U.S. Treasury Market: the high-frequency evidence

PIERLUIGI BALDUZZI[1] and FABIO MONETA[2]

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ABSTRACT

This paper reviews the existing empirical evidence on the time-series behavior of the U.S. Treasury markets at *high frequency*: daily and intra-day data. The use of high-frequency data in econometric analyses is a major recent development in the study of the fixed income markets: the response of prices to scheduled and unscheduled news, conditional-volatility dynamics, and jump and diffusion behavior, can all be examined much more precisely with high-frequency data. High-frequency data are also important for the characterization of the trading environment as they allow us to examine the immediate impact of trading on prices and how this impact is affected by the presence of macro news. Lastly, the presence and impact of high-frequency trading can only be studied by analyzing high-frequency data.

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[1] Carroll School of Management, Boston College, 140 Commonwealth Avenue, Chestnut Hill, Massachusetts, 02467; Tel: (617) 552-3976; Fax: (617) 552-0431; email: balduzzp@bc.edu. [2] Queen's School of Business, Queen's University, 143 Union Street, Kingston, Ontario, Canada, K7L3N6; Tel: (613) 533-2911; Fax: (613) 533-6847; email: fmoneta@business.queensu.ca.

Introduction

This chapter reviews the existing empirical evidence on the time-series behavior of the U.S. Treasury markets at *high frequency*: daily and intra-day data. We believe that the use of high-frequency data in econometric analyses is a major recent development in the study of the fixed income markets, and has important implications for our understanding of how financial markets work. The response of prices to scheduled and unscheduled news, for example, can be examined much more precisely with high-frequency data, by isolating behavior within *narrow* windows surrounding the news releases.[1] The *instantaneous* adjustment to news is what we would expect in a rational, frictionless market. If we were to detect a sluggish response to news, on the other hand, then we would conclude that behavioral effects and/or transaction costs and limits to arbitrage play an important role in these markets.

One can also take advantage of high-frequency data in the study of conditional-volatility dynamics, by relating volatility to macro news and *intra-day* seasonal patterns, and by constructing realized-volatility measures that approximate the true volatility process as sampling becomes more frequent. In addition, jump and diffusion behavior becomes easier to separate at high frequency.

High-frequency data are also important for the characterization of the trading environment. For example, researchers are able to investigate how liquidity changes during the trading day and around news releases. By using high-frequency data it is also possible to examine the immediate impact of trading on prices and how this impact is affected by the presence of macro news.

Moreover, bond risk premia can be better estimated using high-frequency data. It is possible to distinguish between days with and without macro news announcements, and, within announcement days, between volatile price behavior surrounding announcements and behavior further away from the announcements. This allows us to better understand the way bond risk premia are earned: e.g., the possible time-variation of conditional risk premia vs. the constant risk premia implied by the expectation hypothesis (EH), and the

[1] Andersen et al. [3], for example, show that the response to US macroeconomic news is stronger in the bond market than in the equity and foreign exchange markets.

possible compensation for macro risks.

Lastly, the advent of high-frequency trading (HFT) in several markets—including the fixed income markets—has attracted a great deal of attention.[2] By definition, the presence of HFT can only be identified by analyzing high-frequency data.

Indeed, several studies using high-frequency data for the U.S. Treasury markets have appeared during the last two decades and this is an ideal moment to review them. This is a *selective* review, though, which emphasizes what *we* think are the most important issues when looking at the Treasury markets through a "high-frequency lens." Our up-front apology is offered to any researchers whose papers we have omitted.

The U.S. Treasury market is one of the largest and most important financial markets in the world. Having a better understanding of how this market works is obviously important to practitioners–the main target audience of this review. Specifically, we believe that the studies reviewed in this chapter are relevant for the management, hedging, and pricing of Treasury securities and the many other instruments that are benchmarked against the Treasury yield curve, and also for trading and implementation strategies.

In our review, we start with motivating evidence on the behavior of the U.S. Treasury market during the recent financial crisis. We then focus on literature covering the following four topics: i) the reaction of prices and rates to macroeconomic news; ii) market micro-structure effects; iii) bond risk premia; and iv) the effects of high frequency trading.[3,4] Each section concludes with a brief summary of the main results reviewed.

[2] On June 17, 2014, for example, Bradley Katsuyama testified in front of a Senate panel on the impact of HFT on the equity markets. Katsuyama cited market instability (e.g., the 2010 "flash crash"), co-location (high-speed traders gaining trading-time advantage by placing their computer servers as close as possible to trading venues), and conflicts of interest (e.g., fees that trading venues pay brokers to execute transactions on their platforms) as troubling HFT-related developments. Katsuyama had gained notoriety as the main character in Lewis [64], which chronicles the "discovery" of HFT on the part of Katsuyama and his team at the Royal Bank of Canada. In the wake of the publication of Lewis [64] in March, 2014, several regulatory agencies disclosed that they were taking action against HFT firms.

[3] There are also studies formulating and testing models of the term structure of interest rates at high frequency (weekly and daily data), such as Rudebusch [77], Balduzzi et al. [4], Farnsworth and Bass [34], Piazzesi [74], and Lu and Wu [68]. These studies are beyond the scope of this review.

[4] The review of studies of HFT in the bond markets could have been incorporated in the other three sections. Yet, the recent interest in the effects of HFT has prompted us to dedicate a separate section to the topic. We expect that future editions of this chapter will devote even more space to this important trend.

1 The U.S. Treasury markets during the financial crisis

It is well-known that the financial crisis brought about disruption throughout the fixed income markets. In addition, the Federal Reserve took some unprecedented actions, some of which directed specifically at the Treasury market. Hence, it is natural to ask if and how the U.S. Treasury market was affected. As a first step in addressing this question, we provide a description of several features of the U.S. Treasury markets (cash and futures), during a sample period inclusive of the financial crisis. Specifically, we focus on yields, price volatility, the on-the-run/off-the-run yield spread, trading volume and price impact, settlement fails, and the intra-day price behavior on March 18, 2009.

1.1 Yields

Figure 1 presents the daily behavior of the Fed funds rate target, the three-month T-bill rate, and the ten-year note yield.[5] In this, as well as in the remaining figures, the following dates are highlighted:

1. July 31, 2007: Bear Stearns liquidates two mortgage-backed securities funds—the crisis "begins."

2. January 22, 2008: In an intermeeting conference call, the FOMC votes to reduce its target for the federal funds rate 75 basis points, to 3.5 percent.

3. March 17, 2008: First trading day after Bear Stearns was sold to JPMorgan Chase.

4. September 15, 2008: Lehman Brothers Holdings Incorporated files for Chapter 11 bankruptcy protection.

5. November 25, 2008: The Federal Reserve Board announces the creation of the Term Asset-Backed Securities Lending Facility, under which the Federal Reserve Bank of New York will lend up to $200 billion on a non-recourse basis to holders of AAA-rated asset-backed securities and recently

[5] The Fed funds rate target is from the Federal Reserve Bank of New York, whereas the T-bill rate and the ten-year note yield are the constant-maturity series from the U.S. Department of the Treasury.

originated consumer and small-business loans. The Federal Reserve Board also announces a new program to purchase direct obligations of housing-related government-sponsored enterprises (GSE)—Fannie Mae, Freddie Mac and Federal Home Loan Banks—and mortgage-backed securities (MBS) backed by the GSEs.

6. December 16, 2008: The FOMC votes to establish a target range for the effective federal funds rate of 0 to 0.25 percent.

7. March 18, 2009: The FOMC decides to increase the size of the Federal Reserve's balance sheet by purchasing up to an additional $750 billion of agency MBSs, bringing its total purchases of these securities to up to $1.25 trillion this year, and to increase its purchases of agency debt this year by up to $100 billion to a total of up to $200 billion. The FOMC also decides to purchase up to $300 billion of longer-term Treasury securities over the next six months to help improve conditions in private credit markets.

8. June 24, 2009: The Fed announces extensions of and modifications to a number of its liquidity programs—the crisis "ends."

Figure 1 about here

The figure highlights the "leading" behavior of the U.S. Treasury markets: as early as July 2006, both the T-bill rate and the T-note yields were trading *below* the overnight Fed funds rate target (5.25 percent). Indeed, the T-bill rate plots below the Fed funds rate target throughout most of the crisis period, into January 2009. In addition, the ten-year T-note rate was trading below the three-month T-bill between July 2006 and May 2007, leading to an *inverted* yield curve during that period.

Also noteworthy are the dramatic reductions in the three-month rate between September 12 and September 17, 2008 (from 1.49 to 0.03 percent); and in the ten-year yield between October 14 and December 18, 2008 (from 4.08 to 2.08 percent), and between March 17 and March 18, 2009 (from 3.02 to 2.51 percent).

These reductions are associated with episodes of flight-to-quality (during September 2008, after Lehman Brothers filed for bankruptcy), cuts in the Fed funds target rate (on December 16, 2008, the target was cut to a historically low level), and the Federal Reserve's large-scale asset purchases (on March 18, 2009, the Fed decided to start to buy long-term Treasury securities), respectively.

1.2 Volatility

Figure 2 presents the annualized 24-hours realized volatility of the ten-year note futures contract, based on intra-day five-minute returns.[6] The figure highlights an increase in volatility during the financial crisis, with the highest spike on March 18, 2009 (40 basis points, annualized). Interestingly, realized volatility remains somewhat higher and substantially more volatile well *after* the end of the financial crisis, with pronounced spikes on May 6, 2010, and August 9, 2011.[7]

Figure 2 about here

1.3 Off-the-run/on-the-run yield spread

Figure 3 highlights the behavior of the off-the-run/on-the-run spread for ten-year securities.[8] This liquidity indicator seems to track very well some of the salient episodes during the financial crisis. The spread quickly increases from zero to 18 basis points between June 12 and August 20, 2007, and spikes on March 17, 2008, to 41 basis points. In the aftermath of the Lehman default, the spread climbs from 40 basis points (9/15/2008) to an overall peak of 91 basis points (11/3/2008). The spread then follows a downward trend,

[6] Daily realized volatility is calculated as,

$$RV_t = \sqrt{250} \times 100 \times \sqrt{\sum_{n=1}^{N} r_{nt}^2},$$

where r_{nt} denotes five-minute continuously compounded returns during the 24-hours trading day.

[7] May 6, 2010, is the day of the "flash crash" when the Dow Jones Industrial Average experienced the greatest intra-day point decline (almost 1000 points). On August 9, 2011, a Federal Reserve's statement indicated plans to keep "exceptionally low" interest rates in place until at least mid-2013.

[8] The ten-year *off-the-run* par-yield series is computed by Gürkaynak et al. [49] from the CRSP daily U.S. Treasury file, and updated by the Board of Governors of the Federal Reserve. The ten-year *on-the-run* yield is calculated by the authors, also based on the CRSP daily U.S. Treasury file.

with a substantial reduction between March 17 (60 basis points) and April 2 (42 basis points).

1.4 Trading volume and price impact

In Figures 4 and 5, we present the behavior of weekly trading volume in the inter-dealer market as well as the (standardized) Amihud illiquidity measure (Amihud [1]), for the T-bill sector, and for the T-note and T-bond sector around the ten-year maturity.[9,10]

Figure 4 about here

Figure 5 about here

Trading volume in the T-bill sector is generally upward trending and displays higher volatility during the crisis. In the notes and bonds sector, on the other hand, trading volume trends downwards, during the crisis, and upwards, after the crisis. The illiquidity measure displays pronounced volatility during the crisis, for both T-bills and notes and bonds. The T-bill illiquidity measure exhibits the most pronounced spikes during the first year of the crisis, with the highest increase during the week that includes January 22, 2008, when the Fed fund rate target was cut by 75 basis points. Especially apparent, in the case of T-bills, is also the reduction of the level and volatility of the illiquidity measure after December 16, 2009. The T-bond/T-note illiquidity measure, on the other hand, exhibits the largest spikes during the second year of the crisis, especially after the Lehman Brothers bankruptcy.

[9] The data on inter-dealer trading volume is from the Federal Reserve Bank of New York. The series presented in the figures are de-seasonalized, to eliminate end-of-the-year effects.

[10] The Amihud measure is calculated as the absolute value of the weekly change in yield, divided by weekly trading volume. For the T-bill sector, we use the six-month T-bill rate; for the T-note and T-bond sector, we use the ten-year yield. For ease of interpretation, the illiquidity measure is de-meaned and standardized. Goyenko et al. [45] demonstrate the usefulness of the Amihud measure as a measure of price impact, in the context of equity trading.

1.5 Fails

A "fail" is a transaction that did not settle. Figure 6 reports the weekly dollar value (in $ millions) of transactions in the U.S. Treasury market that failed to settle.[11] Settlements fails had been observed prior to the financial crisis—most notably, after September 11, 2001, as a result of the destruction of market infrastructure. Yet, the financial crisis brings about some dramatic spikes in the dollar amount of fails. In particular, during the week ending on October 22, 2008, the dollar volume of fails reaches $2.683 trillion. For a comparison, during the week ending on September 19, 2001, settlement fails amounted to "only" $1.330 trillion.

Figure 6 about here

As discussed by Fleming and Garbade [39], fails are typically caused by the inability/unwillingness of the *seller* to deliver the securities. The main incentive for a seller to avoid a fail is the interest that could have been earned on the transaction proceeds, proxied by the fed funds or general collateral (GC) repo rate. In turn, the cost of avoiding a fail is the cost of borrowing the securities to be delivered. Note that securities are borrowed by first borrowing cash though a repo, at the GC repo rate, and then by lending cash and borrowing securities through a *reverse* repo, at the special repo rate. Hence, the cost of borrowing securities is the differential between the GC and special repo rates. As special repo rates approached zero, as they did during the financial crisis, the GC/special repo rate differential approaches the GC rate itself, the incentive to borrow securities to avoid failing declines.[12]

[11] The series is available from the Federal Reserve Bank of New York and covers settlement fails on the part of dealers. The Federal Reserve Bank of New York reports separately "fails to deliver" and "fails to receive." If a transaction between two dealers fails to settle, it is counted as both a fail to deliver and a fail to receive. If a transaction between a dealer and a customer does not settle, it is counted only as a fail to deliver or a fail to receive. We report the series of fails to deliver. The series of fails to receive behaves in an almost identical similar way, as the vast majority of settlement fails are for interdealer transactions. A transaction is counted as a fail for each day that it does not settle, including nontrading days. The fails series includes both outright and financing transactions (repos).

[12] Note that, in May 2009, the Treasury Market Practices Group introduced a "dynamic fails charge" incentivizing timely settlement; see Garbade et al. [44].

1.6 Intra-day evidence on March 18, 2009

At 2:20 P.M. (ET) on March 18, 2009, the Fed announced a program of outright purchases of Treasury securities, in addition to other securities. As noted earlier, this announcement brought about a substantial adjustment in rates and prices. In Figure 7, we present the intra-day price behavior of the 30-year T-bond and ten-year T-note futures prices on that day, together with the five-minute tick count for the T-note futures contract.

Figure 7 about here

Both futures prices adjust very quickly to the new information, with a surge in tick count for the T-note, and some evidence of over-reaction for the T-bond contract. There is also a moderate increase in both prices during the morning, relative to overnight values, together with an increase in the T-note tick count.[13]

1.7 Summary

The main findings of our review of market indicators during the crisis highlight the following stylized facts:

- Treasury rates, the three-month T-bill rate, in particular, seem to anticipate the drastic reductions in the Fed funds target rate implemented during the 2007–2008 period.
- Intra-day price volatility increases and becomes more volatile with the crisis, but the level and volatility remain elevated well after the end of the crisis.
- The off-the-run/on-the-run spread tracks well the salient episodes of the crisis, and also persists at elevated levels after the end of the crisis.
- The price impact of trades increases and becomes more volatile with the crisis for both the T-bill and T-note markets, although following different patterns. For the T-bill sector, the level and volatility of

[13] Some of the morning activity could be explained by some traders anticipating the Fed decision. Indeed, on December 1, 2008, Chairman Bernanke had delivered a speech indicating that "the Fed could purchase longer-term Treasury or agency securities on the open market in substantial quantities." (Bernanke, Ben S., "Federal Reserve Policies in the Financial Crisis." Speech at the Greater Austin Chamber of Commerce, Austin, Texas, December 1, 2008.)

price impact revert to values *below* those of the pre-crisis period after the crisis, whereas they remain at a somewhat higher level for longer maturity Treasuries.

- Settlement fails increase and become more volatile during the crisis, likely as a result of the increased cost of borrowing Treasury securities.

- The adjustment to the March 18, 2009, announcement of the Fed's Treasury purchase program is a good example of almost instantaneous reaction to the release of "unexpected" news.[14]

The evidence summarized above naturally prompts several questions on the behavior of the U.S. Treasury markets. For example:

- How efficient are the U.S. Treasury markets in incorporating information on future interest rate behavior and Fed policy?

