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Abstract

We propose a new class of dynamic order book models that allow us to 1) study episodes of extreme low liquidity and 2) unite liquidity and volatility in one framework through which their joint dynamics can be examined. Liquidity and volatility in the U.S. Treasury securities market are analyzed around the time of economic announcements, throughout the recent financial crisis, and during flight-to-safety episodes. We document that Treasury market depth declines sharply during the crisis, accompanied by increased price volatility, but that trading activity seems unaffected until after the Lehman Brothers bankruptcy. Our models' key finding is that price volatility and depth at the best bid and ask prices exhibit a negative feedback relationship and that each becomes more persistent during the crisis. Lastly, we characterize the Treasury market during flights to safety as having much lower market depth, along with higher trading volume and greater price uncertainty.

Key words: liquidity, Treasury market, limit order book, financial crisis, volatility, announcement

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1 Introduction

Interest in the dynamics of market liquidity and volatility in the U.S. Treasury securities market stems from the market's many vital roles. Because of their liquidity, Treasury securities are commonly used to price and hedge positions in other fixed-income securities and to speculate on the course of interest rates. The securities' creditworthiness and liquidity also make them a key instrument of monetary policy and a crucial source of collateral for financing other positions. These same attributes make Treasury securities a key store of value, especially during times of crisis.

The flight–to–liquidity premium in Treasury bond prices documented by Longstaff (2004) is a good example of how the plentiful liquidity in the Treasury market is valued by investors. This poses several interesting questions for the U.S. Treasury market. Is liquidity supply available when it is needed most? How is liquidity supply driven by uncertainty and other market factors, and conversely, does the supply of liquidity have any role in dampening or magnifying volatility in the market? How do the dynamics of the Treasury limit order book differ during flight–to–safety episodes?

A dynamic model for liquidity and its interrelation with volatility is highly useful for addressing these questions and exploring other microstructure issues of interest. With the availability of intraday data on the limit order book of Treasury securities in the inter–dealer market, the model can be cast in high frequency time intervals, and can accordingly convey rich and insightful information about the micro behavior of liquidity and volatility in this market.

Our study contributes to the extensive literature on price formation and liquidity in the U.S. Treasury market. This strand of literature includes Fleming and Remolona (1999), Balduzzi, Elton, and Green (2001), Huang, Cai, and Wang (2002), Fleming (2003), Brandt and Kavajecz (2004), Green (2004), Fleming and Piazzesi (2005), Goldreich, Hanke, and Nath (2005), Mizrach and Neely (2007), Pasquariello and Vega (2007), Fleming and Mizrach (2009), Jiang, Lo, and Verdelhan (2011), and many others. However, most of the extant studies use data prior to the 2008 crisis period, leaving market dynamics during the crisis – the most serious to hit the global economy since the Great Depression – less documented.

Being a safe haven for investors, the role of the Treasury market during flight–to–safety episodes is particularly important. An active literature studying the flight–to–safety phenomenon has provided (1) a number of theoretical models (see for example, Vayanos (2004) and Brunnermeier and Pedersen (2009)) and (2) related empirical evidence (see for example, Longstaff (2004), Goyenko and Sarkissian (2008), Baele, Bekaert, and Inghelbrecht (2010), Baur and Lucey (2009), Beber, Brandt, and Kavajecz (2009), Bansal, Connolly, and Stivers (2010), and Baele, Bekaert, Inghelbrecht, and Wei (2012)). While these studies provide great insights into the potential determinants of flight–to–safety episodes, such as the elevated level of risk, the changing risk aversion of investors, the tightening of margin requirements, and so on, little attention has been paid to how the destination of such flights – the Treasury market – is affected by the actions of those investors seeking safe haven. Our paper aims to fill this gap by documenting the behavior of liquidity and volatility during such episodes and by providing an econometric model to isolate the effect of flights to safety on this benchmark market.

Our study is related to papers that have documented asset pricing anomalies that arose during the financial crisis. Fleckenstein, Longstaff, and Lustig (2010) show that a significant mispricing arose during the crisis between Treasury bonds and inflation-swapped TIPS issues with replicating cash flows. Musto, Nini, and Schwarz (2011) document a large and systematic mispricing during the crisis between notes and bonds with identical cash flows. Hu, Pan, and Wang (2011) show that "noise" in Treasury security prices rose sharply during the crisis. Our paper also documents the unusual market behavior during the crisis, but by directly assessing market liquidity. Moreover, while the previously mentioned pricing anomalies are shown to have arisen largely among less traded Treasury securities, our study identifies liquidity declines in the most actively traded Treasury securities.

Our study is also relevant for the general market microstructure literature on price discovery. Price incorporates news and converges to fundamental value through the trading process. The availability of liquidity is critical to that process and therefore modeling the evolution of liquidity can complement and further our knowledge on the dynamics of asset prices. Although equity limit order books have been studied extensively, studies on Treasury limit order books remain scant in comparison. There is no a priori reason to expect empirical findings from equity markets to hold up in the Treasury market. Informed trading is important in equity markets, but less so in the Treasury market, which is driven more by macroeconomic conditions and, in particular, monetary policy decisions and macroeconomic data releases. As a result, the dynamics of price and liquidity in this market could potentially differ from that documented for equity markets.

While market liquidity can be measured in many ways, we focus on market depth – a direct measure of the quantity of securities available for purchase and sale. Henceforth, we will use the two terms liquidity and depth interchangeably.[1] It is useful to note that the

[1]Market depths (in plural) refer to depth at multiple price tiers, while market depth (singular) refers to

distinction between liquidity supply and demand may not be clear in limit order markets. In their comprehensive survey of the limit order book literature, Parlour and Seppi (2008) describe how investors with a demand for liquidity may choose to post aggressive limit orders rather than market orders. Such limit orders have the flavor of both supply and demand. Therefore, while the liquidity available in the order book (on both sides) is often considered representative of the liquidity supply, some of this liquidity could potentially come from demanders of liquidity who happen to have more patience to wait for their orders to be executed at better prices than those who submit market orders for immediate execution. In this paper, we adopt the traditional approach of considering limit orders as the supply side and market orders as the demand side.

