, Goodhart and Payne (1998), Jones, Lamont and Lumsdaine (1998), Bollerslev, Cai and Song (2000), Balduzzi, Elton and Green (2001), Green (2004), Green (2004), Chatrath, Miao, Ramchander and Villupuram (2012), Beber, Brandt and Luisi (2015),
Macroeconomic Announcement Day	Contemporaneous, Lead, Lag	Dummy Variables for Surprises for Nonfarm Payrolls, Initial Jobless Claims, Core-CPI, Core-PPI	Bollerslev, Cai and Song (2000), Andersen, Bollerslev, Diebold and Vega (2003),
Credit Quality	Contemporaneous	Moody's Ratings (Aggregate Net Notches Up/Down)	Ismailescu and Kazemi (2010),
Financial Market Returns	Contemporaneous, Lag	S&P 500 Returns	Hakkio and Pearce (1985), Hakkio and Pearce (1985), McQueen and Roley (1993), Brenner, Pasquariello and Subrahmanyam (2009),
Seasonal – Month of Year	Contemporaneous	December, January	Branch (1977), Schneeweis and Woolridge (1979), Thaler (1987), Chang and Huang (1990), Maxwell (1998),Chordia, Roll and Subrahmanyam (2001) , Hansen and Lunde (2003).
Seasonal – Behavioral/Mood	Contemporaneous	Incidence and Onset of Seasonal Affective Disorder	Branch (1976), Kamstra, Kramer and Levi (2000), Kamstra, Kramer and Levi (2003), Garrett, Kamstra and Kramer (2005), Kamstra, Kramer, Levi and Wermers (2012), Kamstra, Kramer, Levi and Wang (2014),
Seasonal – Trend	Contemporaneous	Linear Time Trend	Lindvall (1977), Boardman and McEnally (1981), Sorensen (1982), Hong and Warga (2000), Cai, Helwege and Warga (2007),
Seasonal – Pricing	Contemporaneous	Dummy Variable for Expensive and Cheap Loan Periods	Murfin and Petersen (2016)
Seasonal – Holiday	Contemporaneous, Lead, Lag	Anticipatory Behavior	Fields (1934), Ariel (1990), Cadsby and Ratner (1992), Kim and Park (1994), Meneu and Pardo (2004),
Leads/Lags of Variables	Lead, Lag	"Set-Up Effects", Delayed Effects	MacKinlay (1997), Tchuindjo (2015), van Dijk, Lumsdaine and van der Wel (2016)

Regardless of credit quality or industry sector, trading activity per bond issue appears very low relative to equity markets. These bonds are, however, actively-traded relative to the larger universe of US corporate bonds. Clearly, the characterization of the FINRA-Bloomberg High-

Yield Index as an index of "actively-traded" issues is relative to corporate bonds and not to markets such as the U.S. equity or Treasury markets.

For purpose of comparison, an actively-traded equity security such as IBM regularly trades at about 7 million times in a day, or a market volume of about $800 million dollars. By comparison, IBM had 21 corporate bonds issues listed on FINRA. Those IBM bonds with a 7 percent coupon and maturing in December of 2045, for example, had a mere 25 transaction records during the prior month. The number of bonds traded in any single transaction ranged from a low of 5,000 bonds to a high of 50,000.[71]

According to the Securities Industry and Financial Markets Association (SIFMA), average daily trading volume in the corporate bond market was $14.3 billion per day during 2008, compared to $551.3 billion in the US Treasury market and more than $1 trillion per day in US fixed-income markets as a whole.

[71] Data are based on price and volume data reported on the FINRA website in December 4, 2009 for both equity and fixed-income securities

Table 3.2

Trading Activity Descriptive Statistics

Investment-Grade Bond Sample	Unfiltered Sample			Filtered Sample		
	Financial	Non-Financial	Full Sample	Financial	Non-Financial	Full Sample
Number of Bonds	262	179	441	262	179	441
Days Traded	546	546	546	506	506	506
Total Trades	1,295,589	718,062	2,013,651	984,362	555,245	1,539,606
Mean Trades Per Day	2,373	1,315	3,688	1,945	1,097	3,043
Std. Dev. Trades Per Day	440	252	669	282	158	419
Mean Par Vol. Per Day $ Mil	805	476	1,280	754	106	395
Std. Dev. Par Vol. Per Day $ Mil	263	170	407	220	142	335
Mean Par Vol. Per Trade $	0.34	0.36	0.35	0.39	0.10	0.13
Mean Trades Per Day Per Bond	9.06	7.35	8.36	7.40	6.10	6.90
Coeff. Of Var. Trades Per Day	0.19	0.19	0.18	0.14	0.14	0.14

High-Yield Bond Sample	Unfiltered Sample			Filtered Sample		
	Financial	Non-Financial	Full Sample	Financial	Non-Financial	Full Sample
Number of Bonds	6	32	38	6	32	38
Days Traded	461	461	461	422	422	422
Total Trades	13,048	118,110	131,158	9,406	90,941	100,858
Mean Trades Per Day	28	256	285	22	216	239
Std. Dev. Trades Per Day	15	81	83	11	63	64
Mean Par Vol. Per Day $	691,345	86,674,654	87,365,999	571,481	79,757,235	80,328,716
Std. Dev. Par Vol. Per Day $	551,213	42,411,057	42,464,888	447,379	33,472,549	33,490,159
Mean Par Vol. Per Trade $	24,426	338,303	307,078	25,638	370,103	336,103
Mean Trades Per Day Per Bond	4.72	8.01	7.49	3.70	7.00	6.50
Coeff. Of Var. Trades Per Day	0.53	0.32	0.29	0.51	0.29	0.27

Note: Investment-Grade volume data is in $ milion, while the smaller High-Yield bonds are straight $ value

F. Empirical Methodology

In this section we estimate the effect of macroeconomic announcements on returns corporate bond market (IG and HY) as well as for the S&P 500 within a distributed lag framework. The distributed lag modeling approach has been common in economics since first introduced by Fisher (1925) in the context of business cycles. They have been applied in virtually all areas of economics, including: agricultural, monetary, and financial economics. The models are particularly useful in analyzing dynamics of economic processes of when institutional or technological rigidities are present.[72] Financial markets tend to be considered to be highly efficient – i.e., that prices reflect all past information – and suggest that no significant lags in performance regressions on financial instruments should be present.

[72] Forest and Turner (2013) study the application of distributed lag models with respect to estimation of cointegrating vectors and demonstrate the superiority of this estimator compared to DOLS.

Note that we would expect residuals from estimated models to be normally, independently and identically distributed. However, regressions of financial market activity often fail to meet this critical standard. In particular, financial market data tend to be plagued with sources of potential econometric misspecifications, such as: outliers, location shifts, measurement error, parameter non-constancy, and fat-tailed distributions.

In order to deal with these issues appropriately, we turn to an econometric approach that is designed to provide robust estimates under such adverse situations. We employ the general-to-specific (Gets) modeling approach, also known as the "LSE/Oxford Approach" of Professor David F. Hendry, which commences from a broad unrestricted model and then employs an automated "testing down" procedure which seeks to reduce the model to a statistically valid representation of the data generating process (DGP) based on the characteristics of the local data generating process.[73]

Foundations of the approach can be found in Hendry (1993) and Hendry (1995), while extensions and improvements are laid out in Hendry and Doornik (2014).[74] Particularly

[73] An extensive review of the Gets modeling literature is provided by Campos and Ericsson (1999).
[74] Automated model selection procedures have also been examined by Phillips (2005)

importance are recent innovations to the methodology, such as impulse indicator saturation (IIS), and step indicator saturation (SIS).[75]

Although these techniques tend to be employed in macroeconomics, Sucarrat and Escribano (2012), offer an application within financial econometrics. We believe the application of these methods in the area of financial econometrics represents a key novelty or innovation in this area of research.[76]

The methodology is carried out using the commercial Oxmetrics software, which is designed by Jurgen Doornik and David F. Hendry of Oxford University.[77] The "Autometrics" procedure is employed to carry out the automated model reduction process.[78] We allow for outlier and structural break detection employing both IIS and SIS to achieve model congruence – i.e., meeting Gauss-Markov criterion. Optimal reductions are sought by reducing the general unrestricted model based on the default tests: normality, heteroscedasticity, Chow test, error autocorrelation test, and ARCH test.[79] Target size is also set at the default p-value of 0.01. The properties of the defaults are studied extensively in Doornik (2009), based on extensive Monte-Carlo simulations.

75 IIS has been explored in Johansen and Nielsen (2009), and Santos, Hendry and Johansen (2008) while the more-recent extension of SIS is detailed by Doornik, Hendry and Pretis (2013) and Castle, Doornik, Hendry and Pretis (2015).

76 Extensions can be found in Campos and Ericsson (1999; Campos, Hendry and Krolzig (2003)

77 Limited academic versions of the software are available at http://www.doornik.com/products.html

78 The programs used to run the regressions are available from the authors upon request.

79 Normality test is that of Doornik and Hansen (2008)

G. Daily Regression Results

1. Performance Analysis

We proceed by estimating equation 3.1, in the form of a standard autoregressive distributed lag model, ADL(L, J, X) with a constant, L^{th}-order autoregressive terms, J distributed lags for exogenous factors X. We also add the parameter $\delta_{k,j}$ and exogenous variable D to denote day-of-week effects.[80]

AUTOREGRESSIVE DISTRIBUTED LAG MODELS (ARDLX)

Equation 3.1: The General Unrestricted Model [GUM0] in ARDLX Form with AR=1

$$\Delta y_t = \mu + \pi_t + \alpha y_{t-1} + \beta_j X_{i,t-l} + \varepsilon_t$$

$$\beta_j X_{i,t-1} I^D_{j,t+1} = \sum_{j=1}^{4} \lambda_j I^D_{j,t+1} + \sum_{j=1}^{4} \sum_{g=0}^{1} \beta x_{i,t-g} + \sum_{m} \phi_m F^M + \sum_{n} \theta_n F^S + \sum_{p} \theta_p F^B + \epsilon_t$$

where $\sum_{j=1}^{4} \sum_{g=0}^{1} \beta x_{i,t-g}$ can be factored into contemporaneous (time = 0) and lagged (time = 1) components.

$$x_{i,t-g} = \left(\sum_{j=1}^{4} \beta_{j,0} SSA_{j,t_0} + \sum_{j=1}^{4} \beta_{j,0} SS_{j,t_0} \right) + \left(\sum_{j=1}^{4} \beta_{j,1} SSA_{j,t-1} + \sum_{j=1}^{4} \beta_{j,0} SS_{j,t-1} \right)$$

80 Specifically, we include contemporaneous dummy variables for weekdays other than Thursday. The choice of eliminating Thursday is based on the existence of a weekly macroeconomic announcement, initial jobless claims, on that day.

Likewise, $\sum_m \phi_m F^M$, $\sum_n \theta_n F^S$ +and $\sum_p \theta_p F^B$ may also be decomposed into their constituent components. Other exogenous variables, include ratings change data, equity market data, and other bond market factors. Behavioral variables, $\sum_p \theta_p F^B$, and $\sum_n \theta_n F^S$ seasonal variables, are also included to capture the underlying data generating process and for additional hypothesis testing.

VARIABLES

Δy_t = first difference of return/interest rate variable Y_t

$x_{i,t}$ = the i'th macroeconomic surprise or other exogenous variable x at time t

$SSA_{j,g}$ = absolute standardized surprise in macro announcement j at lag g

$SS_{j,g}$ = standardized surprise in macro announcement j at lag g

$F_{i,t}^S$ = seasonal factor i at time t

$I_{j,t}^D$ = the dummy variable for a one-period-ahead lead for economic indicator j

i.e., announcement tomorrow for economic indicator j, or "set-up effect"

ε_t = error term~NIID(0,1)

and where,

i = number of seasonal factors

j = the number of macro announcement variables

g = lag length (lag truncation)

PARAMETERS

μ = a constant (mean change in dependent variable (intercept)),

π = a time coefficient,

α = first-order autoregressive term

λ_j = coefficient one-step-ahead macro announcement dummy variable $I_{j,t+1}^D$

θ_n = coefficient on n^{th} seasonal factor dummy variables i ,

β_j = coefficient on surprise in macro announcement j at time g , Results from the estimation of equation 3.1 are provided in table 3.3, where we provide parameter estimates and regression diagnostics for three dependent variables: S&P 500, and the Bank of America/Merrill Lynch Investment Grade and High Yield bond indexes, respectively. All variables were included prior to model reduction, with surviving variables listed with parameter estimates.

We note that the AR(1) terms are reduced out of all three models – i.e., the returns for all three classes of securities exhibit temporal independence. This is a common test of the weak form of market efficiency and provides evidence of the efficiency of these three markets. Further, the lagged terms on macroeconomic surprises, macroeconomic dummy variables, and absolute macroeconomic surprises are *all* eliminated in the model reductions in each of these markets. For the S&P 500, we see that even the contemporaneous announcements are reduced, indicating that any significant effect dies out and is not observable at a daily data frequency. This firmly underscores the finding of semi-strong form market efficiency in the market for blue chip US equities at the index level. But we should be careful not to discount the apparent efficiency of the corporate bond market. There do appear to be announcement effects on bond returns that appear to be present in the daily data, but the effects do not appear to persist beyond one day.

Past research has also confirmed the existence of macroeconomic surprise effects in fixed income markets – which affect risk premia such as the inflation risk premium in the Treasury market. Yet, corporate bonds are also subject to default and liquidity risks, which may complicate things as far as impact of announcements of labor market data such as nonfarm payrolls and initial claims. A higher-than-expected (lower-than-expected) result for payrolls or claims might increase (decrease) the inflation risk premium, while at the same time decrease (increase) the default risk premium. Which effect prevails might change over time, depending on whether market participants weigh inflation risk more than default risk.

Because of this, we need to consider carefully the state of the economy during the period under investigation. During the period of our sample, real GDP grew at over a 3% year-over-year rate each quarter with a maximum growth rate at just under 4.5%. Core-CPI growth increased from a year-over-year rate of 1.7% to just under 2.7%. Thus, one might describe it as a "Goldilocks" period where inflation and GDP growth appeared neither too hot nor too cold.[81] Therefore, we do not believe market participants weighed one risk much more than the other.

Indeed, regression results show that both inflation and labor market activity had an effect in the IG and HY sectors. Surprises in nonfarm payrolls and consumer prices had significant effects in the HY sector, while initial jobless claims and producer prices were significant in the IG sector.

[81] This is not to say there were no economic concerns during the period, as clearly some were alarmed by the degree of leverage in the financial sector. Yet, these pre-Great-Recession conditions were not fully appreciated in the market.

Positive surprises in core-PPI resulted in decreased IG returns – which appears to have more to do with revenue concerns and was likely felt most in the manufacturing and machinery issuers. The coefficient on jobless claims in the IG regression is positive, suggesting returns increased (decreased) when claims were higher (lower) than expected. This may be a result of projected labor costs as opposed to forecasts of economic growth. While the coefficients may not have the same sign as we would expect for Treasury securities, it makes clear that interpreting coefficients of macro surprises in corporate bond return regressions is less clear-cut than in the Treasury market.

However, the fact that announcement day and pre-announcement day dummy variables are dropped from the regressions in the model reduction suggests no "set-up" effects, as seen in the Treasury market by van Dijk, Lumsdaine and van der Wel (2016) in advance of FOMC meetings, nor did the mere existence of an announcement yielding a significant result.[82] Rather, it is the *information content* of the announcement and how that information deviates from expectations that is of interest to market participants, as shown in the majority of studies of macro announcement effects. IG bonds also show a sensitivity to changes in credit quality as the coefficient on the Moody's ratings changes is both positive and significant. This is consistent with a prior that upgrades exceeding downgrades on a given day is a positive for returns in the IG sector.

[82] It should be noted that Heuson and Su (2003), also using the MMS database to explore US Treasury option implied volatility behavior, observe an increase in implied volatility on the afternoon of the day prior to announcements which is followed by a normalization on post–announcement volatilities return as rapidly as cash prices do and that traders are unable to earn arbitrage profits when accounting for transaction costs.

In the HY bond sample, core-CPI has a negative coefficient indicating positive surprises in consumer price inflation decreased returns of HY bonds. This could be a function of either the inflation risk premium or a lack of pricing power that would allow companies to increase profits by raising product prices. Nonfarm payrolls, known to be a focal point for bond market participants, also has a negative coefficient. This is typically what we see in the Treasury market, where we usually see lower-than-expected payroll growth as an indication that inflation pressures remain under control and the likelihood of FOMC rate hikes is reduced. Also interesting is the significant coefficients on S&P volume and one-period lagged S&P return.

The return effect is consistent with the notion that stock returns lead corporate bond returns and may be a function of the increased search time associated with finding counterparties and negotiation trades in the corporate bond market. The results indicate, as expected, the existence of a cross market effect between the corporate debt and corporate equity markets.