- What are the factors behind the time varying volatility of bond returns?

- How important are jumps?

- What affects bond market liquidity?

- Overall, what is the role of macro news in affecting all the above variables?

- Is HFT partly responsible of the surge in trading activity after important announcements?

It is to these questions that we turn next, starting with the response to the release of scheduled macro news.

2 The reaction of bond prices and interest rates to macroeconomic news

This section reviews studies of the impact of macro news (i.e., the surprise component of scheduled macroeconomic announcements such as Nonfarm Payrolls and CPI). We first discuss *level* effects: the impact of

[14]The FOMC meeting was a regularly scheduled meeting, but the announcement of Treasury purchases was *unexpected*.

macro announcements on the prices of U.S. Treasury securities. We then turn to *volatility* effects: general volatility patterns associated with macro news, the effect of macro news on implied volatilities, ARCH and GARCH effects, and the presence of jumps. Note that the response of the U.S. Treasury bond markets to macro news is an ideal "laboratory" to test the informational efficiency of financial markets: i) macro news are public; ii) the timing of the release of macro news is known in advance and there is no evidence of leakages; iii) macro variables are recognized as the main determinants of Fed decisions and the future path of short-term rates; and iv) if we focus on a small window around the announcements, the price change is likely to reflect exclusively the causal impact of the news.

2.1 Level effects

Balduzzi et al. [5] examine the impact of 26 U.S. macroeconomic announcements on Treasury prices, using intra-day data from GovPX for the 7/1/1991–9/29/1995 sample period.[15] The four securities examined are the *on-the-run* three-month T-bill, two-year T-note, ten-year T-note, and a 30-year T-bond. Separately for each announcement k, they estimate the model

$$R_t = \alpha_k + \beta_{1k} S_{kt} + \sum_{j=1}^{J} \beta_{2j} S_{jt} + \epsilon_t, \tag{1}$$

where R_t is the intra-day announcement-window return—from five minutes *before* to 30 minutes *after* the announcement—during day t, S_{kt} is the (standardized) surprise component of announcement k, and S_{jt} is the surprise component of concurring announcements. Money Market Services (MMS) forecasts are used to derive the surprise component of the different macro releases.[16]

[15]GovPX is a service collecting and disseminating price information from the brokered *voice* market for Treasury securities. With the only exception of Jiang et al. [59], all the studies of intra-day behavior in the cash market reviewed in this chapter use the GovPX data set. One earlier study using the GovPX data to analyze the effect of macro news on Treasury prices is Fleming and Remolona [42], who consider the 8/23/1993–8/19/1994 sample period. They find that each of the 25 sharpest price changes in the price of the on-the-run five-year T-note during that period can be associated with a just-released announcement.

[16]Since the beginning of the 1980s, MMS surveyed around 40 market participants weekly (every Friday, except on holidays) for their forecasts of major economic indicators. MMS was acquired by Informa in 2003 and no longer exists; Action Economics is now providing the same survey service.

Their main results can be summarized as follows. First, 17 news releases have a significant impact on the price of at least one of the four securities. Second, these effects vary significantly according to maturity. While nine announcements affect the price of the T-bill, 13 announcements affect the price of the two-year note, 16 announcements affect the price of the ten-year note, and ten announcements affect the price of the 30-year bond.[17] For the ten-year note, the largest significant effect is for Nonfarm Payrolls (-16 basis points for a one standard deviation surprise), whereas the smallest significant effect is for the money-supply measure M2 (-1.1 basis points). Third, macro surprises explain a substantial fraction of price volatility in the aftermath of announcements: the R^2 of the regression model in (1) is as high as 56.7 percent when the authors focus on the response to the employment report. Moreover, the adjustment to news generally occurs within one minute after the announcement. Indeed, for the ten-year note, out of 16 significant announcements, only six impact prices beyond one minute after the release, and none after 15 minutes.[18,19] While the level effect of macro news is exhausted quickly, heightened volatility persists for up to 60 minutes.[20] In summary, the two main messages of this study are that macro news matter for bond prices; and that the bond markets are remarkably efficient at incorporating new information, as exemplified earlier in Section 1.6 with the reaction to the March 18, 2009, Fed announcement. In other words, market participants typically reach very quickly a consensus on what macro news imply for the future trajectory of short-term rates and the future compensation for interest rate risk.[21]

[17] Gürkaynak et al. [48] focus on *forward rates* to better gauge the reaction to macro announcements of yields of different maturity. They use daily data on one-year forward rates, one, five, and ten years forward, for the sample period from January 1990 to December 2002, to evaluate the response to 13 types of macro news and to monetary policy surprises. They find several significant responses as far out as the ten-year forward date.

[18] The speed of adjustment is estimated by regressing returns from τ to 30 minutes after the announcement on the announcement surprises, for different values of τ. The adjustment is complete after τ minutes if the announcement surprise is no longer significant.

[19] This result is in partial contrast with Becker et al. [10] who analyze T-bond futures data for the sample period from November 8, 1988, to December 28, 1990, period. They find evidence of *under-reaction* to news about the consumer price index (CPI): the T-bond futures price systematically responds in the same direction in two of the ensuing 15-minute intervals, until 9:45. In addition, there is evidence of a reversal in the direction of movement of T-bond prices between two and three hours after the CPI news is released. Furthermore, the response to news about the merchandise trade balance is delayed by 15 minutes.

[20] The authors also examine some microstructure effects. They find that trading volume increases immediately after the announcements and persists also for up to 60 minutes; whereas bid-ask spreads widen at the time of the announcements, but then revert to normal values after five to 15 minutes. More discussion of high-frequency microstructure effects can be found in Section 3.

[21] Note that Ederington and Lee [29] refine this result; see Section 2.3. Also note that the advent of HFT is likely to have further accelerated the price response to news in recent years.

In addition to analyzing jump behavior (reviewed later on in this section), Beber and Brandt [9] also study the effect of macro announcements on bond returns. They use daily data on T-bill, T-note, and T-bond futures, for the February 1980–December 2003 sample period, where the macro announcements being considered are the CPI, the Unemployment Rate, the PPI, and Nonfarm Payrolls. The authors employ a regression specification that allows for an *asymmetric* impact of good and bad macro news during different phases of the business cycle,

$$\begin{aligned} R_t &= \alpha_k + \beta_{1k}(1 - X_t)S_{kt}^{+} + \beta_{2k}(1 - X_t)S_{kt}^{-} \\ &\quad + \beta_{3k}X_t S_{kt}^{+} + \beta_{4k}X_t S_{kt}^{-} + \epsilon_t, \end{aligned} \tag{2}$$

where X_t is a business-cycle indicator and S_{kt}^{+} (S_{kt}^{-}) equals the surprise component of the k-th announcement, when the surprise is positive (negative), and equals zero otherwise.

The authors find that announcements are most important when they contain *bad* news for the bond market in *expansions* and, to a lesser extent, good news for the bond market in contractions. The strongest response to bad news is in the release of Nonfarm Payrolls during expansionary periods. This effect is significant at all maturities. The documented asymmetry in price responses is important because it is consistent with a perceived *asymmetric* Fed reaction function, by which positive economic news induce a strong increase in the likelihood of higher future target rates, in expansions, but only a marginal increase, in contractions. In such a setting, the response of bond prices to macroeconomic news depends critically on *both* the content of the news *and* on the phase of the business cycle.

2.2 The impact of monetary policy

The studies reviewed above have not considered Federal Open Market Committee (FOMC) announcements of changes in the stance of monetary policy, as captured by changes in the Fed funds rate target.[22] In

[22]An earlier study of the effect of changes in the Fed funds rate on Treasury rates during the 1974–1979 period is Cook and Hahn [24]. Cook and Hahn [23], on the other hand, study market reactions to changes in the Fed's *discount* rate. More recently,

addition, the Fed, through its open market operations, can directly convey to the markets the stance of monetary policy. The next three articles present evidence on the reaction of the Treasury markets to changes in monetary policy.

Kuttner [63] uses daily data on yields on bills, notes, and bonds, to estimate the effect of target changes on interest rates. The sample covers the 6/6/1989–2/2/2000, period, for a total of 42 changes in Fed funds rate target. One key element of the analysis is the use of daily changes in the fed funds futures rate to measure the unexpected component of the target change,[23]

$$\Delta r^*_{ft} - E_{t-1}(\Delta r^*_{ft}) = \frac{m}{n_t}\Delta f_t, \tag{3}$$

where r^*_{ft} is the target, m is the number of days in the month, n_t is the remaining number of days in the month, and f_t is the spot month's fed funds futures rate.[24] Note that f_t can be viewed as the market's time-t expectation of the average fed funds rate for the current month. The author then regresses Treasury bond-rate changes on unanticipated target changes, finding significant responses at all maturities, albeit decreasing with maturity and ranging from 0.2 (30-year bond) to 0.8 (three-month bill).[25]

Harvey and Huang [51] examine intra-day volatility patterns in the bond futures markets, as they relate to the Fed's open market operations. The analysis uses data for the 1982–1988 sample period.[26]

Gürkaynak et al. [47] examine the intra-day effect of monetary policy announcements from January, 1990, through December, 2004, finding that in addition to changes in the Fed funds rate target, Treasury yields also respond to a "path" factor, which they relate to soft information contained in FOMC statements. van Dijk et al. [80] find that macro news, central bank officials' speeches, and congressional testimony significantly impact the volatility of *expected* Fed funds rate targets, using daily data for the 7/31/2001–9/30/2008 sample period. Expected Fed funds rate targets are constructed using Fed funds futures prices, as in Kuttner [63].

[23] A similar approach to the identification of monetary policy shocks is used by Faust et al. [36] in the context of a standard VAR.

[24] This is the contract that settles based on the current month's *average* Fed funds rate.

[25] Rigobon and Sack [76] note that the change in the expected average fed funds rate could, in turn, be affected by the behavior of bond yields. In other words, there may be a simultaneous-equation bias affecting the estimates of the impact of target changes on interest rates. Hence, the authors use an identification-through-heteroskedasticity approach—see Rigobon [75] for details—to estimate the impact of target-change shocks on interest rates. Studying the sample 1/3/1994–11/26/2001, they find that the estimated response of rates on far-dated Eurodollar futures contracts is much reduced after correcting for the simultaneous-equation bias. A similar approach to identification has been used recently by Wright [82] to estimate the effect of monetary policy shocks during a recent sample when the Fed funds rate has been kept essentially at the zero lower bound.

[26] Fleming and Piazzesi [41] also use intra-day data, but they focus on FOMC announcements, during the more recent 1/1/1994–12/31/2004 sample period. They find that the impact of target-change surprises is conditional on the slope of the yield curve

For both T-bill and T-bond futures contracts, volatility during the 11:30 A.M.-12:00 P.M. Eastern Time (ET) interval ("Fed Time") is higher than during the prior and following one-hour intervals. For example, for the T-bill contract, volatility first increases from 0.99 basis points to 2.06 basis points, and then decreases to 1.62 basis points, going from 10:30–11:30 to 11:30–12:30, and 12:30–1:30. Interestingly, though, Fed Time volatility is generally higher when there are no open market operations (OMO) than on days with OMOs, consistent with Fed actions smoothing market expectations. In addition, the average returns often go in the *opposite* direction of the effect of the OMOs: for example, negative returns are observed for every year in the sample for the T-bond contract, for reserve-adding operations. This is consistent with the market being unable to decode Fed policy targets from Fed's actions.

Fama [32] replicates the analysis of Kuttner [63], using daily data on bill, note, and bond yields, for the 9/27/1983–12/31/1993 and 1/3/1994–12/16/2008 sample periods. During the first sample period, target changes had to be inferred from open market operations; during the second sample period, on the other hand, the Fed publicly announced target changes. The unexpected component of a target change is computed here as the difference between the new target and the previous day's commercial paper rate. During the first sample period, both short-term and long-term rates respond significantly to unexpected target changes. During the second sample period, on the other hand, it is only short-term rates to be affected.

The author argues that the evidence above can be interpreted as supportive of the notion that the Fed controls interest rates. This interpretation, though, is tempered by: i) the fact that the responses of rates to unexpected target changes are smaller at longer maturities; and ii) the fact that unexpected target changes are a small part (17 percent) of the variance of total target changes. Moreover, one can argue that the Fed is an informed agent with private information about how market rates will evolve and uses this information when it changes the target. It is then rational that rates respond to unexpected changes in the target, even when the Fed does not seek to affect rates.

(ten-year minus three-month yield): a steeper yield curve reduces the impact of target-change surprises.

2.3 Realized-volatility patterns

While the previous two sections have focused on the immediate price response to macro news, this section turns to volatility patterns induced by macro news. Essentially, there are two aspect of volatility dynamics that have caught the attention of researchers. First, there is an obvious "burst" in volatility at announcement times, as a result of the immediate reaction of prices to news. Second, volatility may persist at heightened levels as market participants further adjust their views on the economic implications of the just-released economic quantities. The relative importance of the two effects sheds further light on the informational efficiency of the U.S. Treasury market.

Ederington and Lee [28] document that macroeconomic announcements are responsible for most of the time-of-day and day-of-the-week volatility patterns in the U.S. Treasury markets. Focusing on the 11/7/1998–11/29/1991 sample period, the authors first note that prices in the T-bond (futures) markets are much more volatile between 8:30 and 8:35 A.M. ET than during any other five-minute trading period, including the five minutes following the market open (8:20 A.M.) and preceding the market close (3:00 P.M.). Indeed, the standard deviation of 8:30 to 8:35 returns is approximately 2.5 times the next highest five-minute return standard deviation. Since several major macroeconomic statistical releases, including the employment report, the CPI, the PPI, Gross National Product (GNP), the index of leading indicators, and the merchandise trade deficit, are released at 8:30 A.M., these releases are obvious candidates for explaining the pattern. In addition, when the authors control for these announcements, volatility is basically flat both across the trading day and the trading week.

The authors then examine the impact of the announcements using the regression model,

$$|r_{nt} - \bar{r}_n| = \alpha_n + \sum_{k=1}^{K} \beta_{kn} I_{kt} + \epsilon_{nt}, \tag{4}$$

where r_{nt} is the log return during the n-th five-minute interval on day t; $\bar{r}_n$ is the average return for interval n across all days; and I_{kt} is a dummy variable, which equals one if announcement k is released on day t, and equals zero otherwise. The regression model above is estimated separately for each of the five-minute intervals. The following *seven* announcements (listed in order of decreasing impact) have a significant (0.005 p-level) effect on the T-bond futures prices: employment report, the PPI, the CPI, durable goods orders, industrial production-capacity utilization, construction spending-National Association of Purchasing Managers (NAPM) survey, and the federal budget.[27] More importantly, after controlling for these announcements, volatility is basically flat both across the trading day and the trading week.

The authors also explore the speed at which the market adjusts to these news releases, focusing on both market efficiency (serial correlation of returns) and volatility. The major price adjustment occurs within *one minute* of the release and the direction of subsequent price adjustments is basically independent of the first minute's price change. Nonetheless, prices continue to be considerably more volatile than normal for roughly 15 minutes, and slightly more volatile for several hours.

The analysis of Ederington and Lee [28] is taken one step further by Ederington and Lee [29], who focus on the T-bond futures price adjustment *immediately* following the releases, using both ten-second interval returns and tick-by-tick data for the 11/7/1988–10/30/1992 sample period. The authors find that prices adjust almost immediately following a news release—generally within the first *ten seconds*. The price adjusts in a series of small, but rapid, price changes, and the major adjustment to the initial release is basically complete within 40 seconds after the release. There is weaker evidence that the market tends to overreact in this first 40 seconds, and that a small correction occurs in the second or third minute following the release. Volatility remains higher than normal after three minutes. However, consistent with the findings of Ederington and Lee [28], these later price adjustments are independent of the initial price change.

[27] Since 2002 the NAPM survey is called Institute for Supply Management (ISM) survey.

2.4 Macro news and option-implied volatilities

The section above focused on the impact of macro news on *realized* bond volatility. The articles reviewed in this section, on the other hand, examine the relations between macro news and *implied* volatilities and other indicators derived from option prices.[28] In this way we can assess whether macro announcements also have an impact on the volatility *expected* by market participants.