We propose a new joint model of liquidity and volatility based on the multiplicative error model (hereafter "MEM") formally introduced in Engle (2002). There are important features of the U.S. Treasury market that make this modeling choice superior to the standard linear Gaussian framework adopted in many previous empirical models of the limit order book.[2] First, it has been shown that depth tends to disappear prior to economic news announcements (e.g., Fleming and Remolona (1999) and Fleming and Piazzesi (2005)). This paper also documents a large liquidity drop in the fall of 2008. Therefore, the model must be able to accommodate zero or small values of depth with a reasonable probability mass. Secondly, both market depth and volatility are non–negative variables, but under a linear Gaussian framework their predictions are not guaranteed to be non–negative. Even if log transformation is used to avoid the non–negativity issue, researchers run into the problem of exact zero values at which the logged depth or volatility is not defined. The log linear framework is also problematic for predicting small values of depth as these are implicitly treated as extreme events whereas empirical evidence tells us that small values of depth are not uncommon. The new class of models we suggest can easily handle spells of near-zero (and positive valued) liquidity. Lastly, our MEM–based model enjoys the benefit of modeling directly the variables of interest, not their log–transformed counterparts, which can be convenient in interpretation and forecasting.

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the depth at a particular price tier.

[2]For example, Ahn, Bae, and Chan (2001) use a regression framework to study the dynamics of the number of limit orders posted. Likewise, Næs and Skjeltorp (2006) regress trade size and number of transactions on volatility to document the existence of a volume–volatility relationship in the Norwegian equity market. Härdle, Hautsch, and Mihoci (2009) propose a dynamic semiparametric factor approach to modeling liquidity supply, combining non–parametric factor decomposition for the order curve's spatial structure with VAR for time variations of factor loadings. Other studies similar in their use of VAR include Danielsson and Payne (2010) and Hautsch and Huang (2009), among others. Ranaldo (2004) uses an ordered probit regression framework to analyze how the state of the limit order book affects order submission strategy.

The key insight from our model choice is that we make empirical limit order book models look much like asset price volatility models. This has several advantages. First, we can readily borrow many specifications and modeling strategies from the vast volatility literature. For example, we can study the effect of news via so called news impact curves, see e.g., Engle and Ng (1993). Second, we can easily study the interactions of volatility and limit order book dynamics within a well understood and unified framework. Third, non–negativity of depth – and obviously volatility – is guaranteed within the MEM specification. This rules out nonsensical predictions and therefore addresses many of the issues discussed in the previous paragraph.

The cross–fertilization of insights from the volatility literature to that of limit order books goes beyond modeling strategies – it also pertains to measurement. In the past decade, the notion of so–called realized (price) volatility has been extensively studied (see the recent survey by Barndorff-Nielsen and Shephard (2007)). We introduce the notion of limit order book depth realized volatility – which measures the variability of liquidity using high frequency data. Namely, our modeling strategy consists of taking five–minute snapshots of the book as well as measuring one–second changes in the book. The latter allows us to compute for every five–minute interval the realized quadratic variation at all levels of the limit order book.[3] This provides us with a measure of liquidity risk, similar to the quadratic variation measure widely used in the volatility literature to characterize price risk. Thanks to this new measure of realized depth volatility, we can study the impact of liquidity uncertainty on the level of liquidity. Needless to say, the realized depth volatility is obviously also a non–negative process. Hence, our modeling strategy is perfectly suited to include this new measure as well.

Using limit order book data for the 2–, 5– and 10–year U.S. Treasury notes over the period from 2006 to the end of the second quarter of 2010, our class of models identifies several key findings. First, the order book exhibits clustering in all three variables of interest: depth, price volatility, and liquidity volatility (except liquidity volatility at the first tier). More importantly, there is a negative feedback loop between market depth and price uncertainty at the inside bid and ask. For other price levels however, depths tend to lower subsequent price uncertainty but the reverse effect is not present. Submitting orders to the inside queues subjects dealers to adverse execution risk and thus, when price is volatile, it is easy to see why dealers tend to cut back on supplying liquidity at the best bid and ask. There is room for modification or cancelation of orders behind the market when price moves unfavorably,

[3] Technically speaking the limit order book, unlike high frequency returns, is not a martingale difference sequence. We provide several robustness checks with respect to the drift specification.

so price volatility is less of a concern in the decision to supply depth at the outer tiers. In contrast to the negative interaction between liquidity and price uncertainty, we find that an increased level of depth uncertainty tends to bring out more depth, and this is consistent across all price levels. This evidence seems to suggest that liquidity supply tends to increase when it is more valuable to the marketplace, consistent with the findings in Biais, Hillion, and Spatt (1995).

Examining the dynamics of depth and volatility during the crisis period, we find that both become more persistent during the crisis. This dangerous combination provides a great illustration to models of liquidity crashes (for example, Cespa and Foucault (2012)) in that bad shocks to either volatility or liquidity can intensify the negative feedback effect, leading to liquidity crashing while volatility spiking up. Our models also provide consistent evidence with the earlier literature that depth is withdrawn immediately before important economic announcements but then quickly gets refilled once the announcement is released, accompanied by a surge in trading activity and price uncertainty. Furthermore, the news impact curve – a concept standard in the volatility literature but novel in a limit order book context – shows evidence of an asymmetric response of market depth to negative price changes, whereas price volatility does not seem to discriminate between price increases and decreases. Price volatility instead appears sensitive to the magnitude of the value change only. The fact that many dealers take part on both sides of the market, and large price moves may be indicative of important events around which divergences of opinion often rise, could explain this behavior.

Our analysis of the Treasury market during flights to safety contributes new evidence to the discussions of this phenomenon. In particular, the ex ante liquidity supply, namely the limit order book, is substantially lower on flight days – those days when liquidity is especially needed. However, a high level of trading activity is also observed on those days, along with an elevated level of price uncertainty. These patterns collectively suggest that liquidity providers monitor the market more closely on these days and refrain from using limit orders to passively supply liquidity to the market.

The paper is organized as follows. Section 2 presents stylized facts on trading, liquidity and volatility in the U.S. Treasury market. These stylized facts provide the motivation for our modeling approach based on the multiplicative error framework, which we discuss in Section 3. Practical issues with model estimation and the measurement of volatility are also covered in this section. In Section 4, we present and discuss the empirical dynamics of Treasury liquidity and volatility as estimated by our proposed class of models. We then provide an analysis of the Treasury market during flight–to–safety episodes in Section 5. Finally, Section

6 concludes the paper.

2 The U.S. Treasury Market – Some Stylized Facts

U.S. Treasury securities are debt instruments sold by the U.S. government through public auctions and subsequently traded in the secondary market. The secondary market is structured as a multi–dealer, over–the–counter market, in which the dealers trade with their customers, the Federal Reserve Bank of New York, and one another. Inter–dealer trading prior to 1999 was based on a network of voice–assisted brokers. Fully electronic trading started in 1999 with the introduction of the eSpeed platform, followed by the BrokerTec platform in 2000. Mizrach and Neely (2006) estimate that the BrokerTec platform accounts for about 61 percent of all inter–dealer trading activity.