Table 3.3 – Performance Regressions

Independent Variable	S&P 500 Coefficient	Inv. Grade Bonds Coefficient	High-Yield Bonds Coefficient
Constant	-0.19		0.16 **+
SP_VOLUME			-0.04 **
SP_RETURN(-1)			0.03 **+
CPI_SS			-0.05 **
NONFARMS_SS			-0.11 **+
CLAIMS_SS		0.06 **+	
PPI_SS		-0.13 **	
MOODY'S		0.02 **+	
AR 1-2 test:	2.91 [0.0556]	3.04 [0.0489]*	4.55 [0.0110]*
ARCH 1-1 test:	0.32 [0.5707]	0.00 [0.9967]	0.00 [0.9556]
Normality test:	1.26 [0.5327]	2.16 [0.3391]	7.13 [0.0282]*
RESET23 test:	0.00 [1.0000]	0.25 [0.7752]	1.10 [0.3353]
Log-likelihood	-487.69	98.34	674.80
Parameters	21	32	70
Observations	541	540	540

**** Significant at 1%**

****+ Significant at 1% and unanimous selection in terminal models**

Seasonality also comes into play when evaluating market efficiency. Given the assumption of market efficiency, our prior expectations for equities are that both seasonal factors will also be eliminated during the model reduction process. These priors are clearly met, as all seasonal factors are eliminated during the reduction process. This result appears to carry over to both the IG and HY markets and is a sign that these markets, despite the increased time to execute trades, are still weak-form efficient and that prior price information and seasonality cannot be used to predict returns.

But while market efficiency produces strong priors with respect to the performance regressions, it offers little guidance with respect to trading activity and order flow. In the following section we extend our analysis to offer insights that illuminate the relationships between returns and order flow and draw distinctions between these issues, respectively.

2. Analysis of Trading Activity – A. Total Trades & Large-Volume Trades

In this section we present the regression results for trading activity and can compare and contrast those results to those presented in the performance regressions table. Dependent variables are total trades and institutional trades for the IG and HY ratings classes. We note that TRACE caps volume data for trades at $5 million for investment-grade and $1 million high-yield par volume.

Ronen and Zhou (2013) interpret these large-volume transactions as institutional trades. While no database field indicates whether large trades are actually institutional or retail, such an interpretation is very logical. Therefore, in the absence of such an identifier, we also tend to consider these trades to be generated from institutional market participants. Herein, these large-volume trades will be abbreviated as "LVTs."

Table 3.4—Trading Activity Regressions – Total Trades & Large-Volume Trades

Independent Variable	IF_TOT_TRDS Coefficient	IF_LVTTOT_TRDS Coefficient	HF_TOT_TRDS Coefficient	HF_LVTTOT_TRDS Coefficient
Trend	-2.30 **		0.19 **+	
S_US_NOTCHESNETCHG_1		1.78 **		
SP_VOLUME		9.14 **+	32.77 **+	
STRUC_MP_CHEAP	4348.37 **	33.97 **+		30.87 **
ABS_NONFARMS_SS_1	-162.05 **+			
ABS_CPI_SS				8.96 **+
MONDAY	-224.11 **+	-23.05 **+		-8.61 **+
TUESDAY	95.11 **+		30.89 **+	
WEDNESDAY			19.83 **	
FRIDAY	-443.70 **+	-19.60 **+	-38.87 **+	-10.60 **+
MONTH_JAN				25.42 **
MONTH_DEC	-163.40 **+	-15.27 **+	-34.44 **+	-13.61 **
HOLIDAY_NYSE	-2369.94 **+	-28.90 **+	-169.80 **+	-29.29 **+
HOLIDAY_NYSE_+1	-413.48 **+			
EARLY_CLOSE_NYSE	-1885.02 **+	-31.59 **+	-97.11 **+	-32.42 **
SAD INCIDENCE			67.09 **+	
SAD ONSET	-663.62 **+			
AR	1.11 [0.3302]	2.28 [0.1036]	0.49 [0.6118]	1.43 [0.2412]
ARCH	0.02 [0.8759]	1.62 [0.2040]	2.17 [0.1416]	0.90 [0.3420]
Normality	2.04 [0.3609]	4.85 [0.0885]	5.85 [0.0537]	7.34 [0.0255]*
Hetero	0.99 [0.5037]	0.92 [0.5978]	0.85 [0.7226]	1.43 [0.0646]
RESET23	0.20 [0.8169]	6.94 [0.0011]**	0.29 [0.7454]	1.00 [0.3697]

**** Significant at 1%**
****+ Significant at 1% and unanimous selection in terminal models**

Regression results are in stark comparison to those seen in the performance regression, were all seasonals dropped out during the Gets model reduction. The existence of day-of-week effects is apparent, with pronounced drops on Monday and Friday in all four regressions.

The well-known January effect, which we trace back to the tax-loss trading rule of Branch (1977), appears to reveal itself in the HY LVT regression by way of a significant and positive coefficient but does not in the other categories. However, December trading is lower across both measures of trading and for both IG and HY bonds. This may, in fact, be due to the trading rule whereby securities that have decreased in value during the year are sold near the end of the year and bought back early the following year. The evidence is not conclusive, of course, but bears mentioning and deserves continued attention in empirical studies of trading activity.[83]

But while the significance of traditional seasonal factors offer a clear departure from the results of the performance regressions, they are far from surprising. The seasonal factors that are most interesting, and provide the most important insights relative to recent academic literature are the significance of what we call "behavioral seasonal variables" that have only recently been known to financial researchers to affect securities markets.

In the table we see that both the SAD onset and SAD incidence variables survive the Gets model reduction in the total trades regressions. With respect to the IG total trades, a sharp and highly statistically significant decline in the number of trades associated with the onset variable. On the HY side, however, the incidence variable survives the model reduction. These results support prior academic research that showed evidence of "winter blues" in financial markets.

Still, another seasonal factor of interest is the Murfin and Petersen (2016) "loans on sale" factor based on evidence that credit conditions are cheaper during the months of May, June and October. We observe IG total trades to be increased by a large magnitude during this period and

[83] Another very logical result is the significant drop-off in trading activity on market holidays. This result not surprising.

both IG and HY institutional trades are also significantly higher. This is consistent with a hypothesis that more favorable credit conditions attract market activity.

With respect to macroeconomic announcements, the results offer an example of the beauty of the Gets modelling methodology – i.e., the ability of the methodology to discern an optimal specification when competing independent variable definitions are considered in the unrestricted model. We notice that, unlike in the performance regressions where it was the standard surprise in macro announcements that survive the reductions, the absolute standardized surprise is what matters with respect to volume. Thus, the degree to which the data deviates from expectations, not the direction of deviation that drives order flow. The LSE/Oxford Gets methodology is designed to deal with competing variable definition situations like this and this is an excellent example of how it can be used to tackle such problems without experiencing the drawbacks of alternative model reduction methodologies.[84]

3. Analysis of Trading Activity – B. AAA and AAA Financial Trading Activity

For both robustness and in order to examine more-closely the results within specific subsectors, we chose to subsample the AAA and AAA Financial sectors to see if results are consistent with those found above. AAA, in general, is of particular interest as the credit quality of this ratings

[84] These include path dependency and repeated selection, among others. For more elaboration, see Hendry and Doornik (2014).

category is considered to be equivalent to that of US Treasury bonds.[85] Further, the AAA Financial subsector would be seen as more likely to be affected by the same factors that affect treasury bonds as financial companies often depend on the spread between borrowing and lending rates as a source of revenue. We find, however, that the results are highly consistent with those seen above. Absolute surprises in CPI and payrolls data are seen to affect order flow – with large surprises suppressing the flow of trades—while PPI and jobless claims are again removed during the model selection reduction. Seasonal factors for SAD are again significant are the MP seasonal and other commons seasonal factors.

Table 3.5 – AAA and AAA Financial Trading Activity

	AAA TOTAL TRADES	AAA LVT TRADES	AAA FINANCIAL TRADES	AAA LVT FINANCIAL TRADES
Independent Variable	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
Trend			-0.54 **+	
S_US_NOTCHESNETCHG_1		1.50 **+		
SP_VOLUME			21.77 **+	2.31 **+
SP_VOLUME_1			-20.14 **+	-1.53 **+
NONFARMS_SS			15.54 **+	
ABS_CPI_SS		-2.11 **+		-1.72 **+
ABS_NONFARMS_SS_1	-20.05 **+		-15.77 **+	
STRUC_MP_CHEAP	332.71 **+		560.72 **+	
MONDAY	-13.04 **+		-11.85 **+	
TUESDAY	14.75 **+	1.18 **+		
WEDNESDAY		1.70 **+		1.33 **+
FRIDAY	-42.71 **+		-34.13 **+	
MONTH_DEC	-25.36 **	-1.90 **+		
HOLIDAY_NYSE	-255.93 **+		-227.14 **+	
HOLIDAY_NYSE_+1	-39.15 **+		-39.56 **+	
EARLY_CLOSE_NYSE	-182.78 **+		-118.01 **+	
SAD INCIDENCE				2.17 **+
SAD ONSET	-71.86 **+			
AR	0.93 [0.3933]	0.25 [0.7809]	0.66 [0.5161]	0.84 [0.4317]
ARCH	0.14 [0.7131]	0.08 [0.7825]	1.06 [0.3047]	0.00 [0.9948]
Normality	3.61 [0.1643]	39.97 [0.0000]**	0.10 [0.9496]	9.10 [0.0106]*
Hetero	0.69 [0.9303]	0.92 [0.5688]	0.96 [0.5515]	1.71 [0.0102]*
RESET23	1.09 [0.3360]	0.90 [0.4056]	4.51 [0.0115]*	0.93 [0.3937]

**** Significant at 1%**

****+ Significant at 1% and unanimous selection in terminal models**

[85] It should be noted that, despite, the characterization of securities of this rating as 'Treasury equivalents,' no corporation has the power of taxation and would still be considered more likely to be downgraded than the US government.

4. Analysis of Trading Activity – C. Intermediated Trades Intraday Trading Activity

Zitzewitz (2011) offers an important contribution to the research on corporate bond trades by identifying the existence of "paired bond trades" in the data set that arise as a function of inter-dealer intermediation (hereafter IDI) to facilitate transactions between two counterparties. The author finds nearly 40 percent of dealer-client trades are accompanied by an inter-dealer trade for the exact amount and often at nearly the exact same second.[86]

Based on his methodology, we filter out these intermediated trades and create data series to examine in another subset of regressions. The removal of duplicated trades allows us to quantify trading activity in terms of *client demand*. We also suggest that the IDI transactions represent a proxy for the *degree of intermediation* needed to facilitate *ultimate demand* of market participants and represent an opportunity for future research.[87]

With respect to macroeconomic announcements, we see the first evidence of order flow being affected by surprises in PPI. Absolute surprises appear to affect trading with a one-day lag for IG IDI total trades, increasing the number of trades in the session after a surprise. Whereas, HY LVT IDI are reduced contemporaneously on the day of a surprise.

[86] We follow suit by filtering out duplicate trades occurring within a 60 second window. While Zitzewitz (2011) uses a more-recent sample, which includes a data flag to distinguish between dealer-client and inter-dealer transactions, such flag was not available during our sample. However, the data clearly exhibit an abundance of what Zitzewitz refers to as "paired bond trades." Therefore, we employ the same 60 second filter to eliminate distortions arising from inter-dealer intermediation.

[87] Given the relative inactivity in the corporate bond market, the degree of inter-dealer intermediation likely speaks the dealer's willingness to hold corporate bonds in inventory. Zitzewitz (2011) suggests that certain dealer firms are far more likely to require an inter-dealer transaction to facilitate client demand. For example, in Table 5 of the paper, we see that Merrill Lynch and UBS have a far higher percentage of "paired trades" – in excess of 50%. Conversely, Bank of America and Barclays had pairing rates of less than one percent.

A recurring finding across all three sets of regressions is that macroeconomic surprises appear to reduce the number of corporate bond transactions. Economic uncertainty may increase the difficulties traders encounter in finding one another. Thus, a greater search time may be required to complete desired transactions as market participants re-evaluate conditions. Again, given the buy-and-hold nature of this market, it is not overly surprising but, importantly, this does differ with what we see in equity and Treasury bond markets – i.e., announcements proving to be a catalyst to order flow.

Table 3.6

Independent Variable	II_TOT_TRDS Coefficient	II_LVTTOT_TRDS Coefficient	HI_TOT_TRDS Coefficient	HI_LVTTOT_TRDS Coefficient
Trend				
SP_VOLUME	53.386 **+	1.666 **+	11.815 **+	2.469 **+
ABS_PPI_SS_1	45.695 **+			
ABS_PPI_SS				-1.495 **
MONDAY				-0.945 **+
TUESDAY	31.088 **+	1.148 **+	4.892 **+	
WEDNESDAY		1.244 **+		
FRIDAY	-78.720 **+	-1.073 **+	-6.958 **+	-1.243 **
STRUC_MP_CHEAP	733.311 **+			
HOLIDAY_NYSE	-554.854 **+	-3.669 **+	-20.965 **+	-3.626 **+
HOLIDAY_NYSE_-1	-119.735 **+			-1.567 **
HOLIDAY_NYSE_1	227.439 **+			
EARLY_CLOSE_NYSE	-321.619 **+			
EARLY_CLOSE_NYSE_-1				
MONTH_DEC		-2.049 **+	-4.658 **+	-3.586 +
SAD INCIDENCE			-19.671 **+	
SAD ONSET	-126.954 **+			
AR	0.57 [0.5670]	3.58 [0.0287]*	0.15 [0.8575]	0.30 [0.7405]
ARCH	0.13 [0.7144]	1.05 [0.3069]	0.19 [0.6608]	6.06 [0.0142]*
Normality	1.88 [0.3902]	5.45 [0.0656]	8.84 [0.0121]*	9.06 [0.0108]*
Hetero	0.70 [0.9131]	1.59 [0.0509]	1.06 [0.3840]	1.62 [0.0255]*
RESET23	0.99 [0.3724]	0.30 [0.7390]	0.99 [0.3742]	1.45 [0.2352]

**** Significant at 1%**

****+ Significant at 1% and unanimous selection in terminal models**

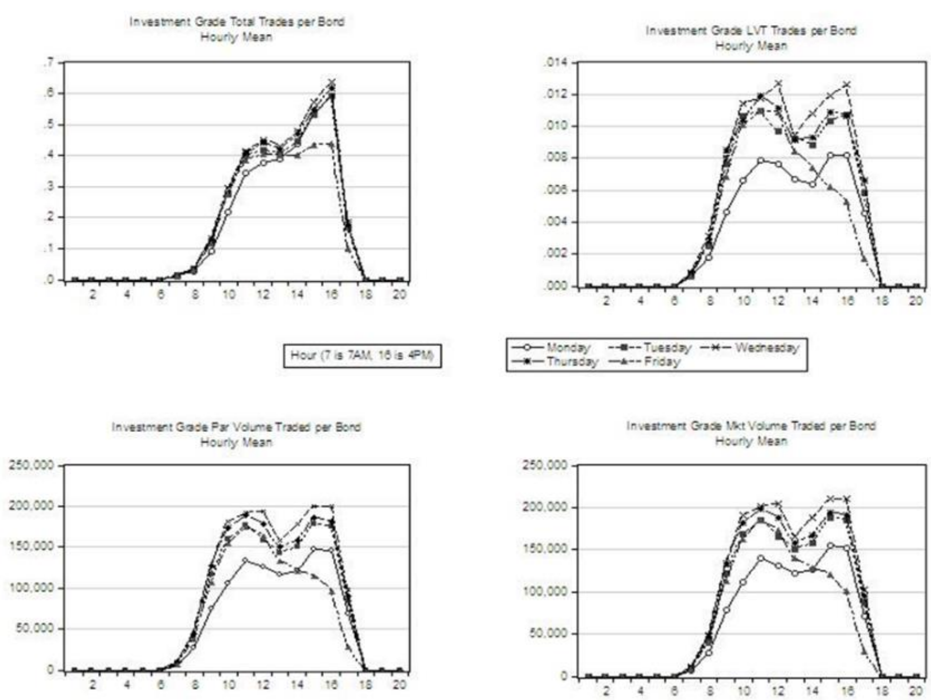
+ Insignificant at 1%, but unanimously selected in terminal models

H. Intraday Trading Activity

The following sets of graphs, offer a glimpse into the intraday trading activity. The set of graphs labeled as Panel 1 are for the investment-grade bonds while Panel 2 reflects activity in the high-yield market.

The double humped structure of trading activity reflects a lull in activity during the middle of the day. We might consider this a “lunch time” effect. Importantly, however, is obvious diurnal patterns that exist in this market. Also, as noted by previous authors with respect to foreign exchange and Treasury bond markets, there is less trading activity on Monday morning and Friday afternoons.