Ederington and Lee [30] focus on the prices of futures options, where the measure of market uncertainty is the implied standard deviation (ISD). The ISD is the value of σ_t obtained from Black's [12] model for futures options,

$$C_t = \exp\left(-r_{ft}T_t\right)[F_t N(d_{1t}) - EN(d_{2t})], \tag{5}$$

and

$$\begin{aligned} d_{1t} &= [\ln(F_t/E) + \sigma_t^2 T_t/2]/(\sigma_t\sqrt{T_t}) && (6)\\ d_{2t} &= d_{1t} - \sigma_t\sqrt{T_t}, && (7) \end{aligned}$$

where C_t is the call price, r_{ft} is the instantaneous riskless rate, T_t is the time to expiration, F_t is the futures price, $N(.)$ is the cumulative normal distribution, and E is the exercise price. The impact of macro announcements on ISDs is evaluated through the regression model:

$$\ln(\sigma_t/\sigma_{t-1}) = \alpha + \sum_{k=1}^{K} \beta_k I_{kt} + \epsilon_t. \tag{8}$$

The analysis is performed on daily data on T-bond futures options contracts for the sample period from November 11, 1988, to September 30, 1992. The macro announcements being considered are the construc-

[28] The implied volatility of *equity* index options, on the other hand, has been employed to study the *comovement* of stock and bond returns; see Connolly et al. [22].

tion spending-NAPM survey, the CPI, durable goods orders, the employment report, federal budget, GNP, industrial production-capacity utilization, merchandise trade deficit, the PPI, and retail sales.

The ISD declines following the release of price-impacting scheduled announcements, where the decline tends to be greater, the shorter the option's time-to-expiration and the greater the announcement's impact on actual volatility. ISDs also tend to fall on Fridays and rise on Mondays, due to the tendency for scheduled announcements to be bunched on Fridays. Since ISDs tend to decline following major scheduled announcements, the authors also investigate whether it is possible to exploit this predictability to earn abnormal returns, by selling options in anticipation of a fall in σ_t. In particular, a strategy selling options in anticipation of the release of the employment report has the highest potential to be profitable. The authors find that this is not the case. The major reason is that, even for delta neutral-positions, losses due to the convexity of option prices and the high price volatility on the day of the announcement offset the profits due to the anticipated ISD decline.[29]

The results of Ederington and Lee [30] are revisited by Beber and Brandt [7] for a different sample period, using both daily and *tick-by-tick* data, from January 1995 to December 1999. Moreover, the analysis is extended beyond ISDs to the entire state-price density (SPD) of bond futures prices, where the SPDs are obtained as Edgeworth expansions around log-normal densities. Specifically, the price of a call option is approximated as:

$$\begin{aligned} C_t &\approx \exp(-r_{ft}T_t)[F_t N(d_{1t}) - EN(d_{2t})] \\ &\quad + F_t \exp(-r_{ft}T_t)\varphi(d_{1t})\sigma_t\sqrt{T_t}\left[\frac{\gamma_{1T_t}}{3!}(2\sigma_t\sqrt{T_t} - d_{1t})\right. \\ &\quad \left. - \frac{\gamma_{2T_t}}{4!}(1 - d_{1t}^2 + 3d_{1t}\sigma_t\sqrt{T_t} - 3\sigma_t^2 T_t)\right], \end{aligned} \tag{9}$$

[29] The profitability of intra-day trading strategies related to macro news is also explored by Faust and Wright [35].

where the first term in the r.h.s. is Black's [12] formula, $\varphi(.)$ is the standard normal density, and γ_{1T_t} and γ_{2T_t} measure *skewness* and *excess kurtosis*, respectively. The three parameters, $\mu_t = \{\sigma_t, \gamma_{1T_t}, \gamma_{2T_t}\}$, are estimated from the cross-section of futures options with the same time to maturity T_t, but different strike prices.

Daily changes in these parameters are then used as dependent variables in the model,

$$\Delta\mu_t = \alpha + \sum_{k=1}^{K} \beta_{1k} I_{kt} + \beta_2 T_t + \epsilon_t, \tag{10}$$

where the announcements being considered are: CPI, PPI, Unemployment Rate, Nonfarm Payrolls, Retail Sales, Industrial Production, Consumer Confidence, NAPM Index, Fed funds rate target, and Housing Starts. In addition, the authors also estimate a model that includes macro surprises (instead of announcement dummies)

$$\Delta\mu_t = \alpha_k + \beta_{1k} S_{kt} + \sum_{j=1}^{J} \beta_{2j} S_{jt} + \beta_{3k} T_t + \epsilon_{kt}, \tag{11}$$

separately for each announcement k, but controlling for contemporaneous announcements. The authors also estimate a version of the regression model above, where the β_1 and β_2 coefficients are allowed to vary depending on whether the surprises are good or bad news for the bond markets.

Consistent with the results in Ederington and Lee [30], the release of macro news (CPI, PPI, and employment report) reduces the uncertainty implicit in the second moment of the SPD, *regardless* of the news content. The direction and magnitude of the changes in the higher-order moments of the SPD, in contrast, depends on the information content. The SPD becomes less (more) negatively skewed and less (more) fat-tailed in response to bad (good) news for the bond market. Furthermore, the results are asymmetric, in that bad news have a greater impact on the higher-order moments of the SPD than do good news.

The changes in the higher-order moments of the SPD cannot be attributed to variation in the physical price process, i.e., changes in the higher-order moments of the objective probability density function (PDF).[30] In fact, the effect of the announcements on the higher-order moments of the PDF is often exactly *opposite* to the effect on the higher-order moments of the SPD. Conversely, the changes in the higher-order moments are consistent with counter-cyclically varying risk aversion. Combining estimates of the SPD with estimates of the PDF obtained from a jump model for the underlying futures price, the authors recover estimates of the implied risk aversion before and after the announcements. They then relate the changes in the implied risk aversion directly to the content of macroeconomic news, finding that *good* news for the economy leads market participants to become *less* risk averse.

Beber and Brandt [8] examine how and to what extent the *ex-post* resolution of uncertainty in financial markets due to the release of macro news is related to the *ex-ante* uncertainty of market participants about the state of the economy. Ex-ante macroeconomic uncertainty is measured using prices of economic derivatives traded in a new auction-based market, launched in 2002 jointly by Goldman Sachs and Deutsche Bank.[31] The underlying is the initial release of a given macroeconomic statistic (Nonfarm Payrolls, ISM index, Retail Sales, and Initial Jobless Claims) on the scheduled announcement date. These economic derivatives are bets on macro news, and their option-implied second moments are a direct measure of uncertainty regarding the news release. The data set covers 233 auctions during the sample period from October 2002 to August 2006.

The authors extract a model-free measure of macroeconomic uncertainty from the observed prices of economic derivatives, σ_{ECOt}, based on the relationship,

$$\sigma^2_{ECOt} = 2\int_0^\infty \frac{C(T_t, E) - \max(0, F_t - E)}{E^2} dE, \tag{12}$$

where F_t, the expected outcome of the release, is calculated based on the prices of puts and calls, using

[30] For a further discussion of the distinction between the PDF and the SPD, see Chapter ??.

[31] Gürkaynak and Wolfers [50] provide an initial analysis of this market, estimating market-based forecasts from the prices of digital options, for the October 2002–July 2005 sample period. They then construct two series of macro news using market-based forecasts and survey forecasts, respectively. They use intra-day data to show that Treasury prices react significantly to the first type of news—Nonfarm Payrolls, in particular—but the reaction to the second type of news is mainly insignificant.

put-call parity. The relationship above is also used to extract ISDs from the prices of options on the ten-year T-note futures contract, and the 30-year T-bond futures contract. Changes in (squared) ISDs from before to after the macro announcements are then related to the measured macroeconomic uncertainty:

$$\Delta\sigma_t^2 = \alpha + \beta\sigma_{ECOt}^2 + \epsilon_t. \tag{13}$$

Across contracts and option expiration dates, higher ex-ante uncertainty about macro fundamentals is significantly associated with greater reduction in the implied volatility of bond options when the economic data are released, and the effect appears to be permanent. Specifically, focusing on the Nonfarm Payrolls announcement, the degree of uncertainty about the economy explains between 26 and 39 percent of the variance of the change in the volatility of T-bond futures. This effect is also economically significant. For example, a high degree of uncertainty equal to one standard deviation above the average macroeconomic uncertainty in the sample, predicts more than a one-third drop in the implied volatility of bond options, compared to less than a 15 percent drop when macroeconomic uncertainty is low (one standard deviation below the average).[32] While the authors do not comment on the nature of the reduction in implied volatilities, we can observe that it must be due to a combination of: i) a reduction in the volatility of bond returns; and ii) a reduction of the risk premium associated with the pricing of interest rate option. The disentangling of these two effects seems to be a worthwhile exercise to be pursued in future research.

2.5 ARCH and GARCH effects

Given the evidence reviewed above regarding the impact of macro news on both realized and implied volatilities, it is natural to ask how the arrival of macro news affects the dynamics of the conditional second mo-

[32] The authors also use macroeconomic uncertainty to explain trading behavior. They find that higher macroeconomic uncertainty is associated with a *greater* increase in transacted volume after the news release. Conversely, there is a negative relation between macroeconomic uncertainty and the change in open interest after the news release; i.e., higher ex-ante uncertainty translates into a larger reduction in open interest after the announcement.

ments of bond returns.[33] This is important in order to understand if the stylized facts concerning the dynamic behavior of the conditional volatility of returns and yields are driven by macro news. Hence, we next examine the dynamics of volatility. We first review studies implemented at the daily frequency. We then turn to the intra-day evidence.

2.5.1 Daily evidence

The motivation of Jones et al. [61] is to understand the drivers of the time variation in the volatility of returns. In particular, while it is a well-documented fact that volatility in financial markets is correlated over time, relatively little is known about why financial market volatility is autocorrelated. One possibility is that the news-arrival process is serially correlated. However, macro-news releases are events where a "lump" of information arrives to the markets, without further information disclosure. Hence, one would expect volatility to display weaker (stronger) persistence after announcement (non-announcement) days. This is the main test performed by the authors, using daily data on returns on five-, ten-, and 30-year Treasury securities for the October 9, 1979, to December 31, 1995, period. The announcements that they focus on are the employment report and the PPI.

The authors estimate an extended GARCH(1,1) model modified to account for differential ARCH and GARCH effects on announcement and non-announcement days,

$$R_t = \mu + \theta I_t^A + \phi R_{t-1} + \sqrt{s_t}\epsilon_t \tag{14}$$

$$s_t = (1 + \delta_0 I_t^A)(1 + \delta_1 I_{t-1}^A) \tag{15}$$

$$h_t = \omega + [\alpha_0 + \alpha_A I_{t-1}^A]\epsilon_{t-1}^2 + [\beta_0 + \beta_A I_{t-1}^A]h_{t-1}, \tag{16}$$

[33] Note that some authors have also investigated the role of macro news for the stock-bond *correlation*; see Christiansen and Ranaldo [20]. Brenner et al. [16] also examine the *joint* effect of macroeconomic announcements on the conditional moments of U.S. Treasury bonds, stocks, and corporate bonds.

where R_t is the return, I_t^A is an announcement-day dummy, and ϵ_t has conditional variance h_t. Across maturities, the ARCH effect is much weaker for announcement shocks ($\alpha_A < 0$). Indeed, the null hypothesis that the impact of announcement-day shocks is zero ($\alpha_0 = -\alpha_A$) cannot be rejected, consistent with the market quickly incorporating public information. Conversely, the GARCH effect after announcement and non-announcement days is essentially the same: on the day after announcement days, conditional volatility decays at the same rate as on other days ($\beta_A \approx 0$). Finally, while announcement-day volatility is significantly higher than non-announcement-day volatility (δ_0 is positive and significant), on days after announcement days, the unconditional volatility is also not statistically greater than on other days (δ_1 is insignificant).[34]

In Christiansen [19], the focus is shifted from univariate volatility patterns to the *covariance* structure of bond returns. Specifically, the author investigates the effect of macroeconomic announcements (employment report and PPI) in a heteroskedastic *multivariate* model of daily excess returns of six government notes and bonds with different maturities (two-, three-, five-, seven-, ten-, and 30-year) for the period from January 1, 1983, to December 31, 1998.

The author estimates an extended GARCH(1,1), with constant conditional correlations. The ARCH effect for bond i is allowed to depend on whether the previous day there was an announcement, and whether the previous announcement-day's return innovation was positive or negative,

$$h_{ii,t} = \omega_i + [\alpha_{i0} + \alpha_{iA} I_{t-1}^A + \alpha_{i-} I_{t-1}^A I_{i,t-1}^-]\epsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}, \tag{17}$$

where $I_{i,t}^-$ is a dummy for negative return innovations. The conditional correlation between any two bond

[34] Interestingly, Li and Engle [65] obtain different results by studying the futures market, rather than the cash market. They use daily T-bond futures data for the sample period from November 9, 1988, to December 31, 1997, and focus on the CPI, PPI, and employment announcements. The authors find that GARCH effects are smaller on announcement days, whereas the opposite is true for ARCH effects. Furthermore, they distinguish between the effects of positive and negative return shocks, finding that positive shocks on announcement days depress volatility on successive days, while negative shocks on announcement days increase volatility. They explain the existence of the announcement leverage effect by the fact that investors take highly leveraged positions on the futures market, which is not the case on the cash bond market.

returns is allowed to differ depending on whether there is an announcement:

$$h_{ij,t} = \rho_{ij}(1 + \rho_{ijA} I_t^A)\sqrt{h_{ii,t} h_{jj,t}}. \tag{18}$$

Consistent with Jones et al. [61], the author finds that announcement shocks do not persist at all; i.e., there are no announcement-day ARCH effects ($\alpha_{i0} + \alpha_{iA} \approx 0$) nor evidence of asymmetries ($\alpha_{i-} \approx 0$). On the other hand, there are significant ARCH effects on non-announcement days ($\alpha_{i0} > 0$). The conditional variance is highly and similarly persistent across bonds of different maturity: $\beta \approx 0.94$. In general, bond returns are strongly correlated ($\rho_{ij} > 0.78$), and the correlation is stronger, the closer the bonds are with respect to the time to maturity. The maturity dependency is substantially dampened on announcement days, which implies that releases of macroeconomic news induce common movements in the government bond market. The rise on macroeconomic announcement days in the conditional covariance of two government bonds is of economic importance (ρ_{ijA} is as high as 0.11) and is a decreasing function of the time to maturity of either of the bonds.

De Goeij and Marquering [26] investigate whether there is an *asymmetric* ARCH effect associated with announcement days and with large macro surprises. Specifically, the authors estimate the volatility model,

$$h_t = \omega_0 + \omega_A I_t^A + [\alpha_0 + \alpha_A I_{t-1}^A]\epsilon_{t-1}^2 + [\beta_0 + \beta_A I_{t-1}^A](\epsilon_{t-1}^-)^2 + \gamma_0 h_{t-1}, \tag{19}$$

where $\epsilon_{t-1}^- = \min\{0, \epsilon_t\}$. A variation of the model above is also estimated, where the announcement-day dummy is replaced by a dummy capturing large macro surprises (greater than one standard deviation, in absolute value). The analysis is implemented on daily data from January 1982 to September 2004 for one-, three-, five-, and ten-year Treasury securities

The main results are as follows. First, conditional variances are much higher on macroeconomic announcement days ($\omega_A > 0$ and significant), and FOMC announcements are especially important for short-term bonds; whereas for long- term bonds, PPI and the employment report are the most important announcements. Second, consistent with Jones et al. [61] and Christiansen [19], announcement-day volatility does not persist ($\alpha_0 + \alpha_S \approx 0$). Third, the asymmetric volatility parameters (β_0 and β_A) are mainly insignificant, consistent with Christiansen [19].

Note that the lack of asymmetric volatility effects in bond returns is in contrast with the widely documented "leverage" effect in equities (see Black [11]), where bad news have a larger impact on volatility than good news.[35] The absence of leverage effects in the volatility of Treasury bonds is to be expected, though, as financial leverage is not applicable to government bonds.

2.5.2 Intra-day evidence

While Jones et al. [61] study ARCH and GARCH patterns at the daily frequency, Bollerslev et al. [13] turn their attention to *intra-day* T-bond futures returns.[36] The analysis is based on a four-year sample period of five-minute returns, from 1994 to 1997, where the key element is a regression model of intra-day seasonal patterns

$$\begin{aligned} 2\ln\frac{|R_{nt}-\bar{R}|}{\sqrt{h_t}/\sqrt{80}} &= \alpha + \sum_{k=1}^{K}\beta_k I_{knt} + \beta_1 n + \beta_2 n^2 \\ &\quad + \sum_{p=1}^{P}\left(\gamma_{cp}\cos\frac{2\pi p}{80}n + \gamma_{sp}\sin\frac{2\pi p}{80}n\right) \\ &\quad + \delta D_{nt} + \epsilon_{nt}, \end{aligned} \tag{20}$$

where R_{nt} is the n-th five-minute return on day t, $\bar{R}$ is the average five-minute return, h_t is the estimated daily variance, 80 is the number of five-minute returns during the trading day, I_{knt} is a dummy variable

[35] The leverage effect is due to equity being a leveraged claim on the assets of the firm: a drop in the value of equity increases financial leverage, which makes equity more risky and increases its volatility.