There are no clearly defined trading hours for this market. Instead, trading spans 22–23 hours per day during the week, commencing around the start of the trading day in Tokyo and fading off with the end of the trading day in New York. During these hours, dealers send in their orders, have their orders executed, or modify or cancel existing orders. Each order specifies the quantity and price, whether it is for purchase or sale, and whether the order is aggressive.[4] Limit orders, when submitted, are queued in the order book according to the price and time priority rules until executed or canceled. Although trading spans almost the entire day, trading outside of the New York trading hours is sparse, so we limit our analysis to between 7:00 and 17:00 Eastern time.

2.1 Data Description

Our analysis is based on order book data from the BrokerTec platform. All order messages sent to this platform are captured and time–stamped to the millisecond. The order book snapshot data is constructed by accumulating these order changes at the corresponding price tiers from the beginning of the trading day. This results in a tick–by–tick dataset with market depths measured in millions of dollars (par value), and prices reported in 256ths of a point, where a point equals one percent of the par value. We focus our attention on the on–the–run 2–, 5– and 10–year notes, as these are the most actively traded Treasury securities. The

[4] Aggressive, or market, orders are executed immediately against best available limit orders on the opposite side of the market. Passive, or limit, orders are queued in the limit order book at the corresponding price level. All orders, whether aggressive or passive, need to specify both quantity and price. Best limit orders on opposite sides with the same price are not automatically executed.

2– and 5–year notes are newly issued every month, while the 10–year note comes out every quarter with reopenings in the following month and – since November 2008 – two months.[5]

Our sample period is January 2, 2006 to June 30, 2010, and thus covers the financial markets crisis of 2008–09, as well as a period before the crisis. We date the start of the crisis to August 9, 2007, when BNP Paribas announced that it could not value assets in three of its investment funds (see Boyd (2007)).[6] There is no clear ending date to the crisis, so we mark the end with the NBER's end–of–recession date of June 2009.

For our empirical analysis, we choose to work with the five–minute snapshot data, supplemented by the one–second snapshot data needed for the computation of the realized volatility measures The five–minute snapshot data are extracted from the tick data described above by taking the last observation of each five–minute interval between 7:00 and 17:00. This results in 120 observations per day, except for those days with an early market close. For such days, we discard data after the recommended closing time.[7] The one–second snapshot data is extracted from the tick data in the same fashion. Although the data is available tick–by–tick, our choice of the five–minute interval is to avoid data errors (e.g., erroneous order messages that enter and exit the book in split seconds) and microstructure noise inherent in ultra–high frequencies. The interval is also long enough for sufficient movements in the book, so that meaningful predictions can be made.

We focus our analysis on the best five price tiers on each side of the market. First, we know from Biais, Hillion, and Spatt (1995) that liquidity is not concentrated at the inside tier. Second, the five–minute sampling implies that depth at different tiers is relevant for the future evolution of the limit order book. We choose to look at five tiers, which mirrors what market participants can see.

[5]We apply the following filters to the data. Since we are exclusively looking at recently issued on-the-run securities, and Treasury securities are issued at a price close to par value, then prices have to be in the vicinity of 25,600 (par value). We adopt a range of 20,000 – 30,000 to remove outliers, a filter that is narrow enough to remove obvious price errors, but conservative enough to still capture valid but extreme prices. For depth variables, we adopt a filter of $10 billion of par value for each price tier, which is roughly one-third the size of the typical issue in our dataset.

[6]Note that the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) considers December 2007 as the start of the recession (http://www.nber.org/cycles.html). However, for the purpose of modeling liquidity in the Treasury market, the earlier date at which the crisis started in the money markets is more appropriate.

[7]Information on recommended early closes in the bond market is from the Securities Industry and Financial Markets Association and is posted here: http://www.sifma.org/uploadedfiles/research/statistics/statisticsfiles/misc-us-historical-holiday-market-recommendations-sifma.pdf.

2.2 Some Stylized Facts

In this section, we document a number of stylized facts pertaining to the 2–, 5– and 10–year notes, with particular focus on their time series behavior through the most recent financial crisis, as well as their patterns around macroeconomic announcements.

Market Depths Decline Sharply During Crisis

As shown in Table 1, prior to the crisis, the average depth at the best price tier for the 2–year note is over $400 million. It plummets to roughly one fifth this level during the crisis period. Coming out of the crisis, the market recovers somewhat, but remains far below the pre–crisis level. Similar trends can be observed for the 5– and 10–year notes: the pre–crisis average depth at the best price tier is about $72 million, before dropping to a level slightly above $20 million during the crisis. However, unlike the partial recovery observed with the 2–year note, liquidity does not seem to improve much after the crisis for the 5– and 10–year notes. Note that Treasury issue sizes have steadily increased over the sample period. So the decline in liquidity we observe during the crisis is not attributable to a declining issue size.

Another observation of interest is that average market depth is highest at the second tier and gradually declines over the subsequent tiers. This is consistent with the finding of Fleming and Mizrach (2009) using BrokerTec data from January 2005 to February 2006. That liquidity is not concentrated at the inside tier is also documented by Biais, Hillion, and Spatt (1995) using order book data for stocks on the Paris Bourse. They attribute this finding to the fact that trading consumes liquidity at the front line.

To see the trend in Treasury market depth throughout the crisis period more closely, we graph daily averages of depth in Figure 1 for the 2–year note (solid line). Graphs on the left are for the inside ask and on the right for the inside bid. Whether on the bid or ask side, market depth starts to decline sharply in mid 2007, providing evidence of mounting pressures in the Treasury market at the onset of the crisis. Liquidity drops sharply again in the fall of 2008 following Lehman Brothers' bankruptcy. Depth then bottoms out towards the end of 2008 and then improves fairly steadily from there. Depths at other tiers as well as the total depth across the best five price tiers have the same time series pattern. The 5– and 10–year notes exhibit very similar trends (not shown), although their recovery following the crisis is not as strong as what is observed with their 2–year counterpart.

Spread Is Tight but Widens Significantly in Late 2008

The bid–ask spread is another useful indicator that supplements our characterization of liquidity in this market. An analysis of the inside spread shows that, for all three securities considered, the spread is quite tight, with an average of slightly above one tick.[8] The tight spread around the small minimum allowable price movement suggests a very liquid market. Its time series behavior - with the inside spread widening significantly and consistently across the three notes in late 2008 – is also consistent with the pattern in market depths that points to a large liquidity drop at the height of the crisis. The 5–year note exhibits the most extreme peak in this period, followed by the 10–year. The spread returns to a level of just over one tick again in 2009 (see Figure 2).