Figure 3.1 – Intraday Investment-Grade Trading Activity – Total Trades and Institutional Trades



Likewise, figure 3.2 depicts the same information with respect to the high-yield market. In both sets of graphs, we notice a distinct double-humped camel shape – what is known as a “Bactrian camel." We can contrast this with the U-shaped intraday trading pattern in the US equity market, seen in figure 3.3.

Figure 3.2 – Intraday High-Yield Trading Activity

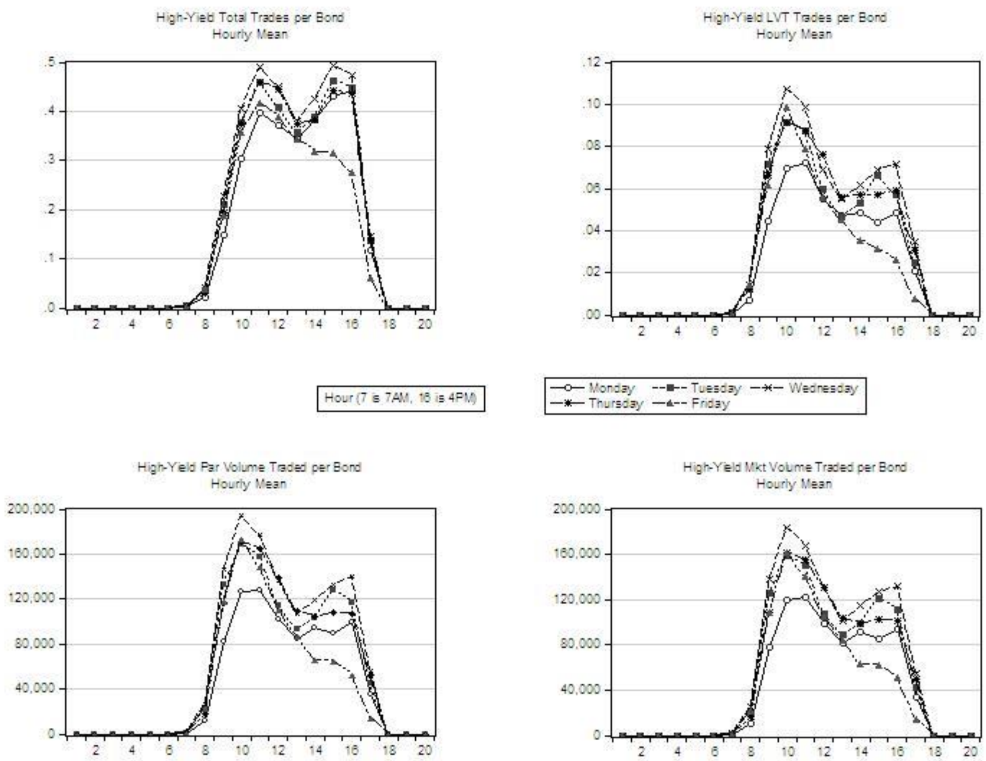
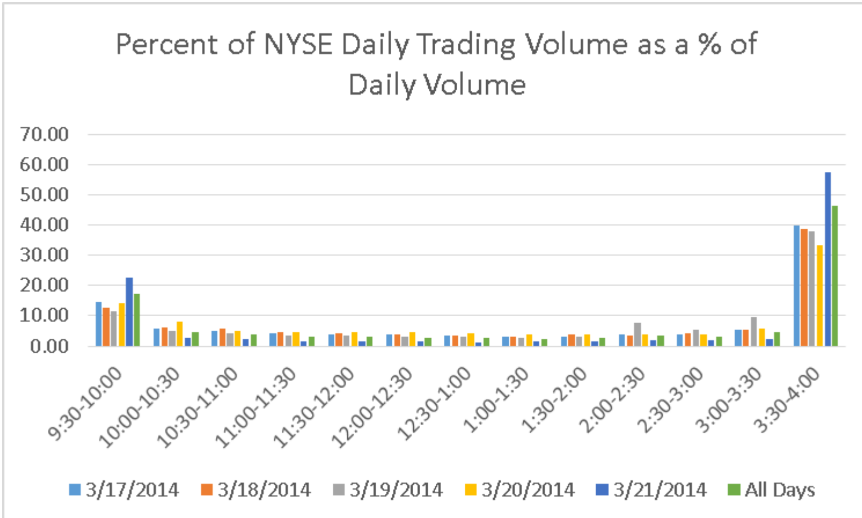


Figure 3.3 – NYSE Equity Trading Activity



I. Conclusions

We explore whether factors that drive trading activity of US corporate bond market. Prior studies have documented a significant response of returns and interest rates to surprises in macroeconomic data in the stock, US Treasury and Treasury futures markets. Likewise, studies have also documented that trading activity changes sharply, based on informational shocks provided by the release of economic data. We contribute to the existing literature by examining how both daily and intraday measures of trading activity are impacted by surprises in macro data as well as various measures of seasonality.

Our main findings are that the thinly-traded market for corporate bonds is less affected by surprises in individual economic reports and that the market is dominated by day-of-week and time-of-day affects. We find that, unlike daily returns on the S&P 500, corporate bonds are sensitive to surprises in both labor market and inflation data. Trading activity is affected by absolute surprises in core CPI and nonfarm payrolls, but neither core PPI nor jobless claims affect order flow.

Perhaps most interesting, however, is the presence of "behavioral seasonal" effects associated with the onset and incidence of seasonal affective disorder. This "winter blues" effect has been seen affecting activity in equity markets by Kamstra, M. J., L. A. Kramer and M. D. Levi (2000, 2003) and with respect to mutual fund asset flows in Garrett, I., M. J. Kamstra and L. A. Kramer (2005). This is the first study to document such an effect in the trading activity in the bond market. Finally, the "loans-on-sale" seasonal effect, first documented by Murfin & Peterson (2014)

CHAPTER IV.

THE EFFECT OF TREASURY AUCTION RESULTS ON INTEREST RATES: THE 1990S EXPERIENCE

A. Abstract

Herein, I examine the secondary-market response of U.S. Treasury returns to pre-auction announcements of supply volumes and post-auction announcements of results from U.S. Treasury auctions during the declining-deficit period of the 1990s. Rate changes are found to differ significantly on auction days for one-year bills. I also find that surprises in the release of bid-to-cover ratios and noncompetitive bidding affect Treasury 30-year returns significantly. Other maturities, however, are relatively unaffected. These results suggest that, during the 1990s, the U.S. Treasury's financing operations were conducted in a manner that exerted no more pressure on the market than that of many regularly-scheduled macroeconomic announcements. The results complement the recent study by Lou, Yan and Zhang (2013) and show the benefits of controlling macroeconomic announcements in analyzing market responses to Treasury auctions.

February 10, 2018

Keywords: Treasury auctions; GARCH modeling; interest rates; volatility; Federal Reserve; Monetary policy, Macroeconomic announcements, US Treasury operations

JEL Classifications: E44, E52, G1, G2

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B. Introduction

Herein, I examine the effect of Treasury auction announcements on interest rates during the 1990s. While an important recent study by Lou, Yan and Zhang (2013) has shed light on the behavior of the market during the period surrounding auctions and brought renewed interest in empirical work in this area, no recent study has evaluated the effect of surprises in auction demand on market rates and returns. Not since Wachtel and Young (1987) and Wachtel and Young (1990), has the market effects of the US Treasury's fiscal policy funding operations been taken up while simultaneously accounting for other announcement effects, such as FOMC and macroeconomic data announcements.[88]

I pick up where earlier studies left off, the period of the 1990s – when macroeconomic announcements were paramount in determining Fed policy and falling deficits reversed the 1980s run-up in interest rates – I am able to characterize these regime-specific results in order to compare findings from the decade before and in the years since this important era. Further, I provide a previously-neglected view of how Treasury market bid-ask prices behave around auctions.

[88] While an intraday study of the auction announcement response might be able to disentangle the effects more adeptly than a daily study, such intraday data are difficult to acquire, particularly over long time periods. The emphasis of this study, however, is on variation that persists beyond extremely short windows around announcements. The choice of daily data is consistent with the other studies mentioned that serve as a benchmark. Prior intraday Treasury market studies include Fleming and Remolona (1999), Fleming (1997) and Balduzzi, Elton and Green (2001). Typically these studies are of short time periods, within a single year. The third paper is the exception, however, the authors model macroeconomic announcement effects on an intraday basis but not Treasury auctions. That study, due to similar time frame, represents an interesting point of comparison to this study.

Specifically, I explore several important questions and relate the findings to the aforementioned studies. I ask the following: How do returns and volatility differ on auction and non-auction days?; How do surprises in auction results impact market rates?; Do Treasury debt funding operations exert a greater effect on interest rate volatility than the monetary policy actions of the Federal Reserve?; and Do results for the actively traded on-the-run securities behave similarly to those of the off-the-run issues?[89]

Results indicate that, even in the declining-deficit environment of the 1990s, *Treasury auctions had a propensity to move markets* – particularly at the long end of the yield curve— at the 30-year maturity. Here, surprises in auction results demonstrated the capacity to increase returns as greater-than-expected auction demand translated into secondary market behavior. However, volatility was not affected to any noticeable degree, nor were bid-ask prices particularly disturbed other than brief one-day spikes that occur infrequently.

These results have important implications for asset pricing and risk management as they offer a sense of sources of jump risk in asset prices. Because effects tend to be short-lived, there is no significant effect on conditional volatility and a one-standard-deviation surprise in auction demand results tend to pose less risk to market participants than those of a one-standard-

[89] Off-the-run Treasuries are the previously-auctioned securities. When a new security is auctioned, it becomes the new "on-the-run" security, while the previously-on-the-run issue becomes the 1st off-the-run issue. Barclay, Hendershott and Kotz (2006) show that trading volume decreases by more than 90% when an issue first goes off-the-run.

deviation surprise in core-CPI, core-PPI or durable goods report. Surprises in nonfarm payrolls and the employment cost index (ECI) are shown to exert a much greater disturbance.

From a modelling perspective, the key contribution is that I show that macroeconomic surprises are key variables that need to be modeled when analyzing the effects of Treasury auction announcements. Failure to model macro announcements is likely to result in omitted variables bias for the parameters in the model and could lead to faulty inferences. Likewise, when studying macroeconomic announcement effects, the researcher would be well advised to also control for contemporaneous auction results, due to the regularity of auction timing and announcement schedules.

1. Treasury market background

As the broadest and most liquid financial market in the world, the market for United States Treasury securities plays a critical role in the global financial system. An active over-the-counter secondary market exists with the majority of trading volume occurring between a group of about 40 primary dealers.[90] By 1997, an average of $125 billion worth of U.S. Treasury securities–about 1.5% of year-end GDP—traded daily in a market that functions virtually around the clock.

[90] Fleming (1997) pg. 9

In addition to its tremendous size and depth, the US Treasury market plays an important role in the financial system by establishing benchmark risk-free rates for a given maturity.[91] Numerous derivative products exist on these issues, and many variable-rate instruments reset based on Treasury yields. Additionally, the bills, notes and bonds traded are widely accepted as "risk-free" assets as the U.S. Government has never defaulted on its debt – a legacy dating back to Treasury Secretary Alexander Hamilton's post-Revolutionary War debt repayment policy.

The central role of this market within the financial system illustrates the importance of understanding potential sources of disruption. Volatility in this market can easily be transmitted to other sectors of the financial market and the world economy.

C. Literature Review

A number of studies have examined the effect of macroeconomic announcements on interest rates, including: Cornell (1983), Jones, Lamont and Lumsdaine (1998), and Flemming and Remolona (1999). Additionally, Kuttner (2002) examines the effect of FOMC policy changes on interest rates while Bernanke and Kuttner (2005) studied the Fed policy effect on equity markets. These papers, in general, document the existence of an announcement day effect arising from the release of monetary policy or macroeconomic surprises.[92]

[91] by "risk-free" we are referring to default risk

[92] More recently, Nikiforov and Pilotte (2017) look at the distribution of price-endings in the US Treasury market. Their finding is that price clustering, volatility and bid-ask spreads all increase substantially in the minutes immediately following macroeconomic news announcements. Each of these measures normalize the hour after the announcement. Effects are strongest for on-the-run notes.

Other studies examining announcement effects on capital markets include, Engle and Ng (1993); Cook and Hahn (1989); Christie-David, Chaudhry and Lindley (2003); Bollerslev, Cai and Song (2000); Balduzzi, Elton and Green (2001); and Urich and Wachtel (1984). But almost no work has been done with respect to the effect of U.S. Treasury funding operations on market behavior.[93]

A natural point of comparison exists between the Federal Reserve and the Treasury. Just as the central bank is expected to conduct open market policy without disrupting the market, the U.S. Treasury is charged with financing its budgetary needs while disturbing the financial markets as little as possible. Just considering the incredible size of government borrowings this appears to be a significantly daunting task. According to Nandi (1997), the U.S. government issued approximately $2 trillion in securities during 1995 alone – this represents more than 25% of that year's total U.S. gross domestic product.

The Treasury market also offers us a rare opportunity to examine how an increase in the supply of government securities at a given maturity affects the prevailing interest rate – i.e., the cost of borrowing.[94] Two notable papers, Schirm, Sheehan and Ferri (1989) and Wachtel and Young (1987), focus on effect of debt and deficit announcements on interest rates.[95] However, to the

[93] Two notable exceptions are Sundaresan (1994) and Nyborg and Sundaresan (1996). However, these excellent articles do not model responses to auction announcements while controlling for macroeconomic announcement surprises.
[94] Supply effects and market segmentation are considered in: Duffee (1996), Simon (1991), and Simon (1994)
[95] Cebula (2013) explores the impact of budget deficits, but on nominal Aaa-rated corporate bond yields.

author's knowledge, only one previously-published paper has specifically examined the effect of Treasury auction demand statistics on returns.[96]

Wachtel and Young (1990) find a small but significant response to post-auction results but no response to pre-auction announcements of auction volume. This study contrasts and builds upon their study of auctions during the 1980s, when government budget deficits rose sharply, and sets the stage for future analysis of the first decade of the 21st century.

A similar conclusion is raised by Lou, Yan and Zhang (2013), who also take up the issue of Treasury auctions. They explore the pre- and post-auction price behavior over a 28-year period. They demonstrate a general increase in secondary market yields prior to Treasury auctions, followed by a subsequent decline. They estimate that this phenomena results in a 9 to 18 basis point issuance cost to the Treasury. I choose to complement their investigations by making use of valuable market expectations data. Additionally, I try to emphasize the importance of modeling both auctions and macroeconomic announcements as there may be a propensity for announcements to distort results when not factored into the model. I do not find any strong evidence to suggest their results would be altered, however, the potential for omitted variables bias is a clear possibility.[97]

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[96] We also note that Bahamin, Cebula, Foley and Houmes (2012) provide an analysis of bid dispersion is positively related to bid-to-cover ratio but negatively related to the percentage of noncompetitive bids and percentage on competitive bids accepted at auction during the period of 1998 to 2010. Post-auction returns were positively related to demand at auction and they suggest that arbitrage opportunities exist between the primary and secondary market during periods of high demand for US Treasury securities.

[97] Lou, Yan and Zhang (2013) isn't based on a regression framework but, in order to model macro-announcements, such a framework would be necessary. I performed tests to examine if results differ when excluding macro

The following research builds on the existing literature by focusing on the announcement-day effect of Treasury auction announcements. I look at both pre-auction announcements of issuance volume as well as auction-day announcements of auction demand. Importantly, I control for the effects of surprises in macroeconomic announcements and Federal Reserve policy announcements.[98]

D. Preliminary Analysis

In this section I perform a preliminary analysis by partitioning interest rate dates between auction and "non-auction" days. I conduct simple t- and F-tests in order to evaluate differential behavior of returns and bid-ask spreads across sub-samples for auction and non-auction days. I look at returns for both the on-the-run and 1st off-the-run securities. This procedure allows us to get a feel for the difference in market behavior when an auction occurs. One might expect the new issuance of Treasury securities to cause returns to decrease as the market digests the fresh supply.

announcements and it does appear that there is a potential for to (perhaps-falsely) achieve positive effects for auctions. I believe it is likely that this result is merely a function of omitted variables bias as, without including announcement, only a miniscule amount of variation in the dependent variable is achieved (even when including AR term in the mean equation). These results are available from the author upon request.

[98] This is consistent with Wachtel and Young (1990) and Kuttner (2002). The research of Lou, Yan and Zhang (2012) provides a number of valuable results with respect to the behavior of the Treasury market during auction periods. They also suggest compelling policy implications, based on the cost of borrowing born by the US government. Additionally, they examine a very long sample period – from 1980 to 2008. However, they do not control for surprises in macroeconomic announcements and monetary policy actions. By focusing on a ten-year sub period and by employing market expectations data, we seek to build on the existing literature. By focusing on a shorter 10-year period, we avoid potential distortions associated with changing monetary policy regimes across the Volcker, Greenspan, and Bernanke FOMC tenures.