[36] In the same vein as Bollerslev et al. [13], Ederington and Lee [31] explore ARCH-GARCH effects, the impact of macro news, and seasonality patterns for the intra-day volatility of T-bond futures contracts. The analysis is performed on ten-minute return data for T-bond futures contracts, from July 3, 1989, to May 28, 1993. Among their main findings is that ARCH effects are *less pronounced* when seasonal patterns and announcement effects are incorporated into the model. Moreover, the GARCH(1,1) model underestimates the impact of the most recent and very distant shocks and overestimates the impacts of shocks with intermediate lags. Finally, volatility persists much longer after unscheduled announcements, as compared to scheduled announcements and, consistent with Christiansen [19], there is little difference in volatility persistence after positive and negative price shocks.

for announcement and week-day effects, and D_{nt} is an expiration-day dummy. The third and fourth term on the r.h.s. of (20) capture a linear and a quadratic intraday time trend, respectively, whereas the fifth term is a Fourier transform capturing more complex intraday seasonal patterns. The authors consider a comprehensive list of 27 macroeconomic announcements and the estimation is carried on in two steps, where h_t is estimated in a first step from a fractionally-integrated GARCH model, which does not account for announcement effects and seasonal patterns.

Consistent with Ederington and Lee [28], there are *two* spikes in intra-day volatility at 8:30 and 10:00 A.M. (ET), respectively, corresponding to the regularly scheduled macroeconomic announcements in the U.S. at these times. There is also an overall U-shaped pattern in the volatility across the day, which gives rise to a strong daily pattern in the autocorrelation of the absolute five-minute returns. After filtering out this periodic pattern, it is possible to identify rapid initial decay in the autocorrelations, lasting one day or so, followed by an extremely slow rate of decay, lasting for up to ten days.

Moreover, the largest returns in the U.S. T-bond market are linked to the release of macroeconomic announcements. At both the daily and intra-day frequencies, the announcement effects have the highest marginal explanatory power for the volatility among the three components (calendar, announcement, and ARCH effects). Most notably, the release of the Humphrey-Hawkins testimony and the employment report generates an average instantaneous jump in volatility of about 2100 and 1400 percent, respectively, along with a 93 and 75 percent increase in the cumulative absolute return for trading days that contain these two particular announcements.[37] Moreover, the 15 most important regularly scheduled macroeconomic news reports result in an increase in the daily cumulative absolute returns in excess of ten percent.

[37]The Humphrey-Hawkins testimony, or Monetary Policy Report, is delivered by the Chairman of the Board of Governors twice a year, in February and July, and reports on the basic state of the United States economy and its financial welfare.

2.6 Jumps

As mentioned above, macro news represent lumpy arrivals of information and generate sudden increases in bond return volatility. This evidence motivates the study of the presence of jumps in interest rates and bond prices. Establishing the presence and importance of jumps is important from an asset pricing perspective. Standard continuous-time term structure models, such as Vasicek [81] and Cox et al. [25], postulate "smooth" behavior of the short rate—i.e., the short rate follows a diffusion process, which is characterized by *continuous* sample paths—and derive implications for yields of different maturities accordingly. The presence of jumps invalidates those relations.[38] Moreover, models of bond options also assume diffusion behavior of interest rates and prices. The presence of jumps requires the modification of those pricing models as well.

2.6.1 Daily frequency

Johannes [60] examines the statistical and economic role of jumps in *continuous-time* interest rate models. The analysis is implemented on daily data on three-month T-bill data, for the sample period from January, 1965, to February, 1999.

To test for the presence of jumps, the paper compares the unconditional and conditional non-normalities in interest rates with analogs generated by candidate diffusion models. The approach is based on a simulation exercise and involves four *steps*:

1. compute sample measures of kurtosis of interest-rate changes;
2. for a given diffusion model (the no-jump null), simulate a large number of sample paths;
3. for each sample path, recompute the measures of kurtosis;
4. compare the sample test statistics with the percentiles of the simulated distribution under the null.

[38] See Piazzesi [74] for an example of term structure model that incorporates short-rate jump behavior as induced by Fed policy.

Two diffusion benchmarks are used to generate the simulated data. The first benchmark is a flexible single-factor model,

$$dr_{ft} = \mu(r_{ft})dt + \sigma(r_{ft})dW_t, \tag{21}$$

where r_{ft} is the short rate, $\mu(.)$ and $\sigma^2(.)$ are flexible functions of r_{ft}, and dW_t is the increment of a Wiener process. The second benchmark is a stochastic-volatility model:

$$\begin{aligned} dr_{ft} &= \kappa_r(\mu_r - r_{ft})dt + r_{ft}^{\gamma}\sqrt{V_t}dW_{1t} && (22) \\ d\ln(V_t) &= \kappa_v(\mu_v - \ln(V_t))dt + \sigma_v dW_{2t}, && (23) \end{aligned}$$

where dW_{1t} and dW_{2t} are increments of Wiener processes.

Neither of the two diffusion models can generate kurtosis measures consistent with those of observed three-month T-bill rates. For example, at the daily frequency, the 99th percentile of the empirical distribution of the unconditional kurtosis measure is 15.48, whereas the sample unconditional kurtosis is 24.30.

The author then introduces a flexible short-rate model that allows for jumps,

$$d\ln(r_{ft}) = \mu(r_{ft})dt + \sigma(r_{ft-})dW_t + d\left(\sum_{n=1}^{N_t} Z_n\right), \tag{24}$$

where N_t is a point process with random intensity $\lambda(r_{ft})$, and Z_n is normally distributed, with mean zero and constant variance σ_Z^2. The fourth and sixth moments of (log) interest rate differences allow to identify $\lambda(.)$ and σ_Z^2, whereas the first and second moments allow to identify $\mu(.)$ and $\sigma(.)$, respectively.

Jumps play a *dominant role* in interest rate dynamics. At low rates ($r_{ft} \approx 5\%$), jumps generate more than half of the conditional variance of interest rate changes. At high rates ($r_{ft} \approx 15\%$), jumps generate almost two-thirds of the conditional variance of interest rate changes. The daily probability of a jump is about six percent, at low rates, and more than 20 percent at high rates, with a three standard deviation jump-move corresponding to approximately 50 basis points, at low rates, and as much as 150 basis points at high rates.

The author then estimates jump times and sizes and examines the 1979–1982 and 1991–1993 periods in detail. Each of the large interest rate moves during these two periods can be identified as jumps, and coincide with *unexpected* news arrivals, both scheduled and unscheduled.

The author also examines the pricing implications of jumps in interest rates. While jumps have little impact on the yield curve, they are important in the pricing of out-of-the-money options.

Beber and Brandt [9] focus specifically on the role of *scheduled* macro news in affecting the arrival rate and size of jumps in bond prices. They use daily data on T-bill, T-note, and T-bond futures, for the February 1980–December 2003 sample period. The macro announcements being considered are: CPI, Unemployment Rate, PPI, and Nonfarm Payrolls.

The authors estimate a model of bond futures returns,

$$r_t = \mu_t + \epsilon_{1t} + \epsilon_{2t}, \tag{25}$$

where ϵ_{1t} is normal with mean zero and variance h_t, whereas ϵ_{2t} follows the jump process,

$$\epsilon_{2t} = \sum_{n=1}^{N_t} Z_{jt} - \theta_t \lambda_t, \tag{26}$$

where Z_{jt} is normal with mean θ_t and constant variance. The conditional mean return depends on the phase of the business cycle,

$$\mu_t = \mu_{1t}(1 - X_t) + \mu_{2t} X_t. \tag{27}$$

Similarly, the conditional variance of the normal innovation follows the GARCH(1,1) process

$$h_t = \omega_0 + \omega_t \epsilon_{t-1}^2 + \gamma_0 h_{t-1}, \tag{28}$$

where the ARCH effect ω is *time-varying* and depends on X_t and the ex-post, time-t estimate of the likely number of jumps occurred between time $t-1$ and time t. The jump arrival rate λ_t is a function of what announcements are taking place on a given day:

$$\lambda_t = \lambda_0 + \sum_{k=1}^{K} \lambda_k I_{kt}. \tag{29}$$

The mean jump size θ_t depends on four announcement surprises (CPI, PPI, Unemployment Rate, and Nonfarm Payrolls) in a way that, in turn, is business-cycle dependent,[39]

$$\theta_t = (1 - X_t)\left(\theta_{01} + \sum_{k=1}^{K+1} \theta_{1k} S_{kt}\right) + X_t \left(\theta_{02} + \sum_{k=1}^{K+1} \theta_{2k} S_{kt}\right). \tag{30}$$

The estimates of the model in (25) show that macroeconomic news has a substantial impact on bond volatility, by increasing jump intensities—especially in the case of the employment report—and by affecting the distributions of the jump size. The relation between macroeconomic news and jumps depends on the combination of the announcement type, the maturity of the bond, and the phase of the business cycle. Specifically, the proportion of releases resulting in a jump decreases dramatically for short maturities and is generally lower in recessions. Jumps on announcement days are associated predominantly with Nonfarm Payrolls releases, but CPI news becomes relatively more associated with jumps in recessions, and at medium maturities. As in prior studies, jump volatility is not persistent: the ARCH effect is all but muted after a jump is likely to have taken place.

[39] Because the Unemployment Rate is released together with Nonfarm Payrolls, there are only three announcement dummies I_{kt}.

2.6.2 Intra-day frequency

The analysis of jumps is taken to the *intra-day* frequency by Andersen et al. [2], who study tick-by-tick transaction prices for the T-bond futures contract. The sample covers the period from January 1990 through December 2002.

In the presence of jumps, as the sampling frequency increases, the realized bond return volatility,

$$RV_{t+1}(\Delta) \equiv \sum_{n=1}^{1/\Delta} r^2_{t+n\Delta,\Delta}, \tag{31}$$

converges to,

$$\lim_{\Delta \to 0} RV_{t+1}(\Delta) = \int_t^{t+1} \sigma^2(s)ds + \sum_{t<s\leq t+1} Z^2(s), \tag{32}$$

where the second term is the sum of the squared jumps that occurred between t and $t+1$. Hence, in order to separately identify the two components of the realized quadratic variation, the authors use the concept of *realized bi-power variation*,

$$BV_{t+1}(\Delta) \equiv \frac{1}{(2/\pi)} \sum_{n=2}^{1/\Delta} |r_{t+n\Delta,\Delta}||r_{t+(n-1)\Delta,\Delta}|, \tag{33}$$

which converges to:

$$\lim_{\Delta \to 0} BV_{t+1}(\Delta) = \int_t^{t+1} \sigma^2(s)ds. \tag{34}$$

The contribution of jumps to the volatility of returns can then be estimated by:[40]

$$\lim_{\Delta \to 0} RV_{t+1}(\Delta) - BV_{t+1}(\Delta) = \sum_{t<s\leq t+1} Z^2(s). \tag{35}$$

Based on sample counterparts of (34) and (35), the authors construct estimates of the components of the realized variation attributable to continuous-sample-path variation, $C_{t+1}(\Delta)$, and to jump variation, $J_{t+1}(\Delta)$. They then formulate and estimate a heterogeneous autoregressive realized-volatility model that differentiates between the two components,

$$\begin{aligned} RV_{t,t+h} &= \beta_0 + \beta_{CD} C_t + \beta_{CW} C_{t-5,t} + \beta_{CM} C_{t-22,t} \\ &\quad + \beta_{JD} J_t + \beta_{JW} J_{t-5,t} + \beta_{JM} J_{t-22,t} + \epsilon_{t,t+h}, \end{aligned} \tag{36}$$

where $C_{t-h,t}$ and $J_{t-h,t}$ are h-day trailing averages of C_t and J_t, respectively.

The authors find that jumps dynamics are much less persistent (and predictable) than continuous sample path dynamics. In addition, the estimates of (36) show that the continuous-variation measures are always significant in predicting realized volatility, whereas, in most cases, the jump-variation measures are not.

Jiang et al. [59] identify jumps in bond prices based on the "variance swap" approach: in the absence of jumps, the difference between *simple* returns and *log* returns captures 1/2 of the instantaneous return variance. The variance-swap measure is defined as

$$SWV_{t+1} \equiv 2 \sum_{n=1}^{1/\Delta} (R_{t+n\Delta,\Delta} - r_{t+n\Delta,\Delta}). \tag{37}$$

Under the no-jumps null, $SWV_{t+1}(\Delta)$ is "close" to $RV_{t+1}(\Delta)$.

The analysis is implemented on intra-day (five minute) BrokerTec data for two-, three-, five-, and ten-

[40] Since the difference between realized volatility and realized bi-power variation can turn negative, in estimation, the authors use the quantity $\max\{RV_{t+1}(\Delta) - BV_{t+1}(\Delta), 0\}$.

year T-note and the 30-year bond for the sample period from January 2004 to June 2007.[41] The authors identify a large number of jumps for all maturities. For example, there are 120 jumps in the two-year note prices during the sample period. Overall, the average jump size is more than ten times the five-minute return standard deviation.

With identified jumps, the authors search for potentially related economic news or events. They identify an extensive list of pre-scheduled macroeconomic news and events as potential causes of bond price jumps. The list includes major news announcements widely considered in the existing literature, such as Initial Jobless Claims, CPI, Nonfarm Payrolls, Retail Sales, PPI, Consumer Confidence, and the Institute for Supply Management (ISM) index. The list also includes announcements that have been considered less important and thus largely omitted in previous studies, for example, the NY Empire State Index (a regional economic indicator published by the Federal Reserve Bank of New York). Overall, the authors find that a large number of jumps occur during pre-scheduled macroeconomic news announcements. For example, about 90 percent of jumps in the two-year note prices occur within ten minutes of pre-scheduled news announcement times.[42]

2.7 Summary

This section has reviewed several articles analyzing the high-frequency, time-series properties of interest rates and bond prices. The organizing theme of this section is the impact of macro news. In summary, the following main patterns arise:

- Among the different macro announcements impacting prices, the Nonfarm Payrolls Announcement, often referred by market participants as the "king" of announcements, dominates both level and volatility effects. Other important announcements across studies are the NAPM/ISM index and the PPI.

- Announcements regarding the Fed funds rate target are also important, with a stronger effect at short

[41] BrokerTec is an electronic trading platform supported by ICAP.
[42] The authors also study the relationship between jumps and liquidity shocks; we will review their analysis in Section 3.

maturities. However, it is difficult to determine whether this is a causal, or simply an information effect.

- Macro news is responsible for most of the time-of-day and day-of-the-week volatility patterns in the Treasury markets. In particular macro news leads to significant increases in bond price volatility on the day and at the time when the news is released.

- The release of macro news reduces option-implied volatility, more so, the higher is the ex-ante uncertainty on the news release.

- The increase in volatility is not persistent, though: ARCH effects in the aftermath of macro news are not significant.

- Interest rates and bond prices "jump" at the time of news announcements, but also at the time of important unscheduled news.

3 Market microstructure effects

This section reviews literature studying high-frequency market microstructure effects in the U.S. Treasury markets.[43] By microstructure effects, we denote a variety of patterns related to trading activity, execution costs, and the informational environment, such as: trading volume, bid-ask spreads, and the price impact of trades. The recognition of these patterns is crucial for the effective implementation of trading strategies on the part of market participants. For example, Green [46] documents that the price impact of trades is higher after macro announcements. This should lead *uniformed* traders to avoid implementing trades in the aftermath of announcements. It is also worth noting that the studies referenced in this section analyze

[43] A few studies provide a descriptive analysis of liquidity patterns in the voice and electronic markets. Fleming [37] studies liquidity during both day and overnight trading, using intra-day data for the 4/4/1994–9/19/1994 sample period. Fleming [38] estimates and evaluates a set of different liquidity measures using intra-day data for on the on-the-run bills and notes during the 12/30/1996–3/31/2000 sample period. Mizrach and Neely [71] document the transition of trading from the voice market to an electronic market, the eSpeed electronic communication network (ECN), founded by Cantor Fitzgerald and Co. Fleming and Mizrach [40] use data from January 2001 to February 2006 to characterize trading activity and liquidity on the BrokerTec ECN for the on-the-run two-, three-, five-, ten-, and 30-year Treasury securities.

sample periods during which HFT was not yet likely to be prevalent. In Section 5, we turn specifically to how HFT has recently affected the trading environment in the U.S. Treasury market.

3.1 Microstructure effects in the cash market

Fleming and Remolona [43] use intra-day data to examine not only the volatility effects of macro announcements, as Ederington Lee [28] do for bond futures, but also the behavior of trading volume and bid-ask spreads. The authors focus on three 8:30 A.M. ET announcements: the employment report, the CPI, and the PPI.[44] The sample period is from August 23, 1993, to August 19, 1994.