Trading Volume Does Not Drop Until Late 2008

In contrast to the drop in market depth – a measure of the ex ante liquidity supply – that happens right at the beginning of the crisis in August 2007, actual trading volume is on the rise during the first half of the crisis (see graphs (a) and (b) in Figure 1, where trading volume is depicted by the dash line). It is only after Lehman's failure that we observe a major slide in trading volume which continues largely until the end of 2008, when both market depth *and* trading activity seem to almost vanish altogether. From that point on, they improve and move together.

Volatility Shoots Up During Crisis

As can be seen from Table 1, price volatility roughly doubles during the crisis for all three securities. However, only the 2–year note's volatility returns close to its pre-crisis level, whereas volatilities for the two longer term notes remain higher than they were before the crisis. This evidence again supports the finding that the 2–year note is the most liquid and resilient among the three securities considered. Across the best five tiers in the book, price volatility is slightly higher for the outer tiers.

Graphs (c) and (d) in Figure 1 provide a closer look into the time series trends in the inside tier's price volatility. In the second quarter of 2007, price volatility is already rising and shoots to a new elevated level on August 9, 2007 – when the crisis is widely believed to start. It keeps increasing and reaches its peak around the time of Lehmans bankruptcy, after which it gradually declines and almost reverts back to its pre–crisis level. Price volatility at

[8]The tick size for the 2– and 5–year notes is one 128th of a point. It is one 64th of a point for the 10-year.

the inside tier closely resembles the trend in trading activity (as shown in graphs (a) and (b) in the same figure). Active trading intensifies the price discovery process and it is thus not surprising to see trading volume and price volatility moving closely together. For brevity, we do not show in this figure the price volatility at other tiers as they exhibit similar time series trends as just described.

For the depth volatility variable, Table 1 shows that the inside tier stands out as having significantly higher depth volatility than the outer tiers. This is a natural result since liquidity at the first tier inherits an additional source of randomness from trading. This randomness does not pertain to order execution alone. The pick–off risk inherent in posting orders at the inside tier may require more intense order management and modification activities. We also observe an increase in the volatility of depth during the crisis period, but at a more moderate rate than that of price uncertainty, and a weak post–crisis recovery. Since the depth volatility measure has been standardized by the depth level, it looks reasonably comparable across the three securities.

Liquidity and Volatility Exhibit Clear Intradaily Patterns

Figure 3 shows the intraday patterns of market liquidity and volatility measures at the first tier over five–minute intervals.[9] Since the patterns are quite consistent across securities, and across different price tiers for the same security, we show here only the 2–year note and only the first tier.

Depth in the book builds up in the morning, reaches its peak shortly before noon and gradually declines from there, especially after 15:00. There are major dips in depth shortly before 8:30, 10:00 and 13:00. Trading is most active in the morning hours and shows distinct jumps immediately after the drops in market depth described above. There is also a mild peak at 15:00, after which trading diminishes. The peak at 15:00 coincides with the pricing of fixed income indices and hence likely reflects increased trading demand by investment managers who are seeking to rebalance their portfolios, while minimizing tracking errors relative to the indices.

Price volatility is also generally higher in the morning, and fades off toward the end of the day. This is very different from the well–documented U–shape pattern of volatility in equity markets: high around opening and toward market closing. Instead, in the Treasury market,

[9]While previous studies have examined the intraday patterns of bid-ask spreads and price volatility in this market (e.g., Fleming and Remolona (1997), Fleming and Remolona (1999)), we believe our intraday analysis of depth and depth volatility is novel.

price volatility closely tracks the pattern of trading activity, which peaks in the morning and falls off gradually after 15:00.

The volatility of liquidity exhibits a less clear intraday pattern than its price volatility counterpart, but also peaks at the 8:30 and 10:00 time marks. We see volatility spikes slightly lagging liquidity drops around the key time marks above, and in addition around 14:15.

Depths Disappear Immediately Before Announcements

The spikes at certain times documented in the intraday patterns of liquidity and volatility coincide with the release times of major economic announcements: 1) macroeconomic announcements released at 8:30, 2) macroeconomic announcements released at 10:00, 3) announcements of Treasury auction results shortly after 13:00, and 4) announcements of the Federal Open Market Committee's rate policy decision around 14:15 ("FOMC announcements").[10] For a complete list of major announcements, their frequency and time of release, see Appendix A.

To differentiate market behavior around these announcements, we separate days with each of the above news categories from days with no major news and examine the intraday patterns of liquidity and volatility on the news versus no–news days, as in earlier studies.[11] As evident in graphs (a)–(d) of Figure 4, in the short time window before an announcement, market depths largely disappear, especially depth at the first tier, but then immediately return to the book after the announcement has been released. This finding is consistent with the evidence documented in Fleming and Remolona (1999) and Fleming and Piazzesi (2005) that dealers often withdraw quotes before announcements due to inventory risk concerns.

An important observation is that on the days with FOMC rate decision announcements, the order book thins out rather gradually, starting from shortly before noon until reaching the minimum just before 14:15. The order book then refills in the next half hour or so and converges to its no–news day level. This pattern differs from that for other announcements, for which limit orders are cleared from the book just shortly before the announcement time. The anticipation leading up to FOMC announcements suggests that market participants

[10] Announcements after scheduled meetings, which occur eight times per year, were made at about 14:15 during our sample period. Announcements after unscheduled meetings, of which there were two in 2008, do not have a standard announcement time.

[11] We define "no news" days as days without any of the major announcements as listed in Appendix A. For the news days, we separately examine announcements released at a particular time (e.g., 8:30), but include days with announcements released at other times (e.g., 10:00). We therefore observe announcement patterns around the other release times (e.g., around 10:00 on 8:30 announcement days), although typically not as strong as those associated with the release time being examined.

consider monetary policy decision announcements so important to the market that they refrain from taking positions in the order book well before the announcement comes out.[12]

Trading and Volatility Jump Immediately After Announcements

Graphs (e)–(h) of Figure 4 document the intraday patterns in trading activity around major announcements, and graphs (i)–(l) the patterns in short–term price volatility. Trading activity and price volatility both spike in the five–minute window following announcements. The market is bustling during this short time window with the limit order book filling up, trading demand surging and price discovery intensifying. The market then gradually works its way back to the no–news day pattern in the next hour or so, reflecting the time it takes for disagreement over an announcement's implications to be resolved. These graphs once again show that trading activity and price volatility are highly related.