The results of t-tests are presented in table 4.1, with returns provided in panels A and B. While the increased supply might suggest lower returns on auction days, compared to no-auction days, I do not observe this to be the case in the middle or "belly" of the yield curve – i.e., the 5- and 10-year notes. Returns are noticeably lower on bill auction dates but remain positive and are significant at the 5% confidence level. With respect to the 30-year bond, auction day returns data are positive on days with no auction, and negative on auction days. However, despite the large order of magnitude, the difference is not statistically significant. This may be due to the relatively few number of 30-year auctions, as only 30 occurred during the entire decade. Results for the 1st off-the-run (hereafter FTR) returns basically mirror that of the on-the-run (hereafter OTR) returns for each of the maturities under examination.

Bid-ask spreads are presented for OTR and FTR securities in panels C and D. A logical line of thinking in this area might suggest a widening of the bid-ask spread for auction days based on the well-documented preference for newly-issued securities, described in Krishnamurthy (2002). Indeed, a widening *intraday* bid-ask spread was documented by Fleming and Remolona (1999) on days when key macroeconomic data announcements take place which is statistically significant at the time of the announcement. Whether this result applies to Treasury auctions and if it will reveal itself at a daily frequency is unclear. Indeed, in panel D of table 4.1, I see mixed results on this front.

While there is a noticeable widening of the bid-ask spread at the 5- and 30-year maturities, such is not the case for the 1- and 10-year issues – which actually narrow, but at a statistically insignificant level. The widening in the 5-year note is statistically significant at very high confidence level – with a p-value lower than 0.01 for both OTR and FTR securities. Given the tremendous degree of liquidity in Treasury securities, the variation in the spread is small. The fact that the widening reveals itself in the case of the 5-year notes at a daily frequency suggests that auctions can have an effect on spreads.

Table 4.1

Table 1. T-Test: Two-Sample Assuming Unequal Variances

Panel A. - Daily On-the-Run Return (Annualized)

	Year-Bill#		5-Year Note		10-Year Note		30-Year Note	
	No Auction	Auction	No Auction	Auction	No Auction	Auction	No Auction	Auction
Mean	0.0791	0.0246	0.0958	0.2286	0.0987	0.2553	0.1136	-0.2827
Variance	0.0498	0.0181	2.3482	2.0808	2.3185	3.6320	5.4001	6.2183
Observations	1488	81	2402	100	2464	38	2472	30
Hypothesized Mean Difference	0		0		0		0	
df	106		109		38		30	
t Stat	3.40 ***		-0.90		-0.50		0.87	
P-Value one-tail	0.00		0.19		0.31		0.20	
t Critical one-tail	1.66		1.66		1.69		1.70	
P-Value two-tail	0.00		0.37		0.62		0.39	
t Critical two-tail	1.98		1.98		2.02		2.04	

Panel B. - Daily 1st Off-the-Run Return (Annualized)

	Year-Bill#		5-Year Note		10-Year Note		30-Year Note	
	No Auction	Auction	No Auction	Auction	No Auction	Auction	No Auction	Auction
Mean	0.0782	0.0385	0.0899	0.1818	0.0930	0.1841	0.1035	-0.2780
Variance	0.0268	0.0148	0.8496	0.7376	2.1070	3.5789	5.1986	6.0064
Observations	1412	44	2308	61	2331	38	2339	30
Hypothesized Mean Difference	0		0		0		0	
df	48		64		38		30	
t Stat	2.10 ***		-0.82		-0.30		0.85	
P-Value one-tail	0.02		0.21		0.38		0.20	
t Critical one-tail	1.68		1.67		1.69		1.70	
P-Value two-tail	0.04		0.41		0.77		0.40	
t Critical two-tail	2.01		2.00		2.02		2.04	

Panel C. - Daily On-the-Run Bid - Ask Spread

	Year-Bill#		5-Year Note		10-Year Note		30-Year Note	
	No Auction	Auction	No Auction	Auction	No Auction	Auction	No Auction	Auction
Mean	0.0176	0.017314	0.0584	0.0625	0.0585	0.0592	0.0600	0.0625
Variance	0.0000	1.39E-05	0.0002	0.0000	0.0002	0.0003	0.0003	0.0004
Observations	1430	45	2308	61	2331	38	2339	30
Hypothesized Mean Difference	0		0		0		0	
df	47		2307		38		30	
t Stat	0.55		-14.38 ***		-0.26		-0.69	
P-Value one-tail	0.29		0.00		0.40		0.25	
t Critical one-tail	1.68		1.65		1.69		1.70	
P-Value two-tail	0.59		0.00		0.80		0.50	
t Critical two-tail	2.01		1.96		2.02		2.04	

Panel D. - Daily 1st Off-the-Run Bid - Ask Spread

	Year-Bill#		5-Year Note		10-Year Note		30-Year Note	
	No Auction	Auction	No Auction	Auction	No Auction	Auction	No Auction	Auction
Mean	0.0148	0.0144	0.0594	0.0625	0.0609	0.0600	0.0779	0.0813
Variance	0.0000	0.0000	0.0002	0.0000	0.0003	0.0002	0.0007	0.0008
Observations	1394	43	2308	61	2331	38	2339	30
Hypothesized Mean Difference	0		0		0		0	
df	45		2307		38		30	
t Stat	0.69		-10.85 ***		0.36		-0.63	
P-Value one-tail	0.25		0.00		0.36		0.27	
t Critical one-tail	1.68		1.65		1.69		1.70	
P-Value two-tail	0.49		0.00		0.72		0.53	
t Critical two-tail	2.01		1.96		2.02		2.04	

Note & Bond Sample: 1/2/1990 to 12/31/1999

Year-Bill Sample: 9/24/1993 to 12/31/1999

Units: Percentage Return

An alternative approach for evaluating the differential effect between auction and non-auction days is to examine the second moment of the distribution for the two sub-sample data series. Table 4.2 contains the results of a test for homogeneity of variance using the Brown and Forsythe (1974) modified Levene (1960) statistic. The Brown and Forsythe test statistic uses the F-statistic based on absolute deviations from the median, compared to the Levene statistic which is based on the sample mean.

Table 4.2 shows variance to be slightly higher for auction days in three of the four maturities tested. Across each of the four maturities, however, I am unable to reject the null hypothesis of homogeneous variance at an acceptable level of statistical significance.

Although the variance may not differ significantly between auction and non-auction days, other factors may be responsible. For example, contemporaneous macroeconomic data which impacts volatility may also be announced on auction days. Unfortunately, the Brown-Forsythe/Levene F-stat methodology does not allow us to disentangle the impact of the economic announcements from that of the auction announcements unless we isolate auctions effects from that of contemporaneous macroeconomic announcements that have been shown in numerous studies to be key drivers of US Treasury market prices.

Table 4.2

Table 2.
Brown-Forsythe (1974) Modified Levene (1960) Test
of Homogenity of Variance

Panel A. -Daily On-the-Run Return

	5-Year Note		10-Year Note		30-Year Note	
	Auction	No Auction	Auction	No Auction	Auction	No Auction
Variance	0.1561	0.1763	0.2726	0.174	0.4668	0.4055
Observations	100	2401	38	2463	30	2471
df1	1		1		1	
df2	2499		2499		2499	
F-Stat	0.040		0.382		1.825	
P-Value	0.843		0.537		0.177	

Panel B. -Daily 1st Off-the-Run Return

	5-Year Note		10-Year Note		30-Year Note	
	Auction	No Auction	Auction	No Auction	Auction	No Auction
Variance	0.0564	0.066	3.5789	2.1447	0.4508	0.3915
Observations	100	2401	38	2463	30	2471
df1	1		1		1	
df2	2499		2499		2499	
F-Stat	0.000		0.199		2.248	
P-Value	0.998		0.656		0.134	

Note and Bond Sample: 1/2/1990 to 12/31/1999
H0: Homoscedasticity
Units: Percentage Return

However, we may be able to elaborate further, as I can easily identify days when little or no informational activity exerts pressure on the market and see if the lack of announcements result in a less volatile interest rate environment. Table 4.3 displays results from a three-way test adding a sample of “quiet days,” having no auctions, macroeconomic or FOMC announcements.[99]

[99] In this study “quiet days” exclude days when the US Treasury auctioned the maturities under consideration, when the Federal Reserve Open Market Committee had policy meetings or conference calls, and on days when no surprise in any of 26 macroeconomic announcements tracked by MMS occur. The announcement series are as follows: auto sales, business inventories, capacity utilization, consumer

Table 4.3

Table 3.
Brown-Forsythe (1974) Modified Levene (1960) Test of Homogeneity of Variance

Panel A. - Daily On-the-Run Return (Annualized)

	5-Year Note			10-Year Note			30-Year Note		
	Macro†	Quiet††	Auction	Macro†	Quiet††	Auction	Macro†	Quiet††	Auction
Variance	0.2105	0.1309	0.1562	0.2048	0.1309	0.2726	6.2290	4.2719	6.2183
Observations	1369	1032	100	1431	1032	38	1431	1032	30
df1	2			2			2		
df2	2498			2498			2498		
F-Stat	1.543			1.424			1.321		
P-Value	0.214			0.241			0.267		

Panel B. - Daily 1st Off-the-Run Return (Annualized)

	5-Year Note			10-Year Note			30-Year Note		
	Macro†	Quiet††	Auction	Macro†	Quiet††	Auction	Macro†	Quiet††	Auction
Variance	0.0821	0.0443	0.0564	0.1886	0.1217	0.2686	0.4527	0.3035	0.4508
Observations	1369	1032	100	1431	1032	38	1439	1032	30
df1	2			2			2		
df2	2498			2498			2498		
F-Stat	1.872			0.082			1.374		
P-Value	0.154			0.439			0.253		

Sample: 1/2/1990 to 12/31/1999

† Days with economic announcements but no auction specific to that maturity

†† Days with no auction, macroeconomic announcement, or Federal Reserve Board FOMC Meeting/FOMC Conference Call

The table reveals a noticeable drop-off in variance on "quiet days" in all four maturities, compared to days when macro announcements occur. Therefore, the lack of information on quiet days appears to offer traders less opportunity to revise expectations and discover new prices. But we are still unable to reject the null hypothesis of equal variances across all three samples, as auction day variance typically falls somewhere between that of quiet and macro days. One interesting exception is the case of the 1-year bill, where auction days are the lowest variance category for both OTR and FTR bills. Another interesting result, although clearly statistically

confidence, construction spending, CPI, core-CPI (excluding food and energy), durable goods orders, employment cost index, GDP, GDP deflator, goods and services, average hourly earnings, home sales, housing starts, industrial production, index of leading economic indicators, NAPM report, non-farm payrolls, personal consumption expenditures, personal income, PPI, core-PPI (excluding food and energy), retail sales, x-autos retail sales (excluding auto sales), and the unemployment rate.

insignificant, is the case of the 10-year note. For that maturity, auction days have the highest variance. It should be noted that the year bill auctions tended to be large and frequent, while the 10-year note auctions were generally smaller and less frequent offerings.

What is critical to take from these results is that simply designating trading days into quiet-, macro- and auction-day categories and testing variance is *not enough* to tell whether auctions exert significant volatility effects on markets. Therefore, I am not yet able to judge how much auctions affect volatility in Treasury bond returns.

However, the Treasury market literature does offer some guide as to how best to proceed and better evaluate the role of auctions in a more meaningful way. An extensive literature documents the important role that information content of macroeconomic announcements play in determining return behavior. Therefore, the potential benefits seem obvious for taking both the information content of macro and auction announcements as well as the market's expectation at the time of announcement. To effectively evaluate the effect of Treasury auctions on rates, a more detailed and sophisticated analysis is required.

In the following sections I consider the market's response to the information content provided in post-auction results from a more technical perspective. I begin in section II by introducing the information provided in these announcements. I provide details of Treasury auction announcements that market participants rely on, offer descriptive data to convey a historical perspective of auction behavior during the period under investigation, and propose a solution to modeling auction expectations to facilitate the GARCH models that will ultimately be used to perform the main analyses of this study. The goal is to perform the study while taking the most relevant market factors into consideration. Results up to this point clearly demonstrate that disentangling macro-announcement effects from auction effects is difficult. Thus, I shall incorporate both into the analysis.

E. Auction Statistics of Interest

We often assess the level of auction demand by analyzing statistics that are made available by the US Treasury following each auction. Such information is released shortly after the auction close through the wire services and can be found the following day in the Wall Street Journal.[100] This release includes statistics such as the auction yield, bid-to-cover ratio, and amount of noncompetitive bids. The latter two measures offer market participants insight into the level of demand during the auction process and tend to be the most widely-reported and followed of the statistical release.

We would expect this information to be relevant to those trading in the secondary market, especially in cases when a surprise in auction demand is conveyed. Indeed, the financial press often relates post auction performance to signals provided in the auction results. On November 5, 1998, Gregory Zuckerman of the Wall Street Journal reported the following:

[100] Historical data are available via www.treasurydirect.gov

> *"The tone in the market was badly hurt by an auction of $12 billion of 10-year that proved 'just terrible' in the words of a trader. The bid-to-cover ratio, or ratio of bids to available securities, was just 1.52, well below the average of 2.3 from the past dozen auctions and the lowest in 20 years, according to Goldman Sachs."*[101]

The author clearly suggests that market participants benchmark auction statistics based on the trend they have observed for recent auctions at a given maturity.

Likewise, market analysts often view noncompetitive bidding as an indication of demand for the new issue. On May 10, 2000, Sonoko Setaishi of the Wall Street Journal quoted a bond trader's post-auction assessment:[102]

"'Strong 'noncomps' offset the bid-to-cover ratio,'"

This is another example of how practitioners adapt to information from the auction bidding process. It is indicative of how the market also uses noncompetitive bidding as a measure of auction demand. Further, it shows that the surprise in one of the post-auction statistics (in this case: bid-to-cover ratio) can potentially be offset by another statistic (noncompetitive bids) – suggesting we should model both. But how exactly are these statistics defined?

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101 "Prices of Treasury Bonds are Sent Tumbling by Stocks' Strength, Fed Worries, Weak Auction" By Gregory Zuckerman. Wall Street Journal. (Eastern Edition). Nov. 5, 1998, pg. 1

102 The trader was Yasunori Sugi of Fuji Bank Ltd.

The bid-to-cover ratio is defined as total auction bids divided by the accepted bids. This is the most popular auction demand statistic by the financial wire services and convention suggests that higher ratios indicate stronger demand.

Noncompetitive bids are typically made by individual investors or small banks as opposed to the primary dealers that actively compete in the auctions. A high level of noncompetitive bids indicate strength in underlying retail demand, which suggests that dealers will have an easier time re-selling the supply purchased at the auction.[103]

To convey some basic information about the auction process, descriptive statistics for auction results are provided in table 4.4 below. We see that the average bid-to-cover ratio decreases as we move from the bill sector, where auctions are 2.20 times "oversubscribed" on average, to the 30-year bond, averaging only 1.27.[104] Furthermore, the standard deviation of this statistic also decreases with term to maturity. Shorter maturities tend to be auctioned in higher volumes and are auctioned more frequently, as well.

[103] Fleming (2003), Fleming and Rosenberg (2007), and Lou, Yan and Zhang (2012) provide excellent discussions of the inner workings of the Treasury market in relation to Treasury auctions and primary dealers.

[104] By oversubscribed, we simply are looking at the excess of the bid- to- cover above 1 – where bids submitted would be exactly equal to those accepted. For example, if the coverage ratio is 3.20, oversubscription be 2.20 = (3.20- 1).

In table 4.4, demand appears to be higher for the short-term sector, although less consistent. Incorporating the level of demand achieved in the auction process may provide a more robust analysis of the announcement effect as clearly all auctions do not result in the same level of activity.

Table 4.4

Table 4. Descriptive Statistics: Auction Results

	Issue	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Auction Size	**30-Year Bond**	10.43	10.00	12.00	8.25	0.85	30
($ Billion)	**10-Year Note**	11.48	11.88	14.00	10.00	1.06	42
	5-Year Note	11.10	11.00	16.00	3.00	1.73	100
	1-Year Note	14.82	15.25	19.44	10.00	3.58	82
Bid-to-Cover	**30-Year Bond**	2.27	2.32	2.82	1.48	0.35	30
	10-Year Note	2.33	2.36	3.15	1.52	0.39	42
	5-Year Note	2.64	2.61	3.76	1.74	0.44	100
	1-Year Note	3.20	3.03	6.44	2.08	0.80	82
Noncomps	**30-Year Bond**	320.07	327.00	937.00	47.00	168.81	30
($ Million)	**10-Year Note**	437.45	449.00	754.00	55.00	197.85	42
	5-Year Note	569.40	552.50	1,172.00	169.00	216.07	100
	1-Year Note	897.18	917.25	1,643.90	347.00	231.36	82

Note and Bond Sample: 1/2/1990 to 12/31/1999

Bill Sample: 9/23/1993 012/31/1999

-+

Unlike the case of macroeconomic announcements, where numerous sources publish surveys of market consensus, *no source* provides market expectations estimates for auction demand statistics. Market participants must rely on past auctions as a benchmark for auction demand or else for alternative metrics for projecting auction outcomes. Using time-series forecasts of post-auction statistics, however, we are able to quantify auction expectations based on the information available to traders prior to the auction and thereby evaluate the impact of a surprise auction outcome on interest-rate levels and volatility.[105]

Therefore, I construct time series models for the auction variables using standard Box-Jenkins ARIMA methods with exogenous regressors. Note, the goal here is not to create a model that captures the most variation in the dependent variable. In fact, overfitting would undermine the forthcoming analysis. Rather, what I seek is to create a reasonable proxy for the market expectation for the auction result. Our proxy is based on the trend from prior auctions as well as other information available to market participants at the time of the auction. The structure of these models is summarized in table 4.5. Final model structure was determined by parsimonious inclusion of predictors based on Akaike information criteria.