In characterizing the market's response, they uncover *two* distinct stages of adjustment. During a brief first stage (two minutes), the release of a major macroeconomic announcement induces a sharp and nearly instantaneous price change—the 8:30–8:31 standard deviation on announcement days is more than 13 times higher than on non-announcement days—with a *reduction* in trading volume. At the time of the sharp price change, the bid-ask spread widens dramatically—the 8:30–8:31 spread is more than seven times higher than on non-announcement days. Since it is public information what drives prices at the time of the announcement, it is likely to be inventory control to drive the spread.[45]

In a prolonged second stage (90 minutes for volume and 60 minutes for volatility), trading volume surges and then persists along with high price volatility and moderately wide bid-ask spreads. During the 9:30–9:35 interval, for example, volatility and trading volume are 1.4 and 1.7 times higher than on non-announcement days, respectively. This extension of the adjustment process is consistent with residual disagreement among investors about the information content of the just-released announcement.

Green [46] studies the informational role of trading on macro announcement days, using trade-by-trade data for the July 1, 1991, to September 29, 1995, sample period. Specifically, the author focuses on trading

[44] Non-announcement days, though, are identified based on the absence of any announcement form a broader set of 18 announcements.

[45] By "inventory control," we denote the compensation required by market makers for the price risk faced on their inventory.

taking place between 8:00 and 9:00 A.M. ET, since many important announcements are made at 8:30. The model used by the author explains *transaction* price changes, ΔP_t, as a function of macro surprises and signed order flow,

$$\Delta P_t = \beta_1 \Delta V_t + \beta_2 (V_t - \rho V_{t-1}) + \sum_{k=1}^{K} \beta_{3k} S_{kt} + \epsilon_t, \tag{38}$$

where $V_t = 1$ if the trade is buyer initiated and $V_t = -1$ if the trade is seller initiated, ρ is the serial correlation coefficient for V_t, and t measures time in transactions. The parameter β_1 quantifies the effect of two trades of *different* sign (a purchase followed by a sale, or a sale followed by a purchase) and captures compensation for *liquidity provision*: the cost of order processing and holding inventory. The parameter β_2, on the other hand, isolates the *informational* effect of innovations in the trading flow $(V_t - \rho V_{t-1})$: the compensation for trading with informed traders (adverse selection costs). The two price-impact parameters, as well as ρ, are allowed to take on different values depending on whether the observation takes place before or after an announcement, or on a day when there are no announcements.[46]

Estimates of β_1 are *negative* and significant, and more so after economic announcements; i.e., a buyer-initiated trade followed by a seller-initiated (a seller-initiated trade followed by a buyer-initiated) trade leads to a price increase (decrease), which is larger after announcements. This suggests that, on average, dealers *consume* liquidity in the U.S. Treasury interdealer market. Estimates of β_2, on the other hand, are positive and significant, and larger after economic announcements; i.e., an unexpected buyer-initiated (seller-initiated) trade impacts positively (negatively) prices, and more so after economic announcements. In other words, the informational impact of trades is stronger after announcements. This is consistent with the explanation suggested by Fleming and Remolona [43] of a disagreement among investors about the information content of the announcements.

[46]More recently, Menkveld et al. [70] estimate a similar regression model using data from the futures market, allowing them to isolate *customer* order flow out of total flow (both dealer and customer). They consider two samples: a sample covering the open-outcry market from 1994 to 1997; and a sample covering the electronic market from 2/3/2009 until 2/11/2010. They find that customer flow is more informative on macro announcement days, than on non-announcement days, and that the announcement-day informativeness of flow is strongest when analyst forecasts are most dispersed.

The analysis is further refined by allowing the announcement-day parameter estimates to differ across the four time intervals: 8:00–8:15, 8:15–8:30, 8:30–8:45, and 8:45–9:00. Both β_1 and β_2 increase, in absolute value, until the 8:30–8:45 time interval, and then decrease. This suggests that both the (negative) compensation for providing liquidity and the informational role of trading increase up to and immediately after the announcements, but then tend to revert to normal levels.

Huang et al. [56] examine the trading behavior of primary dealers in the five-year Treasury-note inter-dealer broker market using intra-day (ten-minute intervals) data for 1998. First, the authors focus on the impact of macro news on liquidity variables. The authors estimate the regression model,

$$Y_{nt} = \sum_{n=1}^{N} \alpha_n D_{nt} + \sum_{k=1}^{K} \beta_k I_{knt} + \beta \tau_{nt} + \epsilon_{nt}, \tag{39}$$

where Y_{nt} is a liquidity variable, D_{nt} is a time-of-the-day dummy, I_{knt} is a non-linear function of the time since the release of announcement k on day t, and τ_{nt} is a time trend. I_{knt} captures the gradual dissipation of the announcement effect as time elapses. The liquidity variables are: i) trading volume; ii) trade frequency; iii) average trade size; and iv) average bid-ask spread. The authors find that 17 macro indicators have a significant positive impact on trade frequency, whereas no announcement has a significant positive impact on trade size. Of the 17 announcements significantly impacting trade frequency, the most important are the employment report, employment costs, and the Beige book. 12 announcements also have a significant positive impact on the bid-ask spread: employment report, employment costs, and the PPI.

The authors then investigate further the nature of the widening of bid-ask spreads. In a similar spirit as Green [46], they separate liquidity and informational effects, by computing the *effective* spread and the *adverse-selection* component of the spread.[47] The effective half-spread is defined as $|P_t Q_t|$, where P_t is the transaction price and Q_t is the midpoint of the prevailing quotes at the time of the trade. The adverse information component is calculated as the difference between the effective and realized half-spreads, where

[47] This approach follows Huang and Stoll [57].

the realized half-spread is defined as the (negative of the) price change for initial trades at the (ask) bid. They find that the adverse-selection component of the spread significantly increases 30 minutes after all the most significant announcements, suggesting trading based on private knowledge of inventory and/or order flow.

Finally, the authors investigate the volume-volatility relationship. They estimate the regression model[48]

$$|r_t| = \alpha + \beta E_{t-1}(V_t) + \epsilon_t, \tag{40}$$

where r_t is here the ten-minute return, V_t is a measure of trading volume, and t measures time in ten-minute intervals. The conditional expectation $E_{t-1}(V_t)$ is assumed to be linear function of lagged volume and volatility. In one specification trade volume is replaced by trade frequency and trade size. Interestingly, the authors find that, while trade frequency impacts volatility positively, the impact of trade size is *negative*. The authors conclude that trade frequency reflects the presence of information-based trading, but trade size does not.

While Green [46] focuses on the informativeness of trades on days of macro announcements, Brandt and Kavajecz [14] measure the response of yields to order-flow imbalances on days *without* major macroeconomic announcements, using intra-day data from January 1992 through December 1999. The main result is that yields respond significantly and negatively to contemporaneous net order flow. Interestingly, most yields react to net order flow for *all* maturities, as opposed to each bond reacting only to its own order flow. In particular, each maturity range has a strong reaction to its own order flow imbalance, but an even stronger reaction to the order flow imbalance at the *two to five-year* maturity range. The explanatory power of order flow is substantial, as high as 25 percent (adjusted R^2) for the on-the-run securities in the two to five-year maturity range, and as high as 28 percent for the first principal component of on-the-run yields.

The evidence that yields react to net order flow for other maturities is consistent with the impact of

[48]While the articles reviewed here focus on the impact of order flow on bond prices prices, Cohen and Shin [21] also study how trading activity is affected by lagged returns, finding evidence of *positive-feedback* trading at high frequency.

order flow capturing a *price-discovery* effect—the aggregation of heterogeneous private information (or heterogeneous interpretation of public information) through trading—rather than an inventory effect. Further evidence of this interpretation is that off-the-run yields only respond to on-the-run order flow, and that lagged order flow does not impact yields. Indeed, if the price impact of trades was driven by an inventory effect, we would expect yields to react to order flow for the same maturity range. Moreover, we would expect off-the-run yields to respond to off-the-run flow. Finally, the effect of inventory build-up would not last and we would expect a positive correlation between yield changes and lagged order-flow imbalances.

Finally, the authors examine the differential impact of order flow when liquidity is high and when liquidity is low. Consistently across maturities, the incremental impact of flow when liquidity is low is negative, and significant in most instances. This finding is consistent with market participants paying more attention to order flow when the subjective valuations are relatively uncertain, and liquidity is therefore low.

The goal of Pasquariello and Vega [73] is to measure the effect of these two complementary mechanisms responsible for daily price changes: i) the aggregation of public news; and ii) the aggregation of order flow. These mechanisms were also considered by Green [46] and Brandt and Kavajecz [14], but Pasquariello and Vega [73] extend both studies by assessing the relevance of each mechanism conditional on the dispersion of beliefs among traders and the public signals' noise. The analysis is performed using intra-day data for the January 1992–December 2000 period.

Following Hasbrouck [52], the authors first specify an empirical model for intra-day net order flow, where half-hour net order flow is regressed on lagged half-hour returns and order flow. The residuals, aggregated at the daily frequency, are used as the innovations $\Omega_t^\star$ in net order flow. In turn, order-flow innovations, together with macro news on announcement days, explain daily bond returns,[49]

$$R_t = \beta_1 \Omega_t^\star + \sum_{k=1}^{K} \beta_{2k} S_{kt} + \epsilon_t. \tag{41}$$

[49]The authors actually use yield changes in the analysis, rather than returns.

The price-impact parameter β_1 is allowed to differ for days with and without announcements. In particular, on non-announcement days, β_1 varies with the dispersion of analyst forecasts concerning upcoming macro announcements. On announcement days, β_1 varies with both the dispersion of analyst forecasts and the public signals' noise, measured by the absolute difference between the actual announcement and its last revision.

During non-announcement days, adverse selection costs of unanticipated order flow are higher when the dispersion of beliefs is high. For instance, a one standard deviation innovations in order flow decreases the two-year, five-year, and ten-year bond yields by 7.19, 10.04, and 6.84 basis points, respectively, on high dispersion days, compared to 4.08, 4.07, and 2.86 basis points on low dispersion days. These differences are economically and statistically significant.

These higher adverse selection costs translate into a higher contemporaneous correlation between order flow changes and bond yield changes. For example, the adjusted R^2 of regressing daily five-year T-bond yield changes on unanticipated order flow is 41.38 percent on high dispersion days, compared to 9.65 percent on low dispersion days. When information heterogeneity is high, informed traders' behavior leads to a "cautious" equilibrium where changes in unanticipated order flow have a greater impact on bond yields.

The release of macro news induces informed traders to trade more aggressively on their private information. Accordingly, the correlation between unanticipated order flow and bond yield changes is lower during announcement days. For example, comparing non-announcement days with announcement days when the employment report is released, the explanatory power of order flow decreases from 15.31 to 6.47 percent, 21.03 to 19.61 percent, and 6.74 to 3.59 percent for the two-year, five-year, and ten-year bonds, respectively. Yet, when both the dispersion of beliefs and the noise of the public signal are high, the importance of order flow in setting bond prices increases.

He et al. [53] contrast the informational role of trades in the U.S. Treasury market during and outside the regular domestic trading hours, using intra-day data on the five-year on-the-run Treasury note for the

1/1/1992–12/31/1999 sample period. The model is the same as the one estimated in Green [46], which allows to identify the degree of information asymmetry and the compensation for liquidity provision.

The main results are as follows. First, the informational impact of trades varies considerably over the 24-hour day. Informational impact is greatest during the pre-open period (7:30–8:30 A.M. ET) than during any other trading period. Notably, the informational impact during the overnight period (5:30 P.M.–7:30 A.M.) is comparable to that during the regular daytime trading period (8:30 A.M.–3:00 P.M.).

Second, consistent with the intra-day price-impact pattern, the informed-trading component of the bid-ask spread is highest in the pre-open period, whereas the liquidity component is highest in the post-close period (3:00–5:30 P.M.). The magnitude of the informed-trading component during the overnight period is comparable to that during the regular daytime trading period.

Third, distinguishing between non-announcement and announcement days, the informational impact of trades peaks during the pre-open period, on days with no macro announcements, whereas it peaks after the news release at 8:30, on days with macro announcements. On average, information asymmetry is higher in the pre-open period on Mondays than on other weekdays. In addition, information asymmetry is higher immediately before than after the open of the futures market (8:20 AM), suggesting that private information of client order flow is another important source of information asymmetry in the pre-open period.

In their analysis of the role of jumps, Jiang et al. [59] find that, while a majority of jumps occurs at pre-scheduled news announcement times, the announcement surprises have limited power in explaining jumps in bond prices. They find that *pre-announcement* liquidity shocks also play an important role in bond price jumps. They use several liquidity measures constructed from the BrokerTec data to capture liquidity shocks, including the bid-ask spread, trading volume, and various measures of market depth. Consistent with Fleming and Remolona [43], they find that there is generally a widening of the bid-ask spread and a sharp drop in market depth prior to a news announcement. Interestingly, the widening of the spread and the drop in market depth during the pre-announcement period are more significant on days with jumps than on those without jumps.

To examine the explanatory power of information shocks versus liquidity shocks for jumps in bond prices, they specify and estimate a probit model for the occurrence of jumps. First, pre-announcement liquidity shocks, in particular shocks to the bid-ask spread and market depth, have significant predictive power regarding jump frequency in bond prices. Second, there is a significantly positive relation between announcement surprises and jumps. Third, liquidity shocks remain significant in predicting jumps even after controlling for the effect of announcement surprises.

On the other hand, when it comes to the price impact of net order flow, net order flow has significantly less effect on bond prices *after* jumps occurred at announcement times. This suggests that when uncertainty at announcement times is resolved in the form of jumps, the dispersion of investor belief is reduced, and thus, order flow becomes less informative.

3.2 Joint microstructure effects in the cash market and futures markets

The previous articles characterize microstructure effects in the cash market. The futures market for contracts on U.S. Treasury securities, though, is an important ancillary market. The next article studies the interaction between the two markets.[50,51]

Mizrach and Neely [72] model the interaction between the spot voice markets and the futures market, using data on the on-the-run two-, five-, and ten-year notes, over the 10/1/1995–3/30/2001 sample period. The authors base their analysis on two related measures of *information share*: i) the contribution of shocks to a market to the total variance of the permanent component of prices; ii) the limits of the changes in the price with respect to the elements of the vector of shocks, as the time horizon goes to infinity. The information

[50] See also Brandt et al. [15], who use daily data for the 1995–2000 sample period, to study the interaction between the cash and futures markets. The authors identify the differential impact of different categories of trading in the futures markets on the cash and futures markets.

[51] While our focus is on the bond markets, some authors have also investigated the joint dynamics of liquidity measures in the bond and *stock* markets; see Chordia et al. [18].

shares are based on a vector error correction model estimated daily, using one-minute returns.[52]

The paper highlights the role of the futures markets in U.S. Treasury price discovery. Specifically, the estimates of five- and ten-year spot market information shares typically fail to reach 50 percent from 1999 on. The spot market information shares for the two-year note are higher than those of the five- and ten-year maturities, but also decline after 1998. Relative bid-ask spreads, number of trades, and realized volatility are statistically significant in explaining daily information shares, and capture up to 21 percent of the variability. The authors also regress information shares on daily dummies for 11 macro and FOMC-related announcements. In roughly 1/4 of cases, the release of public information increases the futures market's information share, but macroeconomic announcements rarely explain information shares independently of liquidity.

3.3 Summary

This section has reviewed several articles analyzing high-frequency market-microstructure effects in the cash and futures markets for U.S. Treasury securities. In summary, the following main features emerge:

- Prices adjust almost instantaneously to the releases of macroeconomic announcements, whereas volatility and trading volume remain at an abnormal higher level for more than one hour. This is could be consistent with disagreement among investors about the information content of the just-released announcement.

- Trading impact prices, although with considerable variations throughout the day and across days. In particular, on announcement days, trading is more informative in the aftermath of macro announcements and depending on the degree of information heterogeneity about macroeconomic fundamentals among market participants.

- Bond futures markets contribute substantially to price discovery, especially for long-maturity Treasury securities.

[52] A similar analysis of information shares is performed by Man et al. [69] for the electronic and voice-based spot markets. They find that the electronic market has a much higher information share than the voice market.

Hence, despite the fact that most (if not all) "fundamental" information relevant for U.S. Treasury securities is public, liquidity in this market is not perfect. In particular, there seem to be important price-discovery effects related to the way public information is processed. This feature should be incorporated into bond valuation models.

4 Bond risk premia

In this section we review the evidence on bond risk premia at high frequency. We start with articles documenting the evidence in daily bond returns, and we then turn to the intra-day evidence. High-frequency data allow researchers to study the way risk premia are earned in relation to the release of economic announcements. In addition, the benchmark EH postulates constant expected log returns, in excess of the log risk-free rate. By examining bond returns at high frequency, researchers may be better able to detect time variation in risk premia and, hence, assess the validity of this important benchmark.