3 A New Class of Dynamic Limit Order Book Models

The evidence presented in the preceding section shows that Treasury market depth can sometimes have zero or low values (e.g., at the peak of the crisis, or immediately before economic announcements). The average frequency of low values of depth, i.e., depth being equal to 1 (the minimum order size on BrokerTec) or 0, equals 4% for the inside price tier (bid and ask) for both the 5– and 10–year notes across our full sample, and is naturally much higher on certain days. Likewise, realized volatility at the five–minute frequency is often zero. For the 2–year note, the realized volatility of price equals zero for 22% of the sample observations, regardless of tier, and is again much higher on numerous days.

In our search for a modeling framework that can accommodate zero or low values with a realistic probability distribution and integrate the dynamics of market depth and volatility in one, the multiplicative error model is particularly fitting. In this section, we start with a description of a general MEM formulation proposed in Engle (2002) and explain how this model choice is novel for the Treasury limit order book. We then specify the details of our model, as well as our measurement of volatility. Lastly, we discuss practical issues with the model estimation.

[12]Fleming and Piazzesi (2005) find that uncertainty about the exact announcement time leads to a protracted reduction in liquidity. However, this only explains the decline about five minutes before and not two hours before such events.

3.1 Multiplicative Error Model for Non–Negative Valued Processes

The general formulation of an MEM model is as follows. Let X_t be a non–negative time series of interest. Its dynamics is modeled as:

$$
\begin{aligned}
X_t &= \mu_t \epsilon_t, &(1)\\
\epsilon_t | \Im_{t-1} &\sim D(1, \psi), &(2)\\
\mu_t &= \omega + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j \mu_{t-j} + c' z_{t-1}, &(3)
\end{aligned}
$$

where $\Im_{t-1}$ presents the information set at time $t-1$, ϵ_t is the multiplicative error with a conditional distribution D having unit mean and defined on non–negative support, and z_t are weakly exogenous variables. The persistence of X_t is captured by $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$. The model can be estimated with the exponential quasi log likelihood function

$$
\ln \mathcal{L}(\mathbf{X}; \theta) = -\sum_{t=1}^{T} \left[\ln \mu_t + \frac{X_t}{\mu_t} \right]. \qquad (4)
$$

The asymptotic properties of the QML estimator have been established in Engle (2002). Hautsch (2012) notes that Newey and West (1987) standard errors are robust not only against distributional misspecification but also against dynamic misspecification in the MEM errors.

The general vector MEM is specified similarly. Let $\mathbf{X}_t$ be a K–dimensional process with non–negative components. The dynamics of $\mathbf{X}_t$ are specified as follows:

$$
\begin{aligned}
\mathbf{X}_t &= \boldsymbol{\mu}_t \odot \boldsymbol{\epsilon}_t, &(5)\\
\boldsymbol{\epsilon}_t | \Im_{t-1} &\sim D(\mathbf{1}, \boldsymbol{\Sigma}), &(6)\\
\boldsymbol{\mu}_t &= \boldsymbol{\omega} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{X}_{t-i} + \sum_{j=1}^{q} \mathbf{B}_j \boldsymbol{\mu}_{t-j}, &(7)
\end{aligned}
$$

where $\odot$ indicates the element–by–element product, $\boldsymbol{\mu}_t$, $\boldsymbol{\epsilon}_t$, $\boldsymbol{\omega}$ are Kx1 vectors and $\boldsymbol{\Sigma}$, $\mathbf{A}_i$, $\mathbf{B}_j$ are KxK matrices.

To explain our technical contribution, it is worth elaborating on the key difficulties of the standard linear Gaussian framework – usually adopted among current limit order book models – in modeling non–negative variables like market depth. In the simplest form, such a framework specifies the dynamics of a variable X_t as $X_t = \mu_t + \epsilon_t$. As discussed in Engle (2002), the requirement that the conditional mean is positive means that the corresponding error term has to be no more negative than the mean to ensure the non–negativity of X_t. Accordingly, the range of the error term changes with every observation, presenting a difficulty to estimation. Second, even if $\log(X_t)$ is used to avoid the non–negativity issue, researchers run into the problem of exact zero values at which $\log(X_t)$ is not defined. Therefore, taking the log is not a solution when zeros are valid observations. It is also not a solution when small values are common, as the log–linear model would imply an extreme event probability to these values.

With its multiplicative error structure, the MEM formulation ensures the non–negativity of X_t as long as the conditional error distribution has a unit mean and non–negative support, for which there are many possible candidates. The structure allows us to model market depth and volatility directly, and assigns reasonable probability to low values of these variables. This is important for the Treasury market because, as we saw earlier, the order book thinned out substantially during the crisis period and low values of depth are common immediately prior to important economic announcements. Furthermore, during quiet times, high frequency realized volatility is often zero. Therefore, if we are to model liquidity and volatility in one framework, that framework should be able to accommodate zero or very small values of the dependent variables with appropriate probability distributions.

Additionally, the GARCH–type nature of the multiplicative error model allows us to effectively capture the persistence of market depths. The persistence in the limit order book at intraday frequencies has been documented in the prior literature, see for example Biais, Hillion, and Spatt (1995). Intuitively, depths queue at different price levels in the book waiting to be executed by coming trades. Over a short time interval, say five minutes, we do not expect these queues to vary substantially, especially in the outer tiers, which are not reached until trades or order cancellations exhaust liquidity at the first tier.

The ability of multiplicative error models to capture the non–negativeness and persistence of a dynamic process gives this class of models an important place in the finance literature, since many financial series possess these properties. Important applications of this framework in finance include the modeling of conditional trade duration (see Engle and Russell (1998)), volatility, trading volume and intensities (see Manganelli (2000)), volatility, average trade sizes, trading costs and number of trades (see Hautsch and Jeleskovic (2008)), and absolute returns, daily range and realized volatility (see Engle and Gallo (2006)). However, despite it being a valuable tool for modeling non–negative valued processes, we have not seen an application of this framework among limit order book models.

The closest work to ours, in terms of modeling framework, is by Hautsch and Jeleskovic

(2008). That paper provides a review of the technique and applies it to the modeling of the dynamics of volatility and trade characteristics using order book data from the Australian Stock Exchange, but not the evolution of limit order depths – our modeling object of interest. On the other hand, while the paper by Russell and Kim (2010) models precisely this object, it adopts a different approach. Specifically, for both the buy and sell side, they model the total market depth on the given side and combine it with an estimated distribution of the depth across price levels. Their model therefore never predicts zero depth at any individual price level, a scenario that could plausibly happen in this market as previously discussed. Our newly introduced class of order book models based on the multiplicative error structure allows us to model the evolution separately for each price tier, be able to predict economically sensible possibilities, and uncover interesting insights into the dynamics of liquidity in this important market.