Table 4.5

Table 5. Time Series Models for Auction Statistics

Bid-to-Cover	Model ARIMAX(p,d,q,x)	Regressors X	Adj. R^2	F-statistic	Prob. (F-stat.)	DW	Adj. Obs.	MAPE
1-Year Bill	(2,0,0,1)	A	0.461	18.267	0.000	2.042	82	13.7
5-Year Note	(1,0,1,1)	A	0.251	12.044	0.000	2.056	100	12.1
10-Year Note	(1,1,0,0)	N/A	0.246	7.670	0.002	2.305	42	16.6
30-Year Bond	(0,1,1,0)	N/A	0.352	8.884	0.001	1.980	30	13.0
Noncomps	**ARIMAX(p,d,q,x)**	**X**	**Adj. R^2**	**F-statistic**	**Prob. (F-stat.)**	**DW**	**Adj. Obs.**	**MAPE**
1-Year Bill	(1,0,0,0)	N/A	0.679	86.782	0.000	1.781	82	10.9
5-Year Note	(1,0,0,1)	A	0.620	54.911	0.000	1.888	100	20.7
10-Year Note	(1,0,1,0)	N/A	0.627	23.997	0.000	1.872	42	34.7
30-Year Bond	(1,1,0,0)	N/A	0.127	3.100	0.061	2.172	30	34.3

Note and Bond Sample: 1/2/1990 to 12/31/1999 A= auction volume
Bill Sample: 9/23/1993 012/31/1999 N/A = no exogenous regressors

[105] Wachtel and Young (1990) also use Box-Jenkins methods to model auction expectations.

Table 4.5 displays ARIMAX time-series models used to forecast expected bid-to-cover ratios and noncompetitive bids. The models have autoregressive order p, order of integration d, moving-average order q, and x exogenous predictors. Exogenous predictors include the previously-announced auction volume. The majority of the models have a single AR parameter but several have I(1) structure and/or MA terms.

Combining our forecasts for auction variables with forecasts for macroeconomic variables, I am able to disentangle the effects of contemporaneous announcement effects and thereby obtain a clearer picture of the pressure that the auctions exert on the market. As a result, we are better able to assess the true impact of auctions on the market, gauge the relative importance of auction announcements relative to macro announcements, and discern which auction statistics hold the most weight with market participants.[106]

F. Announcement Effects – Post-Auction Statistics

In this section I present regression results from GARCH-X models of Treasury security returns on auction statistics, macro announcements, fed funds policy and dummy variables for quiet days.[107] The GARCH(1,1) specification includes a single ARCH term and a single GARCH term. I present the model below, followed by a table explaining variables and coefficients. The model takes the following form:

[106] Based on coverage in the financial press, it would seem that there is a preference for the bid-to-cover ratio.
[107] This is simply a standard generalized autoregressive conditional heteroscedasticity model with additional exogenous mean and variance regressors.

Here, $\boldsymbol{R_t}$ is one-day total return on the Treasury security at time t. I include 4 auction variables, $\boldsymbol{X_{i,t}}$, which are standardized surprise variables for the bid-to-cover ratio, volume of noncompetitive bids and two (1,0) dummy variable series indicating announcements of increased or decreased volume, respectively. $\boldsymbol{Z_{i,t}}$ is the standardized surprise in economic indicator i at time t, $\boldsymbol{F_t}$ is the surprise in the federal funds rate in basis points and $\boldsymbol{\varepsilon_t}$ is the residual at time t.[108] Standardized surprises in economic indicators are calculated by subtracting the expected value of the economic variable from the as-reported result from the official release and dividing by the sample standard deviation. Standardization allows us to easily asses the return associated with a one standard deviation surprise in an auction or macroeconomic variable.[109]

Model 4.1

GARCH-X Model Specification:

$$R_t = \mu + \sum_{i=1}^{4} \theta_i x_{i,t} + \sum_{j=1}^{11} \lambda_j z_{j,t} + \phi FFS_t + \gamma QD_t + \epsilon_t$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta_1 AUCDUM + \delta_2 FOMC + \delta_3 QD_t$$

[108] The federal funds rate surprise data are provided by Kuttner, surprises are measured in the (unstandardized) basis point difference between the announced funds rate minus the futures market implied funds rate. Further details are available in: Kuttner (2001)

[109] Fed Funds surprise data are unstandardized.

Variables:

R_t	= Daily total return on US Treasury Security at time t
μ	= Constant (intercept term)
$x_{i,t}$	= 4 Auction standardized surprise variables (Bid-to-Cover Std. Surprise, Noncomps Std. Surprise, Decrease Dummy, Increase Dummy)
$z_{j,t}$	= 11 Macroeconomic standardized surprise variables (Listed in regression results)
FFS_t	= Surprise in Federal Funds Rate based on Kuttner (JME, 2001) and is not standardized
QD_t	= Dummy variable equal to 1 on "quiet days" (none of 26 macro announcements nor maturity specific auction) and 0 otherwise
ϵ_t	$\sim IID(0,1)$ error term following a Student's t-distribution with τ degrees of freedom
h_t	= Conditional Variance Term
ϵ_{t-1}^2	= ARCH term (lagged squared error term)
h_{t-1}	= Garch term (lagged conditional variance)
$AUCDUM$	= Maturity-specific dummy variable
$FOMC$	= Dummy variable equal to 1 on FOMC meetings or conference call days and 0 otherwise

Survey data are from Standard & Poor's MMS and have been widely used in the existing literature as the basis for estimating standardized surprises in macroeconomic data. The OTR and FTR U.S. Treasury return data are created from the CRSP Daily Treasury database.[110] Treasury auction results were compiled from the Treasury Direct website and checked against Bloomberg and the Wall Street Journal. The choice of Treasury security maturities analyzed reflect those government issues that were auctioned throughout the entire span of the decade, as some maturities were eliminated as government borrowing decreased.[111] I provide maturities across the yield curve to enable analysis from the "preferred habitat" and "segmented market" perspective as it is often suggested that certain maturities attract a specific clientele as existence of such effects could reveal itself in differences in behavior at different maturities. I proceed with an analysis of the results for the mean equations for OTR and FTR returns, then continue with additional tests associated with the variance equations.

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[110] The data are available to paid subscribers on WRDS at https://wrds-web.wharton.upenn.edu/wrds/index.cfm?

[111] Additionally, the 2-year note was not included, partly due to the Salomon Brothers scandal during May of 1991 which led to a disruption in the aftermarket supply for that particular issue. The 2-year note is studied extensively in the important recent article by Lou, Yan and Zhang (2013). I sought to complement their study, focusing on a particular time period when US federal budget deficits were declining to offer a contrast to their findings. Given the focus I place on macroeconomic announcements, and due to lack of macro announcement survey data in the period after that investigated in this study, I leave the longer time period for future study if such data becomes available.

Table 4.6

Table 6. - GARCH(1,1) Regressions on Daily On-the-Run Returns

Treasury Rates and Auction Results 1990 - 1999

GARCH(1,1) estimates based on Student's t distribution

	One-Year Bill#		Five-Year Note		Ten-Year Note		30-Year Bond	
Auction Announcement	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**
θ_1 **Bid-to-Cover Surprise**	0.003	0.864	0.542	0.000 **	-0.197	0.304	0.615	0.118
θ_2 **Noncomps Surprise**	-0.001	0.966	0.106	0.474	-0.244	0.308	0.742	0.075 *
θ_3 **Decrease Dummy**	-0.063	0.006 **	0.141	0.646	0.476	0.510	-0.792	0.497
θ_4 **Increase Dummy**	-0.044	0.036 **	0.013	0.969	-0.105	0.746	0.183	0.800
Economic Indicators	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**	**Coeff.**	**P-val.**
λ_1 **Capacity**	-0.075	0.000 **	-0.296	0.007 **	-0.286	0.008 **	-0.457	0.010 **
λ_2 **Confidence**	-0.051	0.001 **	-0.543	0.000 **	-0.530	0.000 **	-0.760	0.000 **
λ_3 **CPI (Core)**	-0.096	0.000 **	-0.614	0.000 **	-0.613	0.000 **	-0.842	0.000 **
λ_4 **Durable Goods**	-0.044	0.055 *	-0.439	0.000 **	-0.476	0.000 **	-0.749	0.000 **
λ_5 **ECI**	-0.079	0.000 **	-1.127	0.000 **	-1.022	0.000 *	-1.717	0.000 **
λ_6 **Hourly Earnings**	-0.083	0.000 **	-0.679	0.000 **	-0.699	0.000 **	-0.835	0.000 **
λ_7 **NAPM**	-0.083	0.000 **	-0.753	0.000 **	-0.723	0.000 **	-1.037	0.000 **
λ_8 **Nonfarm Payrolls**	-0.135	0.000 **	-0.727	0.000 **	-0.722	0.000 **	-1.155	0.000 **
λ_9 **PPI (Core)**	-0.010	0.498	-0.385	0.001 **	-0.385	0.001 **	-0.735	0.000 **
λ_{10} **Retail Sales**	-0.057	0.002 **	-0.297	0.007 **	-0.297	0.006 **	-0.440	0.012 **
λ_{11} **Unemployment**	0.056	0.001 **	0.173	0.087 *	0.175	0.087 *	0.114	0.426
ϕ **Fed Funds Rate**	-0.020	0.000 **	-0.059	0.000 **	-0.058	0.000 **	-0.081	0.000 **
γ **Quiet Day**	0.021	0.004 **	-0.104	0.055 *	-0.108	0.046 **	-0.237	0.005 **
μ **Constant**	0.067	0.000 **	0.171	0.000 **	0.172	0.000 **	0.242	0.000 **
ω **C**	0.017	0.000 **	0.097	0.013 **	0.079	0.034 **	0.048	0.414
α **RESID(-1)^2**	0.167	0.000 **	0.036	0.000 **	0.039	0.000 **	0.029	0.000 **
β **GARCH(-1)**	0.401	0.000 **	0.939	0.000 **	0.935	0.000 **	0.956	0.000 **
δ_1 **BILL_1_AUC_DUM**	-0.007	0.201	-0.254	0.164	0.027	0.913	0.751	0.173
δ_2 **FEDCALLORMEET**	0.011	0.269	-0.069	0.667	-0.041	0.809	-0.318	0.290
δ_3 **QUIET_DAY**	-0.009	0.000 **	-0.074	0.223	-0.052	0.385	0.073	0.510
τ **T-DIST. DOF**	4.095	0.000 **	6.507	0.000 **	6.461	0.000 **	8.159	0.000 **
Durbin Watson	2.32		1.86		1.86		1.94	
Adjusted R-squared	0.08		0.08		0.08		0.07	
Log likelihood	716.96		-4362.85		-4372.44		-5464.37	

Sample: 1/2/1990 to 12/31/1999

One-Year Bill Sample:9/24/1993 to 12/31/1999

** 5% Significance

* 10% Significance

The results from GARCH estimation of OTR securities are provided in table 4.6. and show positive mean equation coefficients on the bid-to-cover ratio for three of the four maturities; The five-year note coefficient, however, is the only one that achieves a reasonable degree of statistical significance – although the 30-year bond has a p-value of 0.118, and warrant some degree of attention given the relative infrequency of bond auctions. The sign of the coefficients are consistent with prior expectation that a larger-than-expected coverage ratio indicates strong demand which causes the market to rally (prices rise as yields decline). The magnitude of the bid-to-cover surprise on the 5-year note is similar, in absolute terms, to that of consumer confidence and greater than that of the unemployment rate, core-PPI, durable goods orders and capacity utilization. Employment cost index and nonfarm payrolls are much larger in magnitude.

With respect to surprises in noncompetitive bidding, the 30-year bond coefficient has the expected sign but, again, is only significant at the 10% level – with a p-value of 0.075. The magnitude of the coefficient is similar, in absolute value, to that of core-CPI, core-PPI, consumer confidence and hourly earnings. It exceeds that of indicators, such as: capacity utilization and retail sales. Three key economic indicators appeared to be much more important to the market: the employment cost index, nonfarm payrolls, and the diffusion index produced by the National Association of Purchasing Managers.[112] These three reports were known to be favorites of then-Federal Reserve Chairman Alan Greenspan, who was a macroeconomic forecaster prior to his tenure at the Fed. Other maturities are highly insignificant and only the 5-year note has the expected sign.

Overall, the results are consistent with Wachtel and Young (1990) in that surprises in auction results can have an effect on Treasury returns but results are not necessarily consistent across different maturities.[113] However, the lack of significance in the case of noncompetitive bids may be an indicator that this measure has fallen out of favor with market participants since the 1980s when they performed their study. Additionally, the 1990s was a declining deficit period, as opposed to the skyrocketing deficit decade of the 1980s. As a result, noncompetitive bidding data may have been less of a factor.

[112] The National Association of Purchasing Managers has been renamed the Institute for Supply Managers or ISM.
[113] Wachtel and Young (1990) model the change in yield, as opposed to return.

Turning our attention to the coefficients on auction volume increases and decreases, we can compare results to two earlier studies. Wachtel and Young (1990) found that neither auction volume levels nor surprises in auction volume had a significant effect on Treasuries during the 1980s. Yet, in a similar study, Wachtel and Young (1987) find that government deficit announcements significantly affect rates. This is not necessarily surprising, given that increased government spending and lower marginal tax rates in the 1980s sent the deficit on a steady upward trajectory. But while their earlier study showed a general sensitivity to higher-than-expected deficits, the effect appeared to be fully priced into the market by the time the Treasury announced how much they would borrow at each maturity. I find that only the 1-year bill appears to be significantly affected by increases or decreases in auction volume on auction days, yet both have a negative sign. This is counterintuitive, yet may be a result of the Treasury changing auction frequency as deficits improved. Perhaps even more important, is the Long-Term Capital Management and Asian Currency crises and the resulting spike in demand for short-term T-bills. We will see additional evidence of this in the bid-ask spread behavior during the crisis period.

Table 4.7 provides results for the FTR Treasury securities. The results largely mirror those presented in the OTR return regressions. This shows that, despite the literature showing that market participants have a strong preference for the OTR securities, returns and volatility behave in the same manner with respect to Treasury auctions. While most of the trading volume is in the OTR securities, FTR security return regressions produce highly similar coefficients. Interestingly, improved statistical significance is seen for the bid-to-cover ratio on the FTR 30-year bond, with a p-value of 0.082. The bid-to-cover coefficient for the FTR 5-year note is nearly half that of its OTR counterpart. However, the decrease in the magnitude of the macroeconomic data surprises are also greatly reduced in the FTR regressions. The ranking of the relative absolute magnitude of coefficients, however, is well preserved.