4.1 Daily evidence

Jones et al. [61] find that average excess returns are significant on the days when employment and PPI data are announced.[53] Specifically, announcement-day average bond excess returns on announcement days exceed non-announcement-day returns between 6.3 (five-year note) and 10.8 (30-year bond) basis points, after controlling for day-of-the week effects.

Li et al. [66] provide a connection between microstructure effects and bond risk premia. Specifically, the authors study the effect of liquidity *risk* and liquidity on the pricing of U.S. Treasury securities. The authors employ intra-day, daily, and monthly data for the January 1992–December 2002 sample period.

[53] Note that Li and Engle [65] test for a GARCH-in-mean effect, where the conditional bond volatility is allowed to impact expected excess returns on announcement days, but not on non-announcement days; i.e., they allow for a risk-return trade-off, but only on announcement days. They find the effect to be insignificant. Christiansen [19] also fails to identify a significant differential risk premium on announcement days.

To estimate a bond's exposure to liquidity risk, the authors use *daily* data to estimate the regression model,

$$R^e_{i,n+1t} = \alpha_{i,t} + \alpha_{i,1t} R_{nt} + \alpha_{i,2t}\,\text{sign}(R^e_{i,n+1t}) V_{i,nt} + \epsilon_{i,n+1t}, \tag{42}$$

where $R^e_{i,nt}$ is the i-th bond return, in excess of the return on an equally-weighted Treasury portfolio, on day n, in month t; R_{nt} is the bond return; sign$(R^e_{i,nt})$ is an indicator function that equals one if $R^e_{i,nt} > 0$, and minus one, otherwise; and $V_{i,nt}$ is trading volume measured in par value. The model is estimated each month for each bond, and the average of $\hat{\alpha}_{i,2t}$ across bonds, $\hat{\alpha}_{2t}$, is used as the liquidity measure for the Treasury market.

Innovations in the liquidity measure are computed as the residuals of the *monthly* regression model,

$$\Delta\hat{\alpha}_{2t} = \beta_0 + \beta_1 \Delta\hat{\alpha}_{2t-1} + \beta_2 \hat{\alpha}_{2t-1} + e_t. \tag{43}$$

In turn, $L_t \equiv 1000 \times \hat{e}_t$ is used as a regressor in the augmented Fama and French [33] factor model for monthly excess returns,

$$\begin{aligned} R_{it} - R_{ft-1} \quad = \quad & \gamma_{0i} + \gamma_{iMKT}(R_{mt} - R_{ft-1}) \\ & + \gamma_{iSMB} R_{SMBt} + \gamma_{iHML} R_{HMLt} \\ & + \gamma_{iTERM} R_{TERMt} + \gamma_{iL} L_t + v_t, \end{aligned} \tag{44}$$

where R_{ft-1} is the monthly risk-free rate, R_{mt} is the stock market return, R_{SMBt} is the size factor, R_{HMLt} is the value factor, and R_{TERMt} is the excess return on a long-term government bond. The parameter γ_{iL} captures the liquidity risk associated with bond i. In addition to liquidity risk, the authors estimate a monthly measure of the probability of information-based trading (PIN_{it}), which is derived from a sequential trade model (Easley et al. [27]). The authors then perform a sequence of *cross-sectional* regressions for monthly excess returns,

$$
\begin{aligned}
R_{it} - R_{ft-1} \quad = \quad & \phi_{0t} + \phi_{MKTt}\hat{\gamma}_{iMKT} + \phi_{SMBt}\hat{\gamma}_{iSMB} + \phi_{HMLt}\hat{\gamma}_{iHML} \\
& + \phi_{TERMt}\hat{\gamma}_{iTERM} + \phi_{Lt}\hat{\gamma}_{iL} + \phi_{PINt}\widehat{PIN}_{it} \\
& + \text{controls} + u_{it}, \qquad (45)
\end{aligned}
$$

where $\widehat{PIN}_{it}$ is the average PIN_{it} over the previous six months. The average values of $\hat{\phi}_{Lt}$ and $\hat{\phi}_{PINt}$ provide an indication of whether liquidity level and/or liquidity risk are priced.

Results of the asset pricing test described above show that liquidity risk is important over and beyond the effect of the level of liquidity. Moreover, there is a *positive* relation between expected Treasury returns and information risk in the cross-sectional regressions. Finally, the compensation for exposure to liquidity risk is economically important. A difference of ten percentage points in liquidity risk leads to a difference in Treasury excess return of nine basis points per annum, which accounts for six percent of the mean excess return. By contrast, the same amount of change in information risk leads to a difference in Treasury excess return of six basis points per year, or four percent of the mean excess return. Hence, while both liquidity and information matter, the economic effect of liquidity risk appears to be greater than that of information risk.

Savor and Wilson [78] examine announcement-day and non-announcement-day bond returns for 30-day T-bills and notes and bonds with maturities one, two, ten, twenty, and 30 years, for the 1958–2009 sample period (1961–2009, for T-bills), focusing on inflation, unemployment, and FOMC announcements.

They find that average T-bill daily returns are significantly lower on announcement days: 0.7 basis points lower, relative to a sample mean of 2.3 basis points for non-announcement days. On the other hand, similar to Jones et al. [61], average note and bond excess returns (maturity above one year) are significantly higher on announcement days, and they increase with the maturity of the instrument. The average excess return differential ranges between 2.6 (five-year note) and 4.5 (30-year bond) basis points.[54]

4.2 Intra-day evidence

Balduzzi and Moneta [6] focus on the *cross-section* of risk premia at announcement and non-announcement times.[55] In addition, within announcement days, the authors distinguish between return behavior in the immediate vicinity of macro announcements—"announcement-window" returns—and behavior further away from the announcements—"non-announcement-window" returns. They examine intra-day futures contracts on two-, five-, ten-, and 30-year notes and bonds, for the 3/2/1993–3/31/2008 sample period, finding that the distinction between announcement- and non-announcement-window returns affords an interesting novel insight: announcement-day bond risk premia are significant, but only for the portion earned outside the announcement windows.

The authors then perform *three* main exercises. First, they estimate the sensitivity of futures returns to 22 announcement surprises and use the estimated sensitivities to construct portfolios mimicking the surprises: "unit-beta" mimicking portfolios. They then estimate the Sharpe ratios earned by the mimicking portfolios. They find that the Sharpe ratios (in absolute value) are remarkably similar across announcements being tracked, which is consistent with a single-factor structure in the response of returns to surprises, and that the Sharpe ratios are mainly earned on announcement days, but outside the announcement windows. They also find significant evidence of predictability in mimicking-portfolio (excess) returns: portfolios mimicking procyclical (countercyclical) macro news earn negative (positive) risk premia, more negative (positive) as interest rates increase and the economy slows down.

The second exercise is to impose and test a single-factor structure in the response of returns to macro

[54] Savor and Wilson [79] also examine announcement-day and non-announcement-day bond returns, for the 1964–2011 sample period, focusing on the same three macro announcements. They find that on announcement days average bond excess returns are positively related to their equity market beta.

[55] Faust and Wright [35] study *conditional* bond risk premia at the intra-day frequency. They examine intra-day futures returns on five- and 30-year notes and bonds for the November 1988 to December 2007 period. They show that bond return predictability is mainly driven by price behavior *within* a 15-minute window surrounding the employment, CPI, PPI, trade balance, retail sales, personal income, durable goods, initial unemployment claims, industrial production, and scheduled FOMC announcements.

news, i.e., they assume that the day-t announcement-window return on the i-th contract, r_{it}^{aw}, follows[56]

$$r_{it}^{aw} = \alpha_i + \beta_{iy} y_t + \epsilon_{it}, \tag{46}$$

where

$$y_t = \sum_{k=1}^{K} \delta_k S_{kt} \tag{47}$$

is a "latent" economic-news factor through which all macro surprises affect bond futures prices. The authors find that the single-factor structure cannot be rejected, where the latent factor mainly loads on the Nonfarm Payrolls, FOMC, and the ISM index announcements.

Third, the authors test the *asset pricing* implications of the single-factor model, i.e., they test the implication that

$$E_{t-1}(r_{it}) = \beta_{iy} \lambda_{yt-1}, \tag{48}$$

where λ_{yt-1} is the conditional risk premium associated with the exposure to the latent factor. The restrictions of the asset pricing model are not rejected.

4.3 Summary

This section has reviewed articles characterizing risk premia in the U.S. Treasury markets. In summary, these are the main results:

- Bond risk premia are mainly earned on announcement days.

- Both the level of liquidity and the exposure to liquidity shocks explain the cross-section of (monthly)

[56]The authors allow for *multiple* announcement windows within the day.

bond risk premia.

- Announcement-day unconditional risk premia are only significant for the portion earned *outside* of the announcement windows. There is also significant time-variation in the intra-day risk premia, with different predictability patterns across different trading periods.

- The cross-section of bond risk premia is explained by the exposure to a single factor capturing macro news.

Overall, the main message is that bond risk premia are earned *unevenly* over time and also display uneven time variation. The fact that both the average risk premia and the time variation of risk premia is especially significant in the proximity of macro-announcement releases supports the notion that macro risk is indeed priced.

5 The impact of HFT

A recent development in the fixed income markets is the increasing role played by HFT.[57,58] The literature on the topic is still evolving and there are no published articles yet. Hence, in this section, we review two studies still at the working paper stage.

5.1 The effects of HFT on liquidity, volatility, and risk premia

Jiang et al. [58] study price data from BrokerTec on the two-, five-, and ten-year note. They examine the 1/2/2004–6/30/2007 sample. Crucial to their analysis is the identification of high-frequency (HF) trades and limit orders. The authors use information on the time of order submission in reaction to changes in market

[57] Note that there are subtle differences between algorithmic trading, automated trading, and HFT. Algorithmic trading (AT) is typically understood as the implementation of automated trade execution strategies on the part of fund managers to buy or sell large amounts of assets. Automated trading is the complete automation of the investment *and* trading process. HFT is understood as a subset of automated trading where trading opportunities arise and are taken advantage of on very small timescales.

[58] While the interest in HFT in the fixed income markets is *very* recent, a few studies have analyzed the effects of AT and HFT on the stock markets, see, for example, Hendershott et al. [54], Hendershott and Riordan [55], Brogaard et al. [17]. The overall conclusion of these studies is that AT and HFT improve liquidity and informational efficiency.

conditions and its subsequent alteration, such as cancellation or execution, to classify HF trades and orders as those that are placed at a speed deemed beyond manual capacity.[59]

The authors characterize HF and non-HF trading and orders before and after macro announcements, finding that both HF and non-HF activity greatly intensifies after macro announcements. They then examine two main issues. First, they explore whether HF trades and orders improve or reduce liquidity and whether they increase or decrease bond volatility. In order to address this issue, they regress the abnormal component of the bid-ask spread and market depth—the deviations from a five-day trailing moving average for the same time of day—on HF trades and orders. They find that HF trades and orders impact positively (negatively) the bid-ask spread before (after) macro announcements. On the other hand, HF trades and orders impact negatively market depth at the best quote, both before and after macro announcements. They also regress abnormal return volatility on HF trades and orders, finding that HF trades increase volatility, more so before than after announcements, and that HF orders only increase volatility before announcements. The authors conclude that HF trading has a negative (mixed) effect on pre-announcement (post-announcement) liquidity.

Second, the authors investigate how informative HF trades and orders are relative to non-HF trades and orders, and what is their role in affecting price efficiency. Specifically, they implement the test of Kaniel and Liu [62], which quantifies the probability that a trade or order anticipates price changes in the right direction. They find that non-HF limit orders are *more* informative than their non-HF counterparts, especially during the post-announcement periods. The authors also regress the five-minute serial correlation in tick-by-tick returns on HF trades and orders. They find that HF trades reduce serial correlation and, thus, improve price efficiency, during the post-announcement period.

In summary, while HF trades and orders generate higher (subsequent) bond return volatility, their effect on market liquidity depends on the information environment. HF activities generally have a negative

[59]Specifically, HF trades are identified as those market orders that are placed within a second of a change in the best quote on either side of the market. HF orders are identified as those orders that belong to one of three different categories: i) orders that are canceled or modified within one second of their placement; ii) orders at the best quote that are modified within one second of a change in the best quote on either side of the market; and iii) orders at the second best quote that are modified within one second of a change in the best quote on either side of the market.

impact on liquidity before announcements, but they are associated with lower bid-ask spreads, especially during post-announcement periods, when information uncertainty is resolved. Moreover, during the post-announcement period, HF trades (limit orders) are more (less) informative than their non-HF counterparts. Finally, their results show that only HF trades have a significant effect in enhancing price efficiency during the post-announcement period.

Liu et al. [67] investigate whether the *intensity* of HF trading has an impact on average returns. They construct a daily HFT intensity factor defined as the average ratio between the number of HF trades and orders and the total number of overall trades and orders across bonds:

$$HFTI_t = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{HFTO_{nt}}{ALLTO_{nt}}\right), \tag{49}$$

where $HFTO_{nt}$ is the number of HF trades and orders for bond n during day t, and $ALLTO_{nt}$ is the total number trades and orders. The authors conjecture that exposure to $HFTI_t$ commands a premium. The rationale behind this conjecture is that HFT can entail both benefits and risks. Among the possible risks are that HFT may overload exchanges, make it more difficult to trade at posted prices, and reduce liquidity at volatile times or when market making is difficult. Combined together, these effects mean that shocks to HFT intensity may generate systematic market disruptions and increase risk.

To test the conjecture above, the authors construct a portfolio long (short) low (high) HFT-beta bonds, where HFT betas are estimated using daily data for the previous 12 months. They then test whether such a long-short HFT mimicking portfolio earns positive excess returns, after controlling for the exposure to several other risk factors.

The analysis is based on data from BrokerTec covering the 1/2/2004–12/30/2011 sample. The main finding is that the HFT mimicking portfolio does earn a significant risk premium, and that this premium does not disappear when the excess returns are regressed on the returns of several other factor mimicking portfolios. In summary, exposure to HFT intensity is priced in the bond markets.

5.2 Summary

This section has reviewed two recent working papers studying the effects of HFT on the U.S. Treasury markets. In summary, these are the main results:

- HFT is substantially higher after scheduled macro news announcements.
- HFT worsens (improves) liquidity before (after) macro news announcements.
- Exposure to HFT is priced.

6 Conclusions

This chapter has reviewed studies of the high-frequency behavior of the U.S. Treasury markets. We believe that the recent focus in the literature on high-frequency data has dramatically improved our understanding of bond-market dynamics, but, in some sense, our scientific journey has just began. For example, while macro news is important, it still explains a relatively small portion of return behavior at announcement times. Moreover, even after controlling for macro news, there are still pronounced residual volatility dynamics that one would like to relate to fundamentals. Order flow moves prices in the Treasury markets, and more so in the aftermath of macro news announcements, precisely when public information should dominate. Moreover, recent years have witnessed a severe financial crisis, unprecedented responses by the Federal Reserve, and the increasing role of HFT. More research is warranted to better understand if any of these changes have caused a structural break in any of the key variables of the U.S. Treasury market. These are only some of the issues that are worth of further exploration within this exciting area of research.

References

[1] Y. Amihud, "Illiquidity and Stock Returns: Cross-section and Time-series Effects," *Journal of Financial Markets (5)*, pp. 31-56 (2002).

[2] T. Andersen, T. Bollerslev, and F. X. Diebold, "Roughing it Up: Including Jump Components in the Measurement, Modeling, and Forecasting of Return Volatility," *Review of Economics and Statistics (89)*, pp. 701–720 (2007).

[3] T. Andersen, T. Bollerslev, F. X. Diebold, and C. Vega, "Real-time Price Discovery in Global Stock, Bond and Foreign Exchange Markets," *Journal of International Economics (73)*, pp. 251–277 (2007).

[4] P. Balduzzi, G. Bertola, and S. Foresi, "A Model of Target Changes and the Term Structure of Interest Rates," *Journal of Monetary Economics (39)*, pp. 223–49 (1997).

[5] P. Balduzzi, E. J. Elton, and T. C. Green, "Economic News and Bond Prices: Evidence from the U.S. Treasury Market," *Journal of Financial and Quantitative Analysis (36)*, pp. 523–543 (2001).

[6] P. Balduzzi and F. Moneta, "Economic Risk Premia in the Fixed Income Markets: The Intra-day Evidence," *Working Paper* (2012).

[7] A. Beber and M. W. Brandt, "The effect of Macroeconomic News on Beliefs and Preferences: Evidence from the Options Market," *Journal of Monetary Economics (53)*, pp. 1997–2039 (2006).