3.2 Model Specification

We specify a joint MEM model of order (1,1) for three variables – market depth, price volatility, and depth volatility – as formulated in equations 5 – 7. The model is estimated separately for each of the best five price levels on both sides of the market, resulting in 10 systems of equations in total. Following Engle and Gallo (2006), we assume a diagonal variance covariance matrix for the error terms, acknowledging that there can be a loss of efficiency if this assumption is false. We capture the possible interdependence among the variables by allowing a fully parameterized coefficient matrix $\mathbf{A}$, and restrict matrix $\mathbf{B}$ to be diagonal. We then estimate the model equation–by–equation using exponential quasi log likelihood function as specified in equation 4 and compute Newey–West standard errors for our estimates. To avoid the overnight effect, we reinitialize the conditional mean of each variable at the beginning of each day, using the average over the 7:00 – 7:55 period of that day, and estimate the model using data from 8:00 through 17:00.

To fix notation, for each of the five price tiers on each side of the market, the vector $\mathbf{X}$ consists of depth (D, or $X^{(1)}$), realized volatility of price (RVP, or $X^{(2)}$) and realized volatility of depth (RVD, or $X^{(3)}$). The dynamics of $\mathbf{X}$ are modeled at a five–minute frequency, indexed by t, as:[13]

[13]More precisely, the time interval t is the product of day d and time of day j where $d = 1, 2, ..., D$ with D being the total number of days in the sample, and $j = 1, 2, ..., J$ with J being the total number of five–minute intervals in a day. In this paper, $J = 120$ for a typical trading day, and $J < 120$ for those days when the bond market closes early.

$$
\begin{aligned}
\mu_t^{(1)} &= (\omega_1 + \alpha_1 X_{t-1}^{(1)} + \beta_1 \mu_{t-1}^{(1)}) + \gamma_2 X_{t-1}^{(2)} + \gamma_3 X_{t-1}^{(3)} + \theta' \mathbf{Z}_{t-1}, \\
\mu_t^{(2)} &= (\omega_2 + \alpha_2 X_{t-1}^{(2)} + \beta_2 \mu_{t-1}^{(2)}) + \gamma_1 X_{t-1}^{(1)} + \gamma_3 X_{t-1}^{(3)} + \theta' \mathbf{Z}_{t-1}, \\
\mu_t^{(3)} &= (\omega_3 + \alpha_3 X_{t-1}^{(3)} + \beta_3 \mu_{t-1}^{(3)}) + \gamma_1 X_{t-1}^{(1)} + \gamma_2 X_{t-1}^{(2)} + \theta' \mathbf{Z}_{t-1}.
\end{aligned} \tag{8}
$$

In the above equations, $\mathbf{Z}$ allows for other potential explanatory variables to enter the dynamics of $\mathbf{X}$. This enables a wide range of specifications designed to explore crisis effects, announcement effects, effects of price changes and any possible asymmetry between positive and negative changes via the so called news impact curve, the role of liquidity demand, and last but not least, effects of flights to safety on Treasury liquidity and volatility.

3.3 Measurement of Volatility

In this paper, we use two volatility measures. One is the volatility of price, and the other is the volatility of depth. Each of the measures is described below.

Volatility of Price

To measure price uncertainty, we use the realized volatility of price for each of the five price levels on both sides of the market (RVP). Beside its simplicity in computation, the main advantage of this measure of volatility, as discussed by Andersen, Bollerslev, Diebold, and Labys (1999), is that it is effectively error– and model–free. For each five–minute interval and for each price tier, the realized volatility is computed as the square root of the sum of the squared second–to–second price changes:

$$
RVP_t = \sqrt{\sum_{k_t=1}^{300} (\triangle P_{k_t})^2},
$$

where $\triangle P_{k_t}$ denotes the one–second price change at second k_t of the five–minute interval t. Since prices are reported in 256ths of one percent of par, this volatility of price inherits the same unit of measurement.

We note that this is a measure of total volatility comprised of both transitory and permanent components. We use this measure as we focus on the short–term dynamic interactions of volatility and liquidity in order to predict their evolution throughout a trading day at high frequency. It is important to note that this measure of volatility is based on intraday prices and not yields. The mapping of price changes to yield changes differs over time due to changes in coupon rates and time to maturity. At an intra–daily frequency, such as the five–minute frequency used in this paper, the difference between the two methods of calculating volatility should be negligible.

Beyond the intraday boundary, however, the difference between volatility computed from prices and that from yields can magnify. Additionally, the trend in volatility over the sample period documented earlier in the paper could change if volatility were computed differently. For comparison, we plot in Figure 5 the monthly average of our five–minute price volatility over the sample period, together with a measure of volatility based on daily yields.[14] The latter volatility measure is computed for each month as the square root of the realized variance for the month. The realized variance is the sum of all squared daily yield (absolute) changes in that month.

As Figure 5 demonstrates, our measure of price volatility closely tracks the volatility of yields, except that it is more variable than the latter given that it is based on higher frequency data. They both document an elevation in uncertainty during the crisis period, peaking around the time of the Lehman Brothers bankruptcy.

Volatility of Depth

To measure liquidity uncertainty, we introduce the notion of realized depth volatility for each of the five price levels on both sides of the market (RVD), which we compute in a similar way to RVP:

$$RVD_t = \sqrt{\sum_{k_t=1}^{300} (\triangle D_{k_t})^2},$$

where $\triangle D_{k_t}$ denotes the one–second depth change at second k_t of the five–minute interval t. The realized volatility computation requires that the one–second depth change series be a martingale difference sequence. To check the robustness of our RVD measure with respect to this assumption, we use an autoregressive specification at various lag lengths to estimate the time–varying drift of depth changes and then compute RVD as the five–minute sum of squared residuals of one–second depth changes.[15] The resulting RVD measures are very similar to the initial RVD computed from raw one–second depth changes, providing support for its use in our subsequent analysis. We also examine the auto–correlation function of the

[14]Daily on–the–run Treasury yields for the 2–, 5– and 10–year maturities are from Bloomberg.

[15]We also experimented with various other specifications, such as including a constant drift or allowing for linear dependence via ARMA models.

one–second depth changes and find them to exhibit no significant serial correlation. Finally, depth in the limit order book can change due to trade execution, limit order submissions, modifications and cancelations. Therefore, our RVD measure captures the extent of liquidity supply and demand imbalances in the order book.