Table 4.7

Table 7. - GARCH(1,1) Regressions on Daily 1st Off-the-Run Returns

Treasury Rates and Auction Results 1990 - 1999

GARCH(1,1) estimates based on Student's t distribution

	One-Year Bill#		Five-Year Note		Ten-Year Note		30-Year Bond	
Auction Announcement	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
θ_1 **Bid-to-Cover Surprise**	0.009	0.588	0.300	0.000 **	-0.119	0.506	0.483	0.082 *
θ_2 **Noncomps Surprise**	0.007	0.686	0.057	0.539	-0.207	0.368	0.595	0.047 **
θ_3 **Decrease Dummy**	-0.047	0.022 **	0.106	0.569	0.378	0.612	-0.923	0.305
θ_4 **Increase Dummy**	-0.044	0.054 *	0.144	0.565	-0.151	0.628	-0.071	0.904
Economic Indicators	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
λ_1 **Capacity**	-0.067	0.000 **	-0.161	0.019 **	-0.289	0.006 **	-0.417	0.028 **
λ_2 **Confidence**	-0.040	0.001 **	-0.361	0.000 **	-0.514	0.000 **	-0.742	0.000 **
λ_3 **CPI (Core)**	-0.080	0.000 **	-0.434	0.000 **	-0.579	0.000 **	-0.846	0.000 **
λ_4 **Durable Goods**	-0.032	0.083 *	-0.299	0.000 **	-0.501	0.000 **	-0.787	0.001 **
λ_5 **ECI**	-0.112	0.000 **	-0.574	0.000 **	-1.032	0.000 **	-1.389	0.000 **
λ_6 **Hourly Earnings**	-0.080	0.000 **	-0.448	0.000 **	-0.634	0.000 **	-0.876	0.000 **
λ_7 **NAPM**	-0.062	0.000 **	-0.504	0.000 **	-0.691	0.000 **	-1.026	0.000 **
λ_8 **Nonfarm Payrolls**	-0.114	0.000 **	-0.614	0.000 **	-0.753	0.000 **	-1.198	0.000 **
λ_9 **PPI (Core)**	-0.014	0.333	-0.217	0.002 **	-0.310	0.005 **	-0.651	0.000 **
λ_{10} **Retail Sales**	-0.055	0.001 **	-0.181	0.005 **	-0.310	0.003 **	-0.415	0.020 **
λ_{11} **Unemployment**	0.032	0.021 **	0.153	0.015 *	0.182	0.068 *	0.390	0.013 **
ϕ **Fed Funds Rate**	-0.018	0.000 **	-0.046	0.000 **	-0.050	0.000 **	-0.035	0.003 **
γ **Quiet Day**	0.017	0.008 **	-0.065	0.043 **	-0.132	0.012 **	-0.185	0.028 **
μ **Constant**	0.071	0.000 **	0.140	0.000 **	0.188	0.000 **	0.180	0.001 **
ω **C**	0.001	0.039 **	0.045	0.003 **	0.082	0.022 **	3.993	0.001 **
α **RESID(-1)^2**	0.055	0.000 **	0.042	0.000 **	0.038	0.000 **	0.025	0.054 *
β **GARCH(-1)**	0.919	0.000 **	0.932	0.000 **	0.934	0.000 **	0.588	0.000 **
δ_1 **BILL_1_AUC_DUM**	0.000	0.943	-0.081	0.227	0.038	0.871	-2.561	0.159
δ_2 **FEDCALLORMEET**	0.000	0.916	-0.047	0.422	-0.018	0.906	-5.502	0.000 **
δ_3 **QUIET_DAY**	-0.001	0.200	-0.046	0.040 **	-0.063	0.258	-1.428	0.009 **
τ **T-DIST. DOF**	5.023	0.000 **	6.507	0.000 **	6.656	0.000 **	3.259	0.000 **
Durbin Watson	2.07		1.87		1.85		1.96	
Adjusted R-squared	0.10		0.11		0.08		0.07	
Log likelihood	920.66		-3085.49		-4279.09		-5503.58	

Sample: 1/2/1990 to 12/31/1999

One-Year Bill Sample:9/24/1993 to 12/31/1999

** 5% Significance

* 10% Significance

While the lack of significance on the 1-year bill and 10-year note auction surprises does stand out, it may be a result of several factors. First, the 10-year note was auctioned only 42 times in ten years. Therefore, we don't have a lot of observations, and an un-modeled factors may come into play. I include 11 of the most important economic announcements in the regressions, however, there are another 15 that have been shown to have importance to bond market participants. Further, every 10-year note auction occurs on a day when at least one of 26 macroeconomic data announcements took place. Clearly modeling not enough factors trades off with modeling too many factors.

Another reason that auction surprise effects may not show up in the regression results is simply that the forecasts of the ARIMAX models may not be a good proxy for expectations at that particular maturity. The R-squared of the forecasting model for 10-year note bid-to-cover was the lowest compared to other maturities. The in sample MAPE for 10-year note bid-to-cover and noncomps, respectively, were the highest compared to other maturities. Clearly modelling expectations for the 10-year note is challenging. Why might this be the case?

An important consideration with respect to the 10-year note, is the fact that the US Treasury temporarily altered their auction cycle at this maturity in 1996 by increasing the number of auctions from 4 to 6 times a year, while at the same time lowering auction volumes. Therefore, a structural change in the expectations generating process would have to be modeled in the ARIMAX model to reflect market expectations accurately, but the change in frequency was so short-lived that accomplishing this would be a challenge. Market participants were likely to experience difficulty forming accurate expectations at this time. As a result, I will primarily opt to emphasize the results at other maturities but present all results in the table.

Likewise, inconsistency in the year bill auction regressions tend to stand out when compared to that of the 5- and 30-year securities. Note that the auction data series start in late 1993, as a result of full auction history data not being available on the Treasury Direct website. Further, the 1-year bill auctions were cut in size from just under 20 billion per auction to just 10 billion per auction at the end of the decade and were phased out completely during the early 2000s before Treasury resumed issuance in 2009 during the Financial Crisis/Great Recession period.

Table 4.8 – Additional Auction Descriptive Statistics

Auction Increases vs. Decreases

	Decreased	Increased	Unchanged	Total
1-Year Bill	35	40	7	82
(%)	42.68%	48.78%	8.54%	100%
5-Year Note	9	17	74	100
(%)	9.00%	17.00%	74.00%	100%
10- Year Note	14	6	18	38
(%)	36.84%	15.79%	47.37%	100%
30-Year Bond	4	9	17	30
(%)	13.33%	30.00%	56.67%	100%

Note and Bond Sample: 1/2/1990 to 12/31/1999

Bill Sample: 9/23/1993 to 12/31/1999

In table 4.8, I provide additional descriptive statistics for announcements of auction terms during the 1990s. We see that, despite the fact that total borrowings declined as the deficit was eliminated, the auctions that existed throughout the decade actually saw more volume increases than decreases. This occurred as auctions at other maturities – e.g., 3-year notes – were eliminated. The 5-year note and 30-year bonds were mostly unchanged while auction volumes for 1- and 10-year securities changed often. Given this scenario, that we see difficulty in modeling bid-to-cover and noncomp expectations for those two maturities, it is not surprising.

G. Announcement Effects on Volatility

In this section elaborate on the variance GARCH modeling to explore the effect that auctions exert on interest rate volatility. Volatility effects have not yet been examined with respect to Treasury auction announcements.[114] The model bears similarity to that of Jones, Lamont and Lumsdaine (1998), who studied the effect of macroeconomic announcement on interest rate volatility, in that I allow dummy variables enter into the variance equation of a GARCH model.

The model structure is further modified to accommodate standardized surprises in the mean equation, doing so obviates the need for an autoregressive term and, I believe, provides a better representation of the underlying error process. We assume the error term t- distribution, with degrees of freedom estimated for each equation.

[114] Lou, Yan and Zhang (2013) incorporate volatility as an independent variable based on implied volatility of Treasury derivatives, but to not analyze the effect of announcements on volatility.

Table 4.9 – GARCH Coefficient Tests

Tests of Coefficient Equality

Panel A. - On-the-Run Garch Equations

Test 1. Null Hypothesis: C(22)=C(23)

Test Statistic	One-Year Bill Value	df	Probability	Five-Year Note Value	df	Probability	Ten-Year Note Value	df	Probability	Thirty-Year Bond Value	df	Probability
F-statistic	2.677	(1, 1544)	0.102	0.605	(1, 2477)	0.437	0.055	(1, 2477)	0.815	2.713	(1, 2477)	0.100
Chi-square	2.677	1	0.102	0.605	1	0.437	0.055	1	0.815	2.713	1	0.100

Test 2. Null Hypothesis: C(23)=C(24)

Test Statistic	Value	df	Probability	Value	df	Probability	Value	df	Probability	Value	df	Probability
F-statistic	4.285	(1, 1544)	0.039	0.001	(1, 2477)	0.975	0.005	(1, 2477)	0.945	1.741	(1, 2477)	0.187
Chi-square	4.285	1	0.038	0.001	1	0.975	0.005	1	0.945	1.741	1	0.187

Test 3. Null Hypothesis: C(22)=C(23)=C(24)

Test Statistic	Value	df	Probability	Value	df	Probability	Value	df	Probability	Value	df	Probability
F-statistic	2.195	(2, 1544)	0.112	0.541	(2, 2477)	0.582	0.051	(2, 2477)	0.950	1.485	(2, 2477)	0.227
Chi-square	4.390	2	0.111	1.082	2	0.582	0.102	2	0.950	2.969	2	0.227

Panel B. - 1st Off-the-Run Garch Equations

Test 1. Null Hypothesis: C(22)=C(23)

Test Statistic	One-Year Bill Value	df	Probability	Five-Year Note Value	df	Probability	Ten-Year Note Value	df	Probability	Thirty-Year Bond Value	df	Probability
F-statistic	0.016	(1, 1525)	0.900	0.157	(1, 2477)	0.692	0.044	(1, 2477)	0.834	2.404	(1, 2477)	0.121
Chi-square	0.016	1	0.900	0.157	1	0.692	0.044	1	0.834	2.404	1	0.121

Test 2. Null Hypothesis: C(23)=C(24)

Test Statistic	Value	df	Probability	Value	df	Probability	Value	df	Probability	Value	df	Probability
F-statistic	0.214	(1, 1525)	0.644	0.001	(1, 2477)	0.979	0.098	(1, 2477)	0.755	15.485	(1, 2477)	0.000
Chi-square	0.214	1	0.644	0.001	1	0.979	0.098	1	0.755	15.485	1	0.000

Test 3. Null Hypothesis: C(22)=C(23)=C(24)

Test Statistic	Value	df	Probability	Value	df	Probability	Value	df	Probability	Value	df	Probability
F-statistic	0.147	(2, 1525)	0.863	0.153	(2, 2477)	0.859	0.130	(2, 2477)	0.878	7.743	(2, 2477)	0.000
Chi-square	0.294	2	0.863	0.305	2	0.859	0.260	2	0.878	15.486	2	0.000

Note and Bond Sample: 1/2/1990 to 12/31/1999 C(22)= Coefficient on Auction Day
Bill Sample: 9/23/1993 012/31/1999 C(23)= Coefficient on FOMC Call of Meeting Day
C(24)= Coefficient on Quiet Day

From Tables 4.6 and 4.7, we see that the variance equation coefficient on the auction dummy variable are all insignificant. However, we do find that quiet days tend to have a negative sign on the coefficient. The OTR results are only significant for the 1-year bill, but FTR results are significant for 5- and 30-year securities. Overall, the results support the Brown-Forsythe tests presented earlier. Auction day volatility does not appear to differ significantly when compared to macro announcement and quiet days. I interpret the combined results as evidence that the US Treasury conducts borrowing operation in a manner that minimizes disturbances to financial markets in terms of volatility, despite the increased scarcity of Treasury supply during declining borrowing periods.

We can further analyze volatility effects by testing variance equation dummy-variable coefficients relative to one another – thereby providing a gauge of volatility caused from Treasury vs. Federal Reserve operating procedures. Additionally, comparison of these results to the earlier results from the Brown-Forsythe tests, to see if the results are consistent when we switch to a GARCH model where macroeconomic announcements enter into both the mean and variance equations.

I tested three hypotheses: 1.) that the coefficients on Treasury auctions and FOMC meetings were equal, 2.) that coefficients on FOMC and "quiet days" were equal, and 3.) that all three were coefficients were equal. Panel A. presents the OTR results, while panel B. shows FTR results. When we look at these F- and chi-squared tests of these hypotheses in table 8, it is clear that we cannot rule out the equality of any of the tests for OTR or FTR notes. However, p-values on test 1 indicate that applying a loose level of significance of around 10% would achieve borderline significant results for the 30-year bond.[115] This suggests that, while we don't have a precise estimates for the parameters themselves, that they are equal appears unlikely. Obviously we would want to exercise extreme caution in emphasizing this result as it could be completely spurious. However it may deserve closer scrutiny over a larger data set with more auction announcements.

For the FTR series, results are insignificant other than in the case of the 30-year bond, where FOMC and quiet days are decidedly different in terms of their contribution to volatility. Again, a nearly significant result is seen between the Treasury and FOMC for the 30-year bond as

[115] The p-value for the 1-year bill is 0.102 but coefficients in the regressions are so insignificant that attempting to draw any inference would be highly inadvisable.

homogeneity of variance cannot be rejected at a standard level of significance, yet the p-vale of 0.121 is not far from rejecting the null at the 10% level.

H. Yield Behavior on Days Surrounding Announcements

In this section, I present results of OLS regressions that include additional leads and lags of auction day dummy variables, so that we can assess the behavior of interest rates in the days surrounding auctions. Lou, Yan and Zhang (2013) provide an analysis of interest rate behavior over an extensive 28-year period from 1980 to 2008. They present evidence suggesting the behavior of rates is consistent with increasing prior to auction days and decline in the days following. While their results are compelling and their data sample is extensive, with many auctions taken into consideration, other factors, such as economic announcements, may warrant consideration.[116]

Employing a regression framework to examine over a narrower time period allows us to see if their findings are robust within a sub-sample that could be characterized as a declining-deficit regime and would be considered as a likely data range where behavior may have been altered. The data from the 1980s are over a rising-interest-rate and increasing-deficit regime. The data from the 2000s, are a mix of the two, with rising deficits and Treasury borrowing but still falling interest rates. So we can think of their study as coving three distinct regimes – each of which may have different behavior.

[116] While they focus largely on the 2-year note, they also provide results showing similar behavior at other maturities. In constructing this study of 1990s behavior, I chose to exclude the 2-year note due to possible effects associated with the Salomon Brothers scandal. However, 5- and 10-year maturities are common to both studies.

In particular, the 1990s were also a period of intense scrutiny of macroeconomic indicators. Fed Chairman Greenspan, having been an economic forecaster, was considered a "data junkie" who would base policy on a wide range of economic indicators. Macro announcement drove activity during this period and incorporating them into the analysis is paramount.

To facilitate this regime-specific analysis that incorporates announcements, I simply re-run regressions for the four maturities under OLS with one-day yield change as the dependent variables and add three auction day dummy variable leads and lags to the set of independent variables from the mean equations in the earlier GARCH regressions. Estimation results of the lead and lag coefficients are presented in table 4.10, with heteroscedasticity and autocorrelation consistent (Newey-West) standard errors and t-statistics.[117]

Results suggest that, when restricting the sample to the 1990s regime and incorporating macroeconomic indicators, there are still positive coefficients in the days prior to 5- year note auctions and zero or negative coefficients on the lags. Similar results are seen in the 10-year note and 30-year bonds. Signs and significance of coefficients are consistent when comparing between OTR and FTR regressions. I conclude that the results found in Lou, Yan and Zhang (2013) hold up to the closer scrutiny as including macroeconomic announcement surprise effects and limiting the sample to a regime where markets were less likely to be disturbed by auction operations does not alter the conclusions of their study.

[117] Daily yield changes are expressed in basis points and are not cumulative, as those presented in Lou, Yan and Zhang (2013). However, this is done intentionally as it allows us to see if the said declines and recoveries in rates around auctions are concentrated in specific days. We limit the leads and lags to three to limit the number of parameters being estimated.

I would, however, emphasize that including macroeconomic announcement data in any study of auction effects on returns or yields in Treasury markets is still advisable, as they have been shown in numerous studies to be a primary source of market movement. Doing so may offer more robust results, while failure to do so introduces a potential source of error and omitted-variables bias. Given the near equal magnitude of auction surprises and macro announcement surprises and the regularity of auction and announcement schedules, neglecting to include macroeconomic announcement variables is potential source of misleading results. Researchers would be advised to err on the side of caution and include all variables that are important to the data generating process in order to have greater confidence in their estimated parameters and standard errors.