[8] A. Beber and M. W. Brandt, "Resolving Macroeconomic Uncertainty in Stock and Bond Markets," *Review of Finance (13)*, pp. 119–155 (2009).

[9] A. Beber and M. W. Brandt, "When It Cannot Get Better or Worse: The Asymmetric Impact of Good and Bad News on Bond Returns in Expansions and Recessions," *Review of Finance (14)*, pp. 1–45 (2010).

[10] K. Becker, J. E. Finnerty, and K. Kopecky, "Macroeconomic News and the Efficiency of International Bond Futures Markets," *Journal of Financial Markets (16)*, pp. 131–145 (1996).

[11] F. Black, "Studies in stock price volatility changes," *Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section,* American Statistical Association, pp. 177–181 (1976).

[12] F. Black, "The Pricing of Commodity Contracts," *Journal of Financial Economics (3)*, pp. 167–179 (1976).

[13] T. Bollerslev, J. Cai and F. M. Song, "Intraday Periodicity, Long Memory Volatility, and Macroeconomic Announcement Effects in the US Treasury Bond Market," *Journal of Empirical Finance (7)*, pp. 37–55 (2000).

[14] M. W. Brandt and K. A. Kavajecz, "The Impact of Orderflow and Liquidity on the Yield Curve," *Journal of Finance (59)*, pp. 2623–2654 (2004).

[15] M. W. Brandt, K. A. Kavajecz, and S. E. Underwood, "Price Discovery in the Treasury Futures Market," *Journal of Futures Markets (27)*, pp. 1021–1051 (2007).

[16] M. Brenner, P. Pasquariello, and M. Subrahmanyam, "On the Volatility and Comovement of U.S. Financial Markets around Macroeconomic News Announcements," *Journal of Financial and Quantitative Analysis (44)*, pp. 1265–1289 (2009).

[17] J. Brogaard, T. Hendershott, and R. Riordan, "High-Frequency Trading and Price Discovery," forthcoming *Review of Financial Studies*.

[18] T. Chordia, A. Sarkar, and A. Subrahmanyam, "An Empirical Analysis of Stock and Bond Market Liquidity," *Review of Financial Studies (18)*, pp. 85-129 (2005).

[19] C. Christiansen, "Macroeconomic Announcement Effects on the Covariance Structure of Government Bond Returns," *Journal of Empirical Finance (7)*, pp. 479–507 (2000).

[20] C. Christiansen and A. Ranaldo, “Realized Bond-stock Correlation: Macroeconomic Announcement Effects,” *Journal of Futures Markets (27)*, pp. 439–469 (2007).

[21] B. H. Cohen and H. S. Shin, “Positive Feedback Trading Under Stress: Evidence From the US Treasury Securities Market,” *Working Paper* (2003).

[22] R. Connolly, C. Stivers, and L. Sun, “Stock Market Uncertainty and the Stock-Bond Return Relation,” *Journal of Financial and Quantitative Analysis (40)*, 161–193 (2005).

[23] T. Cook and T. Hahn, “The Information Content of Discount Rate Announcements and Their Effect on Market Interest Rates,” *Journal of Money, Credit, and Banking (20)*, pp. 167–180 (1988).

[24] T. Cook and T. Hahn, “The Effect of Changes in the Federal Funds Rate Target on Market Interest Rates in the 1970s,” *Journal of Monetary Economics (24)*, pp. 331–351 (1989).

[25] J. C. Cox, J. E. Ingersoll, Jr., and S. A. Ross, “A Theory of the Term Structure of Interest Rates,” *Econometrica (53)*, pp. 385–407 (1985).

[26] P. de Goeij and W. Marquering, “Macroeconomic Announcements and Asymmetric Volatility in Bond Returns,” *Journal of Banking and Finance (7)*, pp. 2659–2680 (2006).

[27] D. Easley, S. Hvidkjaer, and M. O’Hara, “Is Information Risk a Determinant of Asset Returns?” *Journal of Finance (57)*, pp. 2185–2221 (2002).

[28] L. H. Ederington and J. H. Lee, “How Markets Process Information: News Releases and Volatility,” *Journal of Finance (48)*, pp. 1161–1191 (1993).

[29] L. H. Ederington and J. H. Lee, “The Creation and Resolution of Market Uncertainty: The Impact of Information Releases on Implied Volatility,” *Journal of Financial and Quantitative Analysis (31)*, pp. 513–539 (1995).

[30] L. H. Ederington and J. H. Lee, "The Short-Run Dynamics of the Price Adjustment to New Information," *Journal of Financial and Quantitative Analysis (30)*, pp. 117–134 (1996).

[31] L. H. Ederington and J. H. Lee, "Intraday Volatility in Interest-Rate and Foreign-Exchange Markets: ARCH, Announcement, and Seasonality Effects," *Journal of Financial Markets (21)*, pp. 517–552 (2001).

[32] E. F. Fama, "Does the Fed Control Interest Rates?" *Review of Asset Pricing Studies (3)*, pp. 180–199 (2013).

[33] E. F. Fama and K. R. French, "Common Risk Factors In the Returns on Stocks and Bonds" *Journal of Financial Economics (33)*, pp. 3–56 (1993).

[34] H. Farnsworth and R. Bass, "The Term Structure with Semicredible Targeting," *Journal of Finance (58)*, pp. 839–65 (2003).

[35] J. Faust and J. H. Wright, "Risk Premia in the 8:30 Economy," *Working Paper* (2009).

[36] J. Faust, E.T. Swanson, and J.H. Wright, "Identifying VARS Based on High Frequency Futures Data," *Journal of Monetary Economics (51)*, pp. 1107–1131 (2004).

[37] M. J. Fleming, "The Round-the-Clock Market for U.S. Treasury Securities," Federal Reserve Bank of New York *Economic Policy Review (3)*, pp. 9–32 (1997).

[38] M. J. Fleming, "Measuring Treasury Market Liquidity," Federal Reserve Bank of New York *Economic Policy Review (9)*, pp. 83–108 (2003).

[39] M. J. Fleming and K. D. Garbade, "Explaining Settlement Fails," *Federal Reserve Bank of New York Current Issues in Economics and Finance (11)* (2005).

[40] M. J. Fleming and B. Mizrach, "The Microstructure of a U.S. Treasury ECN: The BrokerTec Platform," *Federal Reserve Bank of New York Staff Reports*, no. 381 (2009).

[41] M. J. Fleming and M. Piazzesi, "Monetary Policy Tick-by-Tick," *Working Paper* (2005).

[42] M. J. Fleming and E. M. Remolona, "What Moves the Bond Market?" *FRBNY Economic Policy Review*, pp. 31–50 (1997).

[43] M. J. Fleming and E. M. Remolona, "Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information," *Journal of Finance (54)*, pp. 1901–1915 (1999).

[44] K. D. Garbade, F. M. Keane, L. Logan, A. Stokes, and J. Wolgemuth, "The Introduction of the TMPG Fails Charge for U.S. Treasury Securities," *FRBNY Economic Policy Review*, pp. 45–71 (2010).

[45] R. Y. Goyenko, C. W. Holden, and C. A. Trzcinka, "Do Liquidity Measures Measure Liquidity?" *Journal of Financial Economics (92)*, pp. 153–181 (2009).

[46] T. C. Green, "Economic News and the Impact of Trading on Bond Prices," *The Journal of Finance (59)*, pp. 1201–1233 (2004).

[47] R. S. Gürkaynak, B. Sack, and E. Swanson, "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking (1)*, pp. 55–93 (2005).

[48] R. S. Gürkaynak, B. Sack, and E. Swanson, "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models," *American Economic Review (95)*, pp. 425–436 (2005).

[49] R. S. Gürkaynak, B. Sack, and J. H. Wright, "The U.S. Treasury Yield Curve: 1961 to the Present," *Journal of Monetary Economics (54)*, pp. 2291–2304 (2007).

[50] R. S. Gürkaynak and J. Wolfers, "Macroeconomic Derivatives: An Initial Analysis of Market-based Macro Forecasts, Uncertainty, and Risk," *NBER Working Paper 11929* (2006).

[51] C. R. Harvey and R. D. Huang, "The Impact of the Federal Reserve Bank's Open Market Operations," *Journal of Financial Markets (5)*, pp. 223–257 (2002).

[52] J. Hasbrouck, "Measuring the Information Content of Stock Trades," *Journal of Finance (46)*, pp. 179–207 (1991).

[53] Y. He, H. Lin, J. Wang, and C. Wu, "Price discovery in the round-the-clock U.S. Treasury market," *Journal of Financial Intermediation (18)*, pp. 464–490 (2009).

[54] T. Hendershott, C. M. Jones, and A. J. Menkveld, "Does Algorithmic Trading Improve Liquidity?" *Journal of Finance*, pp. 1–33 (2011).

[55] T. Hendershott and R. Riordan, "Algorithmic Trading and the Market for Liquidity" *Journal of Financial and Quantitative Analysis*, pp. 1001–1024 (2013).

[56] R. D. Huang, J. Cai, and X. Wang, "Information-Based Trading in the Treasury Note Interdealer Broker Market," *Journal of Financial Intermediation (11)*, pp. 269–296 (2002).

[57] R. D. Huang and H. R. Stoll, "Dealer Versus Auction Markets: A Paired Comparison of Execution Costs on Nasdaq and the NYSE," *Journal of Financial Economics (41)*, 313–357 (1996).

[58] G. J. Jiang, I. Lo, and G. Valente, "High Frequency Trading around Macroeconomic News Announcements: Evidence from the US Treasury Market," *Working Paper* (2013).

[59] G. J. Jiang, I. Lo, and A. Verdelhan, "Information Shocks, Liquidity Shocks, Jumps, and Price Discovery—Evidence from the U.S. Treasury Market," *Journal of Financial and Quantitative Analysis (49)*, pp. 527–551 (2011).

[60] M. Johannes, "The Statistical and Economic Role of Jumps in Continuous-Time Interest Rate Models," *Journal of Finance (49)*, pp. 227–260 (2004).

[61] C. M. Jones, O. Lamont, and R. L. Lumsdaine, “Macroeconomic News and Bond Market Volatility,” *Journal of Financial Economics (47)*, pp. 315–337 (1998).

[62] R. Kaniel and H. Liu, “So What Orders do Informed Traders Use?” *Journal of Business (79)*, pp. 1867–1913 (2006).

[63] K. N. Kuttner, “Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market,” *Journal of Monetary Economics (47)*, pp. 523–544 (2001).

[64] M. Lewis, “Flash Boys (A Wall Street Revolt),” *Norton, New York*, (2014).

[65] L. Li and R. F. Engle, “Macroeconomic Announcements and Volatility of Treasury Futures,” *Working Paper* (1998).

[66] H. Li, J. Wang, C. Wu, and Y. He, “Are Liquidity and Information Risks Priced in the Treasury Bond Market?” *Journal of Finance (64)*, pp. 467–503 (2009).

[67] X. Liu, I. Lo, M. Nguyen, and G. Valente, “High-frequency Trading and Treasury Bond Returns” *Working Paper* (2014).

[68] B. Lu and L. Wu, “Macroeconomic Releases and the Interest Rate Term Structure,” *Journal of Monetary Economics (56)*, pp. 872–884 (2009).

[69] K. Man, J. Wang, and C. Wu, “Price Discovery in the U.S. Treasury Market: Automation vs. Intermediation,” *Management Science (59)*, pp. 695–714 (2013).

[70] A. J. Menkveld, A. Sarkar, and M. van der Wei, “Customer Order Flow, Intermediaries, and Discovery of the Equilibrium Risk-Free Rate,” *Journal of Financial and Quantitative Analysis (47)*, pp. 821–849 (2012).

[71] B. Mizrach and C. Neely, “The Transition to Electronic Communications Networks in the Secondary Treasury Market,” *Federal Reserve Bank of St. Louis Review (88)*, pp. 527–541 (2006).

[72] B. Mizrach and C. Neely, "Information Shares in the U.S. Treasury Market," *Journal of Banking and Finance (32)*, pp. 1221–1233 (2008).

[73] P. Pasquariello and C. Vega, "Informed and Strategic Order Flow in the Bond Markets," *Review of Financial Studies (20)*, pp. 1976–2019 (2007).

[74] M. Piazzesi, "Bond Yields and the Federal Reserve," *Journal of Political Economy (113)*, pp. 311-344 (2005).

[75] R. Rigobon, "Identification Through Heteroskedasticity," *Review of Economics and Statistics (85)*, pp. 777–792 (2003).

[76] R. Rigobon and B. Sack, "The Impact of Monetary Policy on Asset Prices," *Journal of Monetary Economics (51)*, pp. 1553–1575 (2004).

[77] G. D. Rudebusch, "Federal Reserve Interest Rate Targeting, Rational Expectations, and the Term Structure," *Journal of Monetary Economics (35)*, pp. 245–74 (1995).

[78] P. Savor and M. Wilson, "How Much Do Investors Care About Macroeconomic Risk? Evidence From Scheduled Economic Announcements," *Journal of Financial and Quantitative Analysis (48)*, pp. 343–375 (2013).

[79] P. Savor and M. Wilson, "Asset Pricing: A Tale of Two Days," *Journal of Financial Economics (113)*, pp. 171–201 (2014).

[80] D. van Dijk, R. L. Lumsdaine, and M. van der Wel, "Market Set-Up in Advance of Federal Reserve Policy Rate Decisions," *Working Paper* (2014).

[81] O. Vasicek, "An Equilibrium Characterization of the Term Structure," *Journal of Financial Economics (5)*, pp. 177–188 (1977).

[82] J. Wright, “What Does Monetary Policy Do to Long-Term Interest Rates at the Zero Lower Bound?,” *Economic Journal (122)*, pp. 447–466 (2012).