Our realized volatility of depth measure complements well the realized price volatility in enhancing our understanding of the various sources of uncertainty in the market. On the one hand, the volatility of liquidity is closely related with the volatility of price. When the book is fluctuating actively, the resulting temporary order imbalances induce increased short–run price volatility (see Handa and Schwartz (1996)). This is particularly likely to happen with a thin book. For example, a market order can create a large imbalance causing the price to change, or sweep more than one tier's depth causing the price queues to move forward. In that case, we would expect the volatility of depth and volatility of price to move together and leave similar effects on liquidity supply. On the other hand, for a deep book, it is possible for the depth to change without an accompanying change in price. Accordingly, examining the volatility of depth and whether it helps to predict the subsequent level of liquidity provides understanding not possible with the volatility of price alone.

For our empirical model estimation, we standardize our liquidity volatility measure by the corresponding market depth at the beginning of each five–minute interval to remove the scale effect, making this effectively a measure of volatility relative to the size of the limit order book.

3.4 Diurnal Pattern Adjustment

As shown earlier, our variables of interest, namely depth, volatility variables and trading volume, exhibit clear diurnal patterns, making it necessary to remove such seasonality before the models can be estimated. We choose a non–parametric method to adjust for this intraday pattern by dividing the relevant variable at a given time interval by the average for that time interval, essentially assuming a multiplicative seasonality effect. For example, market depth observed at the end of the 9:15–9:20 interval on a given day is adjusted by the level of depth typically observed at that time.

We are careful to account for the different levels of depths and volatility across the pre–crisis, crisis and post–crisis periods by using three sets of intraday averages corresponding to the three sub–sample periods, as opposed to just one set of overall sample averages. In addition, we compute these sets of intraday averages from days without any important public announcements concerning FOMC rate decisions, macroeconomic conditions or Treasury auctions to avoid distorting the typical intraday seasonality with markedly different patterns observed on days with such announcements.

For depth variables, we favor the median as the average statistic in the seasonality adjustment to avoid possible distortion caused by extreme depth values on the seasonally–adjusted depths. For all other variables, we use the mean instead of the median as the latter can be zero at certain quiet intervals of the day.

4 Empirical Analysis

In this section, we present and discuss the dynamics of depth and volatility as revealed by our MEM–based class of models. Given the qualitative similarity in findings and for brevity, we report here the results for the 2–year note only.

4.1 The Baseline Model

We first estimate the baseline model as specified in equation (8) with no covariates and present the results in Table 2. The table has three panels: the top one for liquidity dynamics, the middle for price volatility dynamics, and the bottom for depth volatility dynamics. We flag those coefficients that are not significantly different from 0 based on the 5% significance threshold with an asterisk $*$. We discuss each panel in turn.

Liquidity Dynamics

As expected, order book depth exhibits a high level of persistence, as represented by the sum $\alpha + \beta$ being close to 1. In addition, depths at the best bid and ask prices are negatively impacted by price volatility, whereas depths at outer tiers tend to increase with volatility. This may reflect the unwillingness of market participants to supply depth at the first tier for fear that their orders will be adversely executed in a volatile market. Yet, at the same time, higher volatility may help increase the probability of execution for limit orders at outer tiers, making the option inherent in these orders more valuable for the limit order traders. Therefore, during volatile times, depth could move away from the first tier and toward the outer tiers.

The negative linkage between price volatility and depth at the first tier is also consistent with the evidence documented by many previous studies, including Næs and Skjeltorp (2006), that an increased level of trading is often associated with moments of high price volatility.

More active trading could deplete liquidity in the book that is not subsequently replenished fast enough, especially if potential liquidity suppliers hesitate to supply liquidity to a volatile market. The shrinkage of liquidity following a rise in volatility is also in line with a proposition put forth by Caballero and Kurlat (2008) that when asset price volatility rises, the risk of illiquidity rises.

The variability of order book depth also shows a significant effect on the subsequent level of depth. Following intervals of active movements in the book, liquidity supply becomes more plentiful. This is intuitive, whether one interprets the volatility of depths as representative of supply uncertainty (e.g., that associated with increased order modifications/cancellations), or as a sign of a strong demand for liquidity (e.g., that associated with increased trading activity). In the former interpretation, the uncertainty of supply may increase the payoffs to those who can actually provide liquidity, thus encouraging them to supply more. Similarly, if it is the strong demand for trading that induces frequent movements of liquidity, the demand would increase compensation for liquidity provision and subsequently invite more depth. This finding supports Biais, Hillion, and Spatt (1995)'s conclusion that more liquidity is supplied when it is valuable to the marketplace.

Price Volatility Dynamics

We see evidence of price volatility clustering, although not to the same extent as the clustering of depths. More importantly, lower depth at any tier predicts a subsequent increase in price volatility, consistent with Parlour and Seppi (2008)'s assessment that prices are more volatile in thin markets, as the lack of liquidity hinders the price discovery process, causing more uncertainty about the security value. This evidence is also consistent with the idea that depth is withdrawn in advance of expected price changes (e.g., macroeconomic announcements). That is, causality may be reversed, with expected volatility leading to lower depth.

The liquidity–volatility feedback loop at the inside price tier on both sides of the market isolates the effect of adverse execution risk on dealers' liquidity supply decision. This dynamic interaction could help explain episodes of liquidity and volatility feeding on each other and exacerbating a bad shock that could originate from either the liquidity side or the volatility side. The liquidity drop and the heightened volatility during the recent financial crisis as shown in Figure 1 is a good example. Our evidence provides empirical support for the theory of liquidity crashes put forth by Cespa and Foucault (2012), although the focus of their theory is on the liquidity–volatility feedback among multiple assets. Here we provide evidence that this theory is also at work for one asset.

Let us turn to the role of depth uncertainty on price uncertainty. The different sign of the effect for the first tier, as compared to the rest of the book, deserves some close attention. Increased volatility of depth at the first tier predicts lower price volatility, while the opposite is true for other tiers. Apparently, depth at the first tier changes in large part due to trading, but depths at the other tiers change mostly by order addition, modification, or cancellation. So in the former case, if we associate the high volatility of depth with active trading in the market, it is understandable how price volatility can be subsequently reduced. The latter case, however, is a better reflection of supply uncertainty on the part of liquidity providers, which arguably means they are also uncertain about security value, explaining the accompanied increase in price volatility.