Table 4.10 – Days Surrounding Auctions

Interest Rate Behavior on Days Surrounding Treasury Auctions

Panel A: On-the-Run Issues

	Macro & Other Variables Included					**Macro & Other Variables Excluded**			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
BILL_1_AUC_DUM(3)	-0.009	0.013	-0.674	0.501	BILL_1_AUC_DUM(3)	-0.008	0.014	-0.588	0.557
BILL_1_AUC_DUM(2)	0.013	0.013	0.978	0.328	BILL_1_AUC_DUM(2)	0.015	0.014	1.082	0.279
BILL_1_AUC_DUM(1)	0.008	0.005	1.604	0.109	BILL_1_AUC_DUM(1)	0.007	0.005	1.482	0.139
BILL_1_AUC_DUM(-1)	-0.001	0.007	-0.084	0.933	BILL_1_AUC_DUM(-1)	0.001	0.007	0.112	0.911
BILL_1_AUC_DUM(-2)	0.003	0.006	0.534	0.593	BILL_1_AUC_DUM(-2)	0.002	0.007	0.235	0.815
BILL_1_AUC_DUM(-3)	-0.003	0.005	-0.539	0.590	BILL_1_AUC_DUM(-3)	0.001	0.005	0.091	0.927
NOTE_5_AUC_DUM(3)	0.016	0.005	3.288	0.001 **	NOTE_5_AUC_DUM(3)	0.019	0.005	3.903	0.000 **
NOTE_5_AUC_DUM(2)	0.006	0.006	1.021	0.308	NOTE_5_AUC_DUM(2)	0.009	0.007	1.369	0.171
NOTE_5_AUC_DUM(1)	0.005	0.005	0.961	0.337	NOTE_5_AUC_DUM(1)	0.008	0.005	1.445	0.149
NOTE_5_AUC_DUM(-1)	0.000	0.006	0.020	0.984	NOTE_5_AUC_DUM(-1)	0.000	0.006	0.039	0.969
NOTE_5_AUC_DUM(-2)	-0.011	0.006	-1.957	0.051 *	NOTE_5_AUC_DUM(-2)	-0.010	0.005	-1.912	0.056 *
NOTE_5_AUC_DUM(-3)	-0.005	0.005	-0.945	0.345	NOTE_5_AUC_DUM(-3)	-0.004	0.006	-0.706	0.480
NOTE_10_AUC_DUM(3)	0.007	0.010	0.727	0.467	NOTE_10_AUC_DUM(3)	0.008	0.011	0.723	0.470
NOTE_10_AUC_DUM(2)	0.002	0.008	0.186	0.852	NOTE_10_AUC_DUM(2)	0.004	0.009	0.431	0.666
NOTE_10_AUC_DUM(1)	-0.014	0.008	-1.818	0.069 *	NOTE_10_AUC_DUM(1)	-0.014	0.008	-1.784	0.075 *
NOTE_10_AUC_DUM(-1)	-0.012	0.007	-1.747	0.081 *	NOTE_10_AUC_DUM(-1)	-0.018	0.007	-2.374	0.018 **
NOTE_10_AUC_DUM(-2)	-0.011	0.008	-1.383	0.167	NOTE_10_AUC_DUM(-2)	-0.011	0.008	-1.301	0.194
NOTE_10_AUC_DUM(-3)	0.004	0.009	0.410	0.682	NOTE_10_AUC_DUM(-3)	0.008	0.009	0.835	0.404
BOND_30_AUC_DUM(3)	0.013	0.010	1.224	0.221	BOND_30_AUC_DUM(3)	0.016	0.010	1.516	0.130
BOND_30_AUC_DUM(2)	-0.003	0.006	-0.457	0.648	BOND_30_AUC_DUM(2)	-0.001	0.006	-0.178	0.859
BOND_30_AUC_DUM(1)	0.008	0.007	1.163	0.245	BOND_30_AUC_DUM(1)	0.010	0.007	1.369	0.171
BOND_30_AUC_DUM(-1)	-0.006	0.013	-0.481	0.630	BOND_30_AUC_DUM(-1)	-0.008	0.013	-0.614	0.539
BOND_30_AUC_DUM(-2)	-0.034	0.009	-3.774	0.000 **	BOND_30_AUC_DUM(-2)	-0.033	0.009	-3.486	0.001 **
BOND_30_AUC_DUM(-3)	-0.013	0.009	-1.369	0.171	BOND_30_AUC_DUM(-3)	-0.012	0.009	-1.435	0.151

Panel B: Ist Off-the-Run Issues

	Macro & Other Variables Included					**Macro & Other Variables Excluded**			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**		**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
BILL_1_AUC_DUM(3)	0.005	0.005	1.021	0.307	BILL_1_AUC_DUM(3)	0.007	0.005	1.469	0.142
BILL_1_AUC_DUM(2)	-0.005	0.005	-0.876	0.381	BILL_1_AUC_DUM(2)	-0.003	0.005	-0.587	0.557
BILL_1_AUC_DUM(1)	0.005	0.005	1.012	0.312	BILL_1_AUC_DUM(1)	0.005	0.005	0.938	0.349
BILL_1_AUC_DUM(-1)	-0.001	0.007	-0.202	0.840	BILL_1_AUC_DUM(-1)	0.000	0.007	0.067	0.947
BILL_1_AUC_DUM(-2)	-0.001	0.005	-0.135	0.893	BILL_1_AUC_DUM(-2)	-0.001	0.006	-0.205	0.837
BILL_1_AUC_DUM(-3)	-0.002	0.005	-0.464	0.643	BILL_1_AUC_DUM(-3)	0.000	0.005	0.015	0.988
NOTE_5_AUC_DUM(3)	0.013	0.004	3.285	0.001 **	NOTE_5_AUC_DUM(3)	0.016	0.004	4.073	0.000 **
NOTE_5_AUC_DUM(2)	0.001	0.005	0.265	0.791	NOTE_5_AUC_DUM(2)	0.004	0.006	0.774	0.439
NOTE_5_AUC_DUM(1)	0.002	0.005	0.379	0.704	NOTE_5_AUC_DUM(1)	0.004	0.005	0.945	0.345
NOTE_5_AUC_DUM(-1)	-0.001	0.005	-0.180	0.857	NOTE_5_AUC_DUM(-1)	0.000	0.005	-0.069	0.945
NOTE_5_AUC_DUM(-2)	-0.011	0.005	-2.340	0.019 **	NOTE_5_AUC_DUM(-2)	-0.011	0.005	-2.258	0.024 *
NOTE_5_AUC_DUM(-3)	-0.004	0.005	-0.764	0.445	NOTE_5_AUC_DUM(-3)	-0.003	0.005	-0.556	0.578
NOTE_10_AUC_DUM(3)	0.010	0.010	1.062	0.288	NOTE_10_AUC_DUM(3)	0.011	0.010	1.030	0.303
NOTE_10_AUC_DUM(2)	0.001	0.008	0.127	0.899	NOTE_10_AUC_DUM(2)	0.003	0.009	0.340	0.734
NOTE_10_AUC_DUM(1)	-0.013	0.008	-1.612	0.107 *	NOTE_10_AUC_DUM(1)	-0.013	0.008	-1.609	0.108 *
NOTE_10_AUC_DUM(-1)	-0.013	0.007	-1.806	0.071 *	NOTE_10_AUC_DUM(-1)	-0.018	0.007	-2.448	0.014 **
NOTE_10_AUC_DUM(-2)	-0.010	0.008	-1.250	0.211	NOTE_10_AUC_DUM(-2)	-0.010	0.008	-1.156	0.248
NOTE_10_AUC_DUM(-3)	0.003	0.009	0.359	0.720	NOTE_10_AUC_DUM(-3)	0.008	0.009	0.833	0.405
BOND_30_AUC_DUM(3)	0.013	0.011	1.239	0.216	BOND_30_AUC_DUM(3)	0.016	0.011	1.520	0.129
BOND_30_AUC_DUM(2)	-0.004	0.006	-0.735	0.463	BOND_30_AUC_DUM(2)	-0.003	0.006	-0.441	0.659
BOND_30_AUC_DUM(1)	0.007	0.007	1.040	0.299	BOND_30_AUC_DUM(1)	0.009	0.007	1.242	0.214
BOND_30_AUC_DUM(-1)	-0.009	0.012	-0.742	0.458	BOND_30_AUC_DUM(-1)	-0.011	0.013	-0.873	0.383
BOND_30_AUC_DUM(-2)	-0.027	0.009	-2.991	0.003 **	BOND_30_AUC_DUM(-2)	-0.025	0.009	-2.739	0.006 **
BOND_30_AUC_DUM(-3)	-0.009	0.009	-1.071	0.284	BOND_30_AUC_DUM(-3)	-0.009	0.008	-1.112	0.266

Shading in Std.Error column indicates the lower SE comparing when macro are included vs. excluded. In 10 of the 48 cases, the lower SE comes when including macroeconomic variables. Only one estimated SE is lower when excluding macro variables.

Shading in the coefficient column indicates a sign change compared to the coefficient estimate when excluding macro variables.

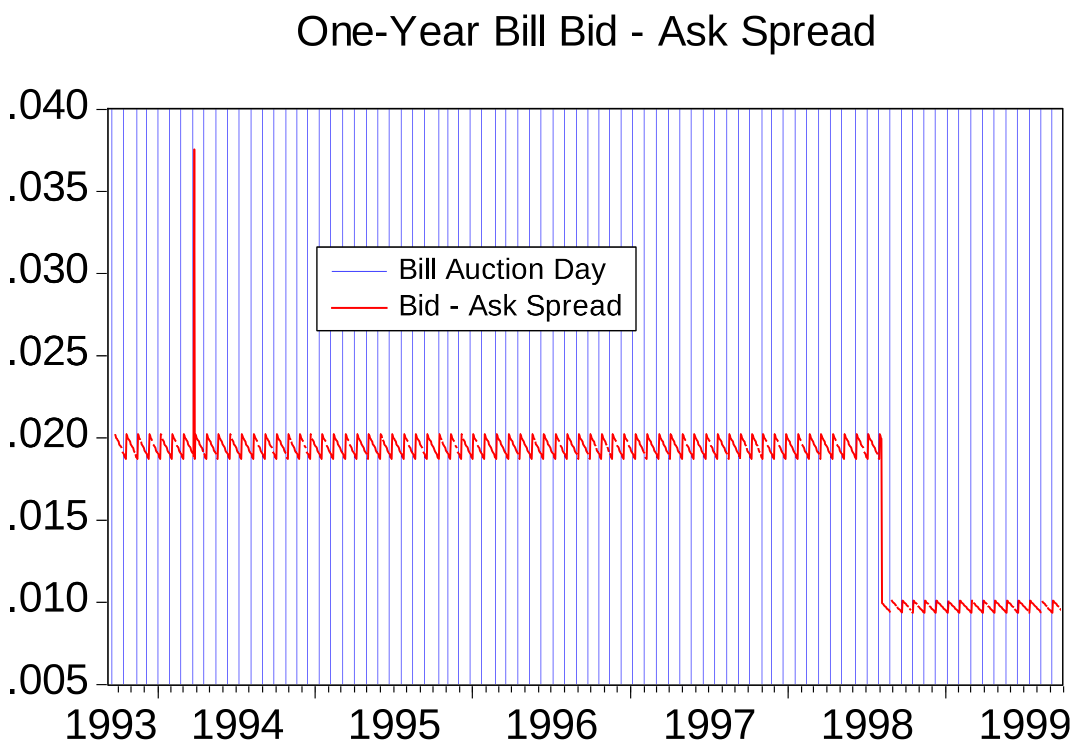
I. Treasury Auctions and Bid-Ask Spreads

Finally, I provide some graphical evidence to show how auctions and bid-ask spreads relate to one another and how this behavior varies across different maturities. The following set of graphics provides a sense of how bid-ask spreads vary over time in the Treasury market. The signature characteristic of the charts is clearly that bid-ask spreads vary very little in the US Treasury market. First I look at the 1-year bill and 5-year note charts.

Figure 1 shows a consistent "jigsaw" pattern in the time series path of the bid-ask spread that seems to vary almost entirely based on the auction schedule, with the transition from peak immediately following auctions, to trough on auction day. The vertical lines represent auction days.

This is a logical pattern consistent with increased supply cutting into dealer profits when new supply of securities is auctioned. However, we also notice occasional level shifts, as we see in the single transient spike in the early part of the decade, followed by a permanent shift in 1998, which may have coincided with either the LTCM crisis or the announcement that 1-year bills were on track to be eliminated due to lower borrowing needs during the economic expansion.

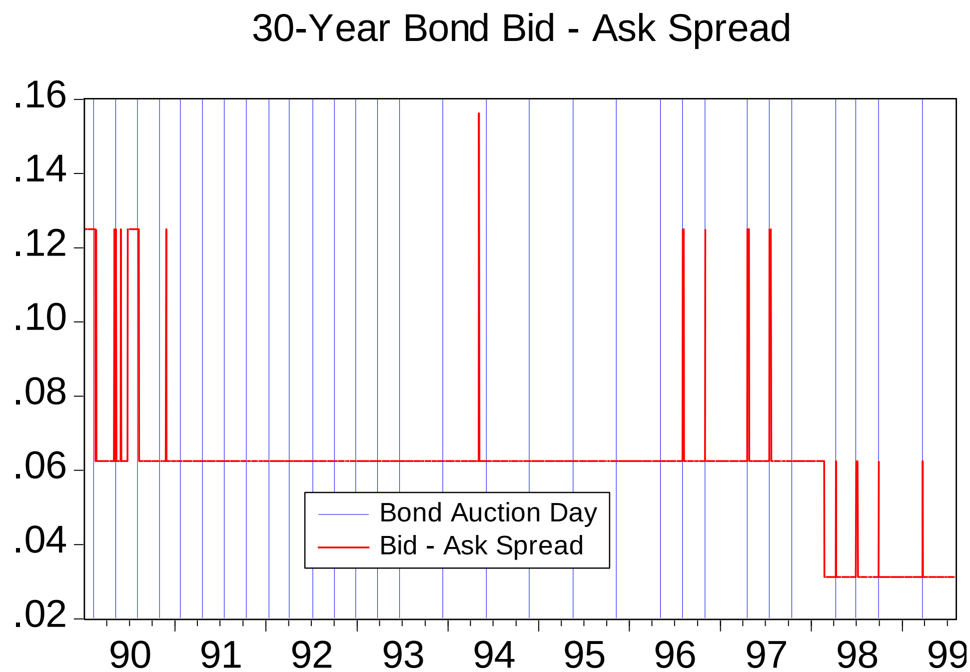
Figure 4.1



The results for the 1-year bill stand in stark comparison to that of the 30-year bond which is displayed in figure 4.2. No jigsaw pattern is associated with the auction schedule as the spread remains unchanged at the daily frequency for extended period of time. Auction frequency changes several times during the sample period and the number of transient spikes increases tremendously, with spikes appearing to be connected to the auction schedule.

Where the 1- and 30-year bear similarity is in that when a shift in the level occurs it is either a doubling of the spread or a cutting in half. Additionally the permanent level shifts both occur at end of sample. Note that the 30-year auction was also eliminated from the Treasury auction schedule.

Figure 4.2



What we can take from this is that the primary market auction schedule and the spreads charged by dealers in the secondary market appear to be closely connected. However, due to the depth and liquidity of the market disturbances to the bid-ask spread are short lived and episodic.

J. Conclusion

The 1990s presented a change of environment in terms of government budget deficits. Cuts in spending and increases in tax rates resulted in improvement on the budgetary front, eventually budget deficits gave way to surpluses by the end of the decade. This led to greater scarcity of Treasury securities.

In this study I examine the secondary-market response of U.S. Treasury rates, returns and bid-ask spreads to the release of details from the government's primary-market auctions during the 1990s. In our preliminary analysis, standard t-tests for differences in mean interest rate changes between auction and no-auction days show that returns differ significantly only for on-the-run 1-year bills and off-the-run 5-year notes. Longer maturities did not reveal differences in mean returns.

However, Brown and Forsyth's F-test of homogeneity of variance indicate no significant effects stemming from the existence of Treasury auctions. I am unable to reject the null hypothesis of homogeneous variance, even when partitioning the sample into auction-, announcement-, and "quiet" days. However, these results do not account for surprises in contemporaneous macroeconomic announcement effects, nor do they take into account the information content of the auction results. This strongly suggests that a more sophisticated analysis would be required to assess more carefully if Treasury auction operations represent a substantial source of disruption to the market.

I proceed by adopting a GARCH model to control for other important announcements including both macroeconomic reports and Federal Reserve target rate changes. In doing so, we are better-equipped to evaluate the significance of specific auction demand statistics and are able to compare the effects of Treasury fiscal policy funding operations to the Federal Reserve's monetary policy operations.

Specifically, I examine how the release of auction details affect US Treasury return movements based on both surprises in auction results (bid-to-cover ratios and volume of noncompetitive bids) and changes in issuance volume.

Consistent with my priors, I find a positive relationship between surprises in bid-to-cover ratios and returns on Treasury notes in three out of four maturities under investigation. The lone exception appears to be more of a function of modeling expectations of the 10-year note which was affected by changes in the auction schedule, as well as having relatively fewer auctions to base estimation on. Additionally, the effect of surprises on this ratio is largely of an equal order of magnitude to coefficients on standardized surprises of several key macroeconomic variables and actually greater than that of some widely followed announcements – such as: unemployment, retail sales and capacity utilization.