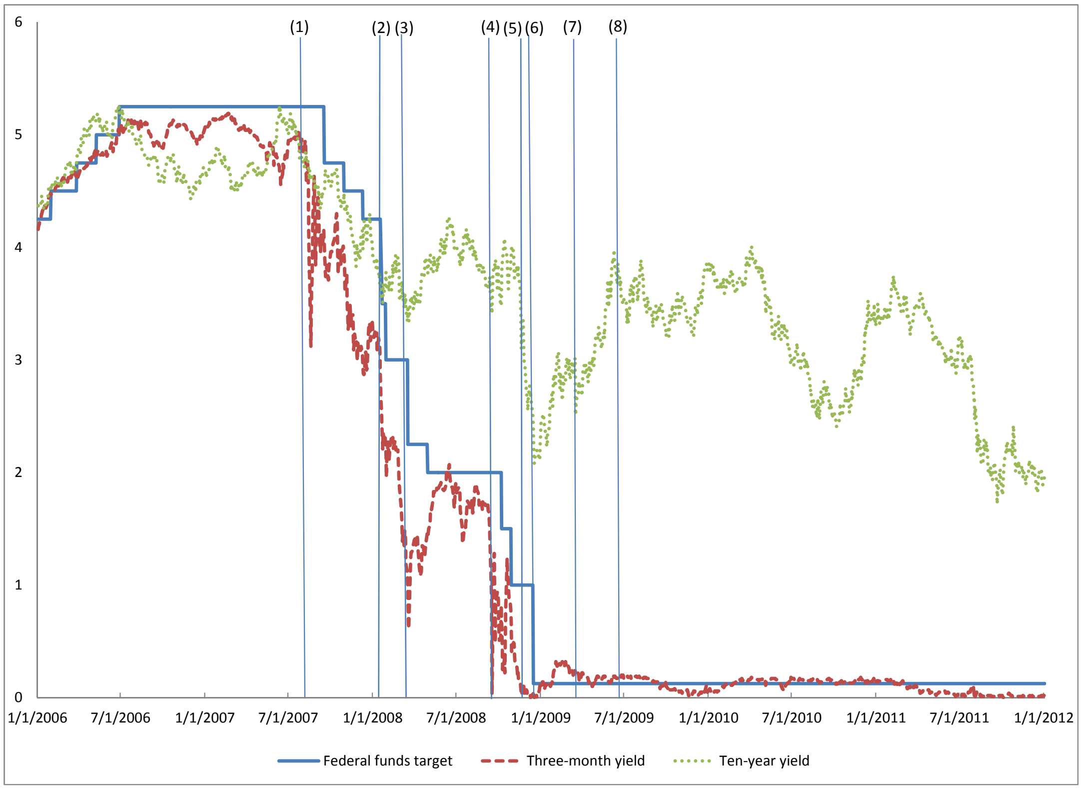

Figure 1: Yields and Fed funds rate target

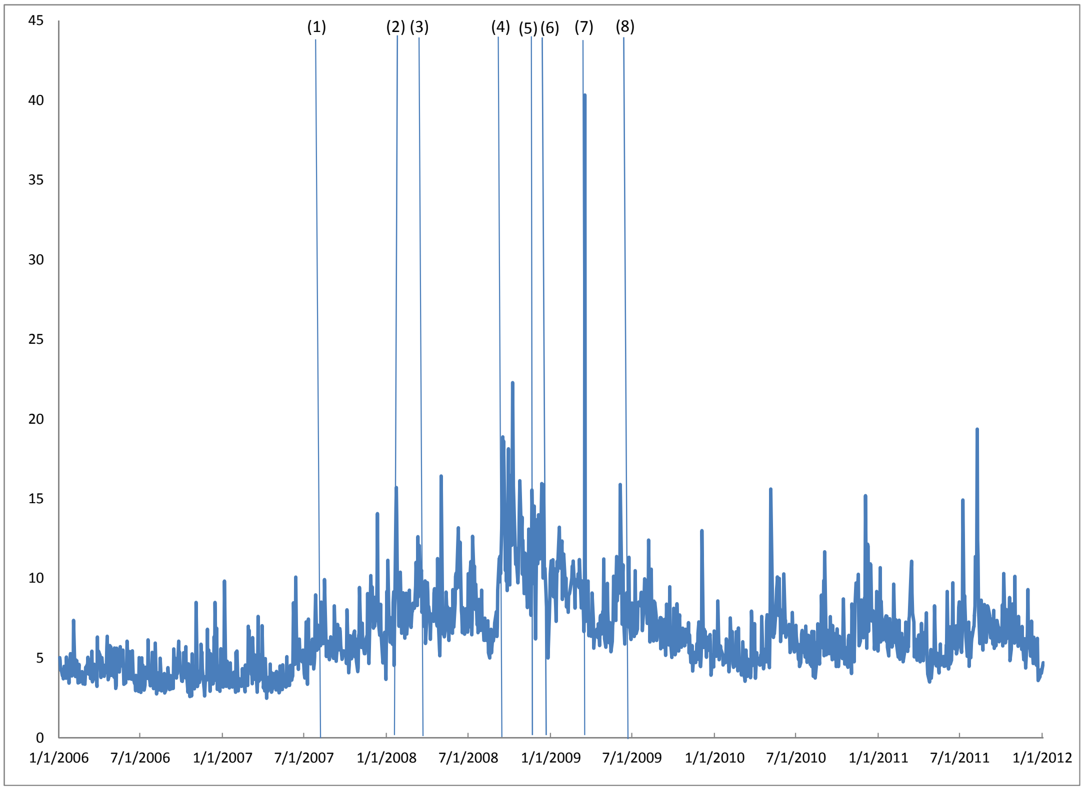

Figure 2: Ten-year futures, daily realized volatility

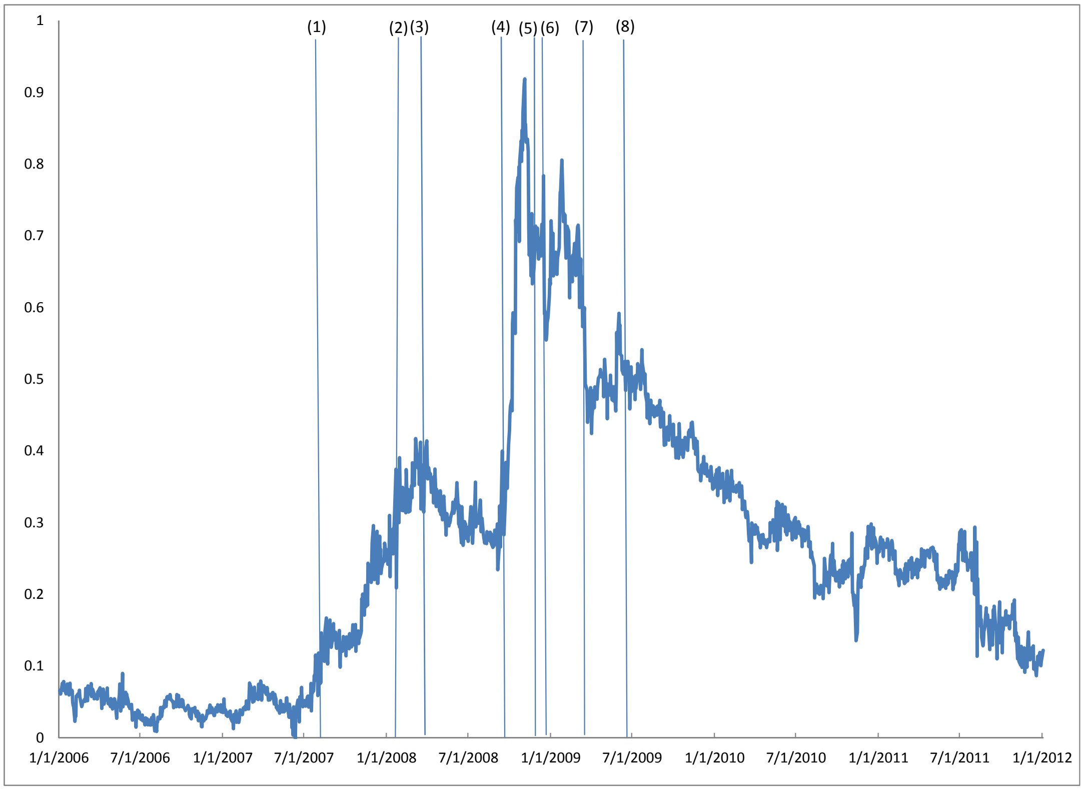

Figure 3: Off-the-run/on-the-run spread

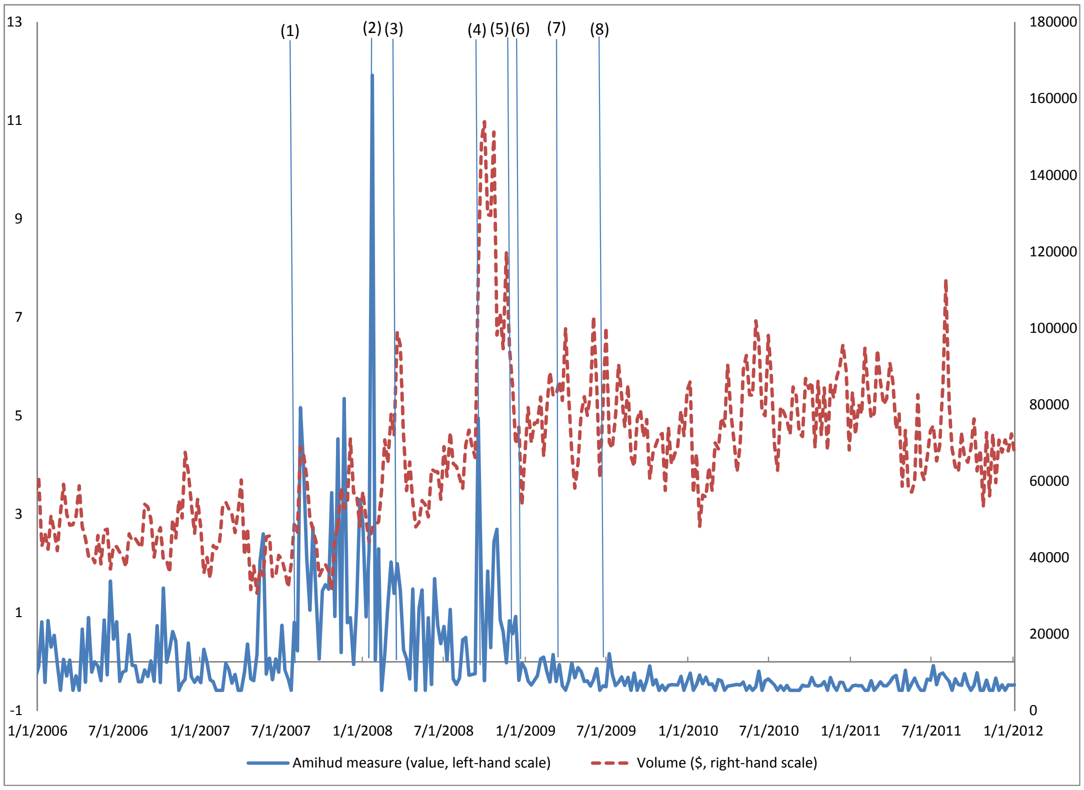

Figure 4: T-bills, volume and Amihud measure

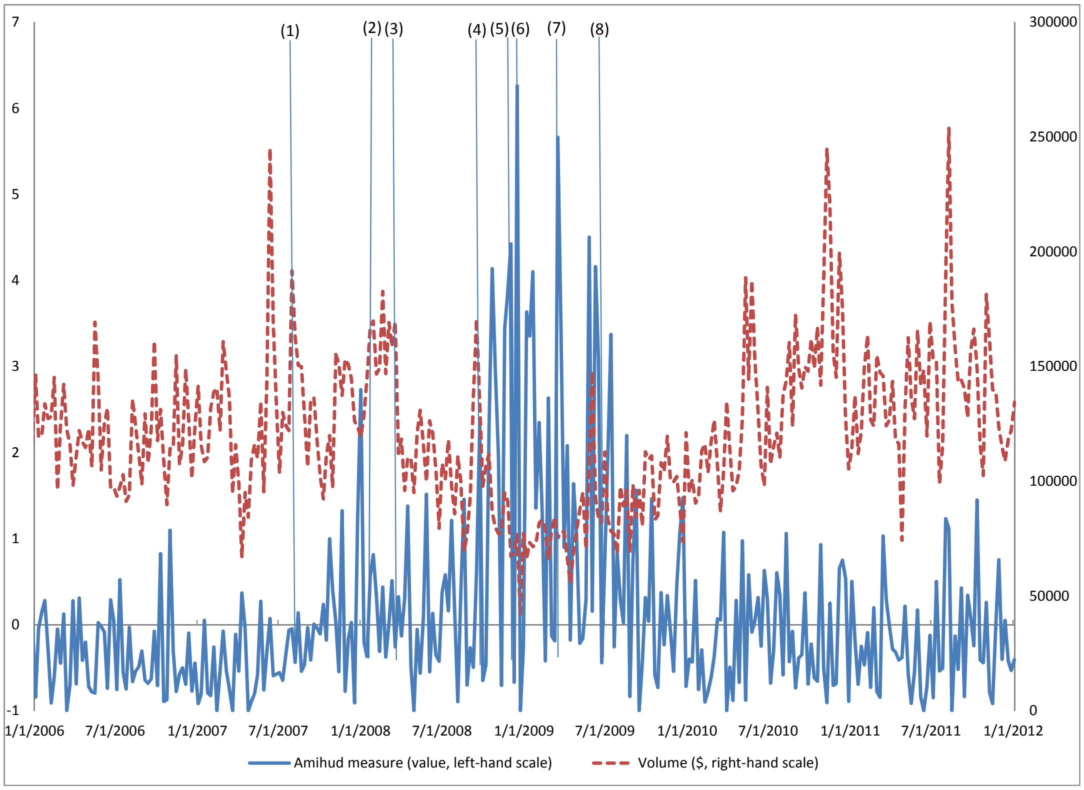

Figure 5: Six- to 11-year notes, volume and Amihud measure

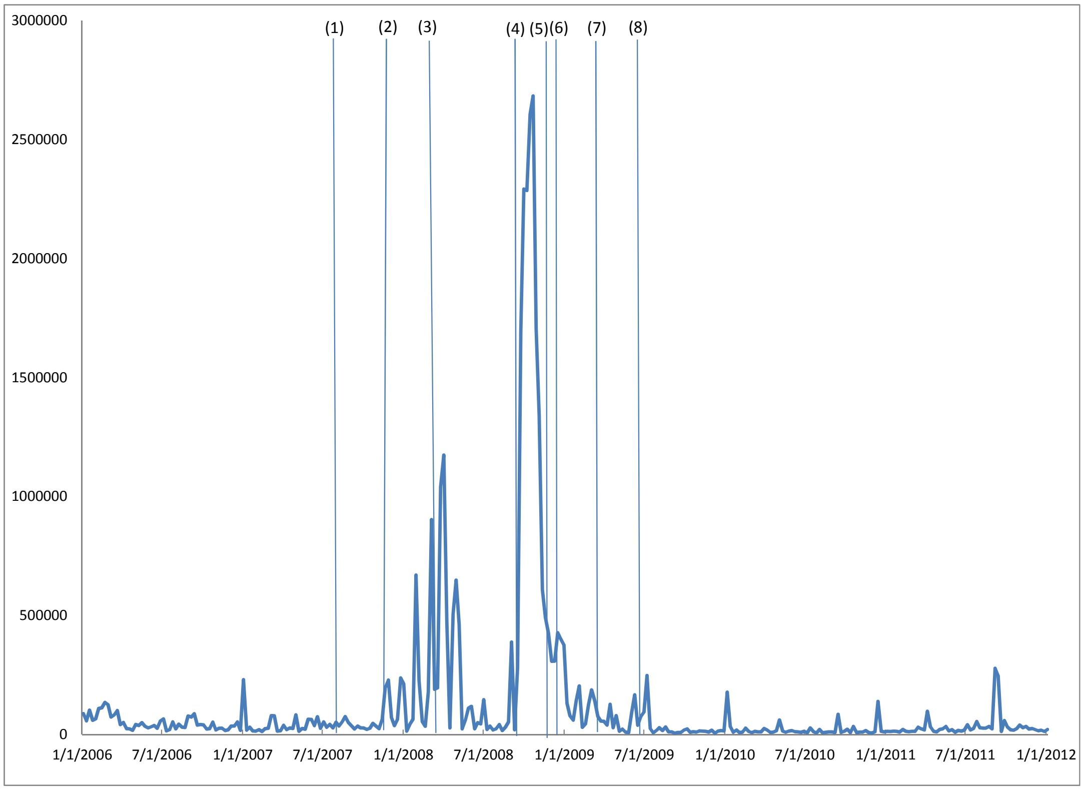

Figure 6: Delivery fails

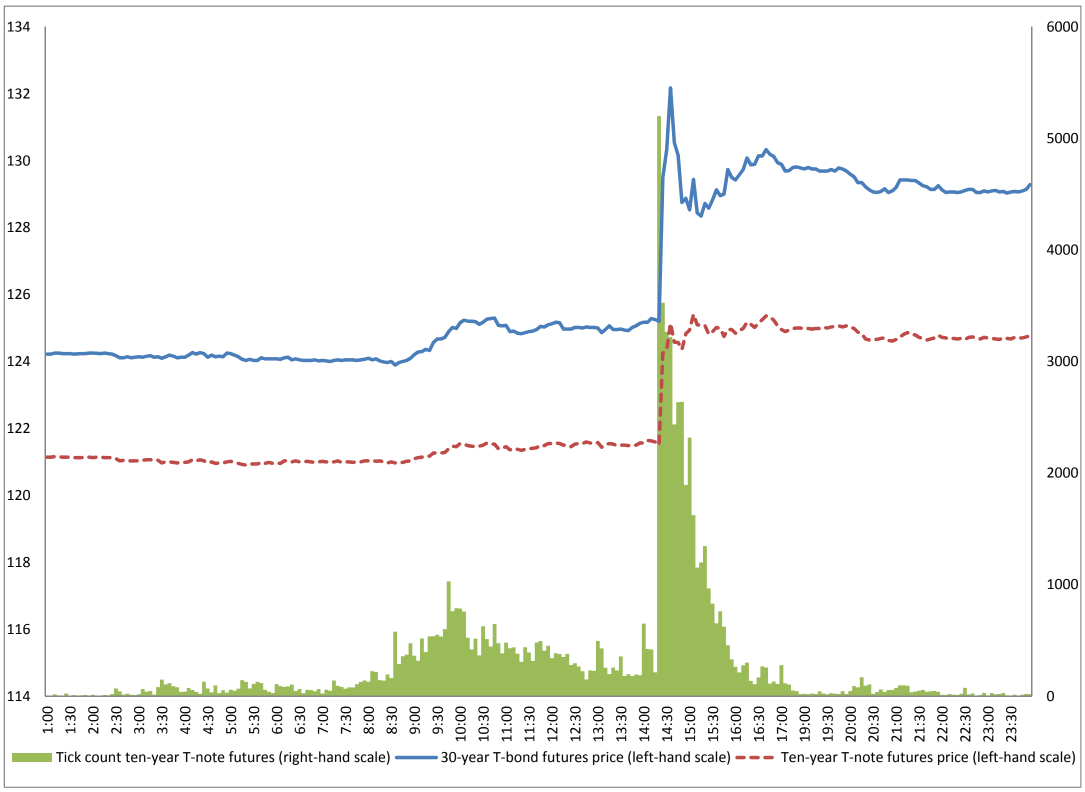

Figure 7: 30-year T-bond and ten-year T-note futures prices on March 18, 2009