Depth Volatility Dynamics

The volatility of liquidity also exhibits clustering at price levels behind the market. At the inside tier, the persistence is quite low, adding to our discussion earlier that the liquidity volatility measure at this tier seems to be closely related with trading activity in the market. Next, increasing liquidity level can predict a subsequent decrease in liquidity volatility relative to the size of the book, but we note that this effect is typically small at the first tier. Finally, price uncertainty is positively related with liquidity uncertainty, although we believe the mechanism is again different between the first tier and the other tiers. At the inside bid and ask, high price uncertainty is associated with increased trading that induces greater variability of depth. For outer price tiers, the fluctuation of depths is often the result of limit order submission, modification, or cancelation activities, which also tend to intensify when price is volatile.

4.2 Announcement Effects

Prior literature on the Treasury market response to economic news, such as Fleming and Remolona (1999), Balduzzi, Elton, and Green (2001), and Green (2004), has documented strong patterns of liquidity and volatility around economic announcements. The analysis of intraday patterns of depths and volatilities in this paper further confirms that depths largely disappear from the order book immediately prior to an economic announcement, but quickly return thereafter. Both trading activity and volatility are high following an announcement. To formally test these patterns, we estimate an MEM model with pre–announcement and announcement time dummies for each of the three dependent variables indexed by i (where $i = 1, 2, 3$ corresponding to depth, price volatility, depth volatility respectively). The specification is as follows:

$$\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta_1 \text{prenews2}_{t-1} + \theta_2 \text{prenews1}_{t-1} + \theta_3 \text{news}_{t-1}, \quad (9)$$

where $prenews2$ is the dummy for the second–to–last five–minute interval before an announcement, $prenews1$ is the dummy for the five–minute interval before an announcement, and $news$ is the dummy for the five–minute interval containing the announcement release. Since these dummies enter the equations with a lag, θ_1, θ_2 and θ_3 in fact capture the pre–announcement, announcement and post–announcement effects respectively on the liquidity and volatility variables.

As shown in Table 3, market depths decline significantly across the top five price levels in the five–minute interval before an announcement, but then increase by a larger magnitude in the announcement interval, reflecting the fast refilling of order book depth once an announcement is released. Depths in the post–announcement five–minute interval continue to show some further increase but the effects start to subside. On the other hand, both measures of volatility are already at elevated levels in the pre–announcement interval, consistent with the withdrawal of orders from the book causing greater fluctuation of prices and depths. The announcement interval witnesses the peak in volatilities, especially the volatility of depth, that come about with the refilling of limit orders and the surge in trading activities following the news arrival. In the five–minute interval following an announcement, both depth and price volatilities are significantly lower, suggesting that the most intense price discovery and order book activities happen within a very short time window. Depth and price volatilities remain high in the next thirty minutes or so, as compared to non–announcement days, but the peak has passed.

4.3 Dynamics During Crisis

To explore whether any of the above dynamics change during the recent crisis, we estimate a specification that incorporates a crisis period dummy, allowing it to have both intercept and interactive effects. For $i = 1, 2, 3$ corresponding to depth, price volatility, and depth volatility respectively, the specification is as follows:

$$\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta_1 \mathrm{DC}_{t-1} + \theta_2 \mathrm{prenews2}_{t-1}$$
$$+\theta_3 \mathrm{prenews1}_{t-1} + \theta_4 \mathrm{news}_{t-1} + \theta_5 \mathrm{DC}_{t-1} X_{t-1}^{(i)} + \theta_6 \mathrm{DC}_{t-1} \mu_{t-1}^{(i)}, \quad (10)$$

where DC is the dummy for the crisis period, defined to be from August 9, 2007 through June 30, 2009, $prenews2$ is the dummy for the second–to–last five–minute interval before an announcement, $prenews1$ is the dummy for the five–minute interval before an announcement, and $news$ is the dummy for the five–minute interval containing the announcement release. With this specification, θ_1 is the estimate for the level effect of the crisis, while θ_5 and θ_6 collectively show the effect of the crisis on the persistence of each dependent variable. The pre–announcement, announcement and post–announcement effects are captured by θ_2, θ_3 and θ_4 respectively, as in the earlier specification with announcement effects (Equation (9)).

Table 4 shows the model estimates. The pre–announcement, announcement and post–announcement effects remain qualitatively similar to those previously documented. Depth is lower during the crisis period, consistent with evidence presented up to this point. A surprising observation is that price volatility is also lower, contradicting the model–free descriptive analysis performed earlier. We suspect that outliers in price volatility during the crisis period may skew our seasonality adjustment factors upward (as these are based on the mean), resulting in lower than expected diurnally–adjusted price volatility.

The key observation from this table is that depth and price volatility tend to be more persistent during the crisis period. The immediate implication of the higher degree of persistence is that bad shocks to these variables take longer to fade away. Considering the negative depth–price volatility feedback loop documented earlier, this finding illustrates how this negative feedback effect can intensify in a crisis.

4.4 Limit Order Book Dynamics and the News Impact Curve

In this section, we build a model that captures any asymmetric response of liquidity, price volatility and liquidity volatility to the changing value of the securities, in the spirit of the news impact curve technique introduced by Nelson (1991) for GARCH models. This original framework is designed to allow the conditional variance process of a given asset's returns to respond asymmetrically to positive and negative price changes. The question we want to address is whether the movement in the best bid–ask midpoint has any bearing on the dynamics of the order book. The data shows that the distance between any two adjacent price levels in the order book is almost always one tick, so the movement in the best bid–ask midpoint is a good indicator of the overall ups and downs of order book prices.

We specify the news impact curve ("NIC") as:

$$\mathrm{NIC}_t = \theta_1 |Ret_t| + \theta_2 |Ret_t| \mathbf{1}_{Ret<0}, \tag{11}$$

where $Ret_t^{S,i}$ is defined as the five–minute return (annualized log return) of the best bid–ask midpoint. This functional form for the NIC particularly suits our needs as the NIC will enter the dynamics of depths and volatilities as a positive covariate. With this specification, the coefficient θ_1 captures the effect of changing price on the dynamics of order book liquidity and volatility, while the coefficient θ_2, if significantly different from zero, will indicate an asymmetric response of liquidity and volatility to negative price changes.

We start with a simple specification that has only the NIC, shown in Table 5. We note that the results on other variables of the model are qualitatively the same as those obtained with the baseline specification. Key findings, such as the negative liquidity–volatility feedback loop at the first tier, and the association of greater depths with subsequently lower volatility of both depth and price, remain. We therefore focus our discussion in this section on the NIC coefficients.

The results show that depth generally responds to price movements, although the response is not uniform across all price tiers. The asymmetric coefficient θ_2 is also mostly significant, implying that negative price movements impact limit order book depth differently. Second, with regard to price volatility, it seems that large price movements predict a subsequent increase in price volatility