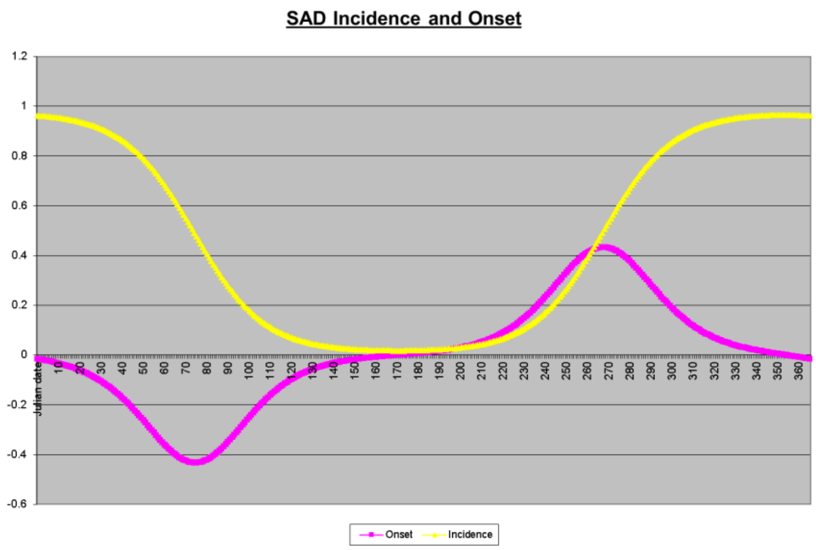
The volume of noncompetitive bids, on the other hand, offers little or no additional explanatory power. Only the 30-year Treasury bond appears sensitive to surprises in this auction statistic. However, that the benchmark 30-year bond coefficient on surprises in noncomps is greater than that of the bid-to cover ratio is notable. Clearly, surprises in auction demand statistics were most important on the long end of the yield curve. The fact that this maturity has the fewest auctions, yet achieves the most significant results underscores the relative importance at this maturity.

With respect to market volatility, I employ a GARCH model to characterize the effect of auction data on conditional variance. I find interest rate volatility to be largely unaffected by the Treasury auction process. By comparison, Federal Reserve policy announcements and quiet days – when no macroeconomic announcement or auction takes place – are shown to have a significant effect on volatility.

The results provide evidence that the U.S. Treasury's financing operations are conducted in a manner that exerts no more pressure on the market than that of most regularly-scheduled macroeconomic announcement. Further, I find the market to be more sensitive to FOMC policy surprises than Treasury operations.

APPENDICES

A. SAD Incidence and Onset



B. – 15 Notable No Announcement Days

15 Days of Bond Market Moves and No Macro Announcements

Sample: 1/1/1990-9/10/2001

	Returns				Spreads		Fed Funds	
Date	OTR 30 Yr Bond	FTR 30 Yr Bond	OTR 10 Yr Note	FTR 10 Yr Note	Change Treas 10-1	Change Baa-Aaa	Bp Chg. Actual	Bp Chg. Expected
2/20/1990	**-7.49**	**-7.50**	**-4.87**	**-4.56**	0.05	-0.02	0	0
8/6/1990	**-9.93**	**-9.80**	**-6.17**	**-6.09**	0.21	-0.02	0	0
8/20/1990	0.96	0.72	0.15	0.04	-0.03	0.07	0	0
10/9/1990	**-6.89**	**-6.75**	**-3.91**	**-3.80**	0.05	-0.01	0	0
11/5/1990	2.93	2.87	1.91	1.97	-0.05	0.09	0	0
8/21/1991	0.87	0.75	0.19	0.08	-0.16	-0.01	0	0
4/9/1992	3.59	3.51	2.06	2.16	0.15	-0.02	-25	-24
5/21/1992	-2.59	-2.51	**-3.40**	**-3.07**	-0.03	0.01	0	0
4/18/1994	**-4.94**	-4.56	**-4.21**	**-4.00**	-0.01	-0.02	25	10
12/8/1994	1.03	0.90	0.42	0.31	-0.18	-0.01	0	0
10/5/1998	0.15	**6.55**	0.40	0.15	-0.04	0.01	0	0
10/8/1998	**-14.81**	**-6.81**	**-9.81**	**-9.84**	0.34	-0.01	0	0
10/9/1998	**-8.00**	**-7.79**	**-5.96**	**-5.38**	0.16	-0.01	0	0
10/13/1998	0.22	2.11	0.17	0.14	-0.13	0.01	0	0
4/19/2001	**-6.90**	**-6.53**	**-4.18**	**-3.82**	0.16	0.00	-50	-43
Sigma r	2.33	2.29	1.53	1.47	0.04	0.02		

	Indicator Saturation Captured				Standardized Returns				Standardized Spreads	
Date	OTR 30 Yr Bond	FTR 30 Yr Bond	OTR 10 Yr Note	FTR 10 Yr Note	OTR 30 Yr Bond	FTR 30 Yr Bond	OTR 10 Yr Note	FTR 10 Yr Note	Change Treas 10-1	Change Baa-Aaa
2/20/1990	XS	XS	XS	XI	**-3.21**	**-3.27**	**-3.18**	**-3.09**	1.26	-1.19
8/6/1990	XI	XS	XS	XI	**-4.26**	**-4.27**	**-4.03**	**-4.14**	**5.29**	-1.19
8/20/1990					0.41	0.31	0.10	0.02	-0.76	**4.17**
10/9/1990	XS			XI	**-2.96**	**-2.94**	**-2.55**	**-2.58**	1.26	-0.60
11/5/1990					1.25	1.25	1.25	1.34	-1.26	**5.36**
8/21/1991					0.37	0.33	0.12	0.05	**-4.03**	-0.60
4/9/1992					1.54	1.53	1.34	1.47	**3.78**	-1.19
5/21/1992				XI	-1.11	-1.10	**-2.22**	**-2.09**	-0.76	0.60
4/18/1994	XI	XS	XS	XI	**-2.12**	-1.99	**-2.75**	**-2.72**	-0.25	-1.19
12/8/1994					0.44	0.39	0.27	0.21	**-4.53**	-0.60
10/5/1998					0.06	**2.86**	0.26	0.10	-1.01	0.60
10/8/1998				XI	**-6.35**	**-2.97**	**-6.40**	**-6.68**	**8.56**	-0.60
10/9/1998	XS	XS	XS	XI	**-3.43**	**-3.40**	**-3.89**	**-3.65**	**4.03**	-0.60
10/13/1998					0.09	0.92	0.11	0.09	**-3.27**	0.60
4/19/2001	XS	XS	XS		**-2.96**	**-2.85**	**-2.73**	**-2.60**	**4.03**	0.00
Saturation	IIS+SIS	SIS	SIS	IIS						
% Captured	40.0%	33.3%	33.3%	46.7%						

Shading indicates the LTCM Crisis
Bold indicates standardized returns greater than 2 standard deviations

Date	Headline/Market Comments	Source
2/20/1990	Foreign and domestic interest rate expectations	
8/6/1990	High inflation fear	Wall Street Journal/ New York Times
8/20/1990	Middle East issues	New York Times
10/9/1990	Rising oil prices, weakening dolar	New York Times
11/5/1990	Falling oil prices	New York Times
8/21/1991	Political coup in USSR	New York Times
4/9/1992	Decline in Federal funds rate	Wall Street Journal
5/21/1992	Credit markets were thrown into turmoil yesterday by an article in the WSJ suggesting that credit conditions would not be eased, and prices of Treasury securities fell sharply	New York Times
4/18/1994	Federal Reserve announced raise in short term interest rates to moderate the economy's growth and stave off inflation pressures	New York Times
12/8/1994	Continued concerns over impact of the bankruptcy of Orange County, California. Hints of fed raising short-term rates again because of signs of the economy improving.	New York Times
10/5/1998	Bond prices surge for biggest one day gain in over a year. Due to global stock market downfall us market affected reinforcing the demand for treasury securities.	New York Times
10/8/1998	Global market weakness boosts short maturities.	New York Times
10/9/1998	After shock of the Federal Reserve's $3.5 Billion bail-out. Worries about a global credit crunch and fears of American economy weakening. Collapsing hedge funds.	Wall Street Journal
10/13/1998	Cedent Corporation calls off a $3.1 Billion American Bankers deal causing all its own brand of stocks to drop. Merrill Lynch and Company eliminated 2,00 jobs in the US	Boston Herald
4/19/2001	Rate cut help auto and housing markets however borrowing costs for credit worthy companies still too high	New York Times

C. – Indicator Saturation FOMC Days 1990s References

FOMC Meetings and Indicator Saturation
99 FOMC Meetings of the 1990s

Date	FOMC Call or Meet	Fed Funds Change (bp)	Fed Funds FF_EXPECTED	Fed Funds FF_SURPRISE	Macro Announcement	OTR Bond 30-Year Return	FTR Bond 30-Year Return	OTR Note 10-Year Return	FTR Note 10-Year Return	OTR 30-Year Bond II Saturated	FTR 30-Year Bond SI Saturated	OTR 10-Year Note II Saturated	FTR 10-Year Note SI Saturated
2/7/1990	X	0	0	0		0.31	0.19	-0.04	0.08				
3/27/1990	X	0	0	0		-0.37	-0.62	-0.14	-0.04				
5/15/1990	X	0	0	0	X	-1.46	-1.27	-1.12	-1.04				
7/3/1990	X	0	-1	1		0.41	0.30	0.63	0.41				
7/13/1990	X	-25	-11	-14	X	1.51	1.52	1.07	1.19				
8/21/1990	X	0	0	0		-0.61	-0.48	-0.60	-0.58				
10/2/1990	X	0	-1	1	X	0.31	0.08	0.54	0.63				
10/29/1990	X	-25	-23	-2		-2.55	-2.28	-1.30	-1.48				
11/13/1990	X	0	4	-4	X	4.53	4.54	2.75	2.68				
11/14/1990	X	-25	-29	4	X	0.74	0.61	0.52	0.29				
12/7/1990	X	-25	2	-27	X	6.69	6.61	3.86	3.63	X			
12/18/1990	X	-25	-4	-21	X	1.23	1.15	0.85	0.72				
1/8/1991	X	-25	-7	-18		-1.92	-1.96	-0.58	-0.56				
2/1/1991	X	-50	-25	-25	X	4.85	4.73	3.02	2.81				
2/6/1991	X	0	4	-4		0.28	0.39	-0.03	0.08				
3/8/1991	X	-25	-9	-16	X	-2.99	-2.83	-1.31	-1.11				
3/26/1991	X	0	0	0	X	0.44	0.41	0.08	0.19				
4/30/1991	X	-25	-8	-17		1.60	1.68	1.23	1.04				
5/14/1991	X	0	-2	2	X	-2.97	-2.69	-1.53	-1.52				
7/3/1991	X	0	3	-3	X	0.78	0.91	0.31	0.42				
8/6/1991	X	-25	-10	-15		2.46	2.48	1.76	1.76				
8/20/1991	X	0	-3	3		0.76	0.64	0.76	0.74				
9/13/1991	X	-25	-20	-5	X	0.41	0.19	0.30	0.40				
10/1/1991	X	0	0	0	X	0.19	0.29	0.40	0.50				
10/31/1991	X	-25	-20	-5		-0.14	-0.03	0.40	0.61				
11/5/1991	X	0	-2	2	X	-2.67	-2.52	-1.24	2.10				
11/6/1991	X	-25	-12	-13		0.41	0.62	0.40	-2.47				
12/6/1991	X	-25	-16	-9	X	3.54	3.23	-1.15	-1.10				
12/17/1991	X	0	2	-2	X	0.96	1.04	0.85	0.82				
12/20/1991	X	-50	-22	-28	X	3.89	3.58	3.49	3.25			X	
2/5/1992	X	0	0	0		0.84	0.71	2.06	1.35				
3/31/1992	X	0	0	0	X	-0.47	-0.59	-0.04	-0.14				
4/9/1992	X	-25	-1	-24		3.59	3.51	2.06	2.16				
5/19/1992	X	0	0	0	X	2.20	2.02	2.09	1.76				
7/1/1992	X	0	0	0	X	1.18	1.25	0.95	0.63				
7/2/1992	X	-50	-14	-36	X	5.68	5.62	4.47	4.27				
8/18/1992	X	0	0	0	X	1.93	1.85	2.26	1.86				
9/4/1992	X	-25	-3	-22	X	3.65	3.62	3.63	3.21			X	
10/6/1992	X	0	-7	7		-3.01	-2.83	-1.62	-1.57				
11/17/1992	X	0	0	0		0.87	0.66	0.88	0.84				
12/22/1992	X	0	0	0	X	1.94	2.00	1.66	1.58				
2/3/1993	X	0	0	0	X	0.82	0.85	0.28	0.28				
3/23/1993	X	0	0	0		1.81	1.50	1.39	1.39				
5/18/1993	X	0	2	-2	X	-1.91	-1.84	-1.93	-1.81				
7/7/1993	X	0	0	0		0.07	-0.03	0.06	-0.05				
8/17/1993	X	0	0	0	X	-0.05	-0.46	-0.51	-0.16				
9/21/1993	X	0	-7	7	X	-3.15	-3.17	-1.27	-1.23		X		
11/16/1993	X	0	4	-4		0.17	0.37	0.95	0.92				
12/21/1993	X	0	0	0		-0.84	-0.55	-0.39	-0.48				
2/4/1994	X	25	13	12	X	-2.62	-2.27	-3.39	-3.05				
3/22/1994	X	25	28	-3	X	4.16	3.99	3.04	2.83				X
4/18/1994	X	25	15	10		-4.94	-4.56	-4.21	-4.00	X	X	X	X
5/17/1994	X	50	37	13	X	8.70	7.84	5.31	5.65	X	X	X	X
7/6/1994	X	0	5	-5	X	-0.58	-0.63	-0.04	0.06				
8/16/1994	X	50	36	14	X	5.09	5.09	2.93	2.77				
9/27/1994	X	0	20	-20	X	-2.03	-2.15	-0.74	-0.61				
11/15/1994	X	75	61	14	X	1.75	2.20	0.57	0.66				
12/20/1994	X	0	17	-17	X	-0.63	-0.61	-0.03	0.07				
2/1/1995	X	50	45	5	X	-1.30	-1.12	-1.35	-1.17				
3/28/1995	X	0	-10	10	X	-3.09	-3.22	-2.45	-2.24				
5/23/1995	X	0	0	0		2.23	2.31	1.67	1.55				
7/6/1995	X	-25	-24	-1		4.68	4.54	3.71	3.63			X	
8/22/1995	X	0	0	0		-0.96	-0.98	-0.73	-0.84				
9/26/1995	X	0	0	0	X	0.28	0.17	-0.49	0.06				
11/15/1995	X	0	-7	7	X	-0.25	-0.71	-0.70	-0.79				
12/19/1995	X	-25	-15	-10		2.62	2.33	1.30	1.24				
1/31/1996	X	-25	-18	-7	X	0.26	0.34	0.83	1.10		X		
3/26/1996	X	0	3	-3	X	-0.18	-0.48	0.42	0.06				X
5/21/1996	X	0	2	-2		-1.06	-0.83	-0.72	-0.54				
7/3/1996	X	0	6	-6		0.07	0.29	0.52	0.42		X		X
8/20/1996	X	0	4	-4	X	-0.05	-0.06	0.07	0.07				
9/24/1996	X	0	13	-13	X	1.47	1.37	1.51	1.51				
11/13/1996	X	0	0	0	X	-0.14	-0.28	-0.05	-0.08				
12/17/1996	X	0	-1	1	X	-1.53	-1.69	-1.11	-1.11				
2/5/1997	X	0	3	-3		-2.18	-2.29	-0.99	-0.89				
3/25/1997	X	25	22	3	X	-2.01	-2.00	-1.46	-1.05				
5/20/1997	X	0	11	-11		0.68	0.72	0.81	0.61				
7/2/1997	X	0	2	-2		1.48	1.43	0.94	1.00				
8/19/1997	X	0	1	-1		0.50	0.25	-0.11	0.17				
9/30/1997	X	0	0	0	X	-0.40	-0.42	-0.05	0.04				
11/12/1997	X	0	4	-4		2.59	3.07	1.45	1.55				
12/16/1997	X	0	1	-1	X	0.19	0.18	0.11	0.09				
2/4/1998	X	0	0	0		0.26	-0.16	0.11	0.11				
3/31/1998	X	0	0	0	X	2.08	2.09	1.67	1.66				
5/19/1998	X	0	3	-3	X	-0.51	-0.63	-0.29	-0.02				
7/1/1998	X	0	0	-1	X	0.00	0.02	0.05	0.31				
8/18/1998	X	0	-1	1	X	-0.36	-0.73	-0.55	-0.70				
9/29/1998	X	-25	-31	6	X	1.38	1.32	0.05	0.40		X		X
10/15/1998	X	-25	1	-26	X	6.73	2.07	8.51	8.50	X		X	X
11/17/1998	X	-25	-19	-6	X	-0.35	-0.02	-0.24	-0.18				
12/22/1998	X	0	2	-2		-4.18	-3.85	-1.80	-1.41				
2/3/1999	X	0	0	0		-0.74	-0.71	-0.75	-0.70				
3/30/1999	X	0	0	0	X	3.16	2.87	1.91	1.72				
5/18/1999	X	0	4	-4	X	0.21	0.11	-0.52	-0.58				
6/30/1999	X	25	29	-4	X	5.01	5.71	3.86	3.96	X	X	X	X
8/24/1999	X	25	23	2		2.74	2.74	1.87	1.99				
10/5/1999	X	0	4	-4		-4.56	-4.83	-2.70	-2.32				
11/16/1999	X	25	16	9	X	-1.63	-1.64	-1.02	-1.02				
12/21/1999	X	0	-2	2		-1.04	-1.20	-0.43	-0.44				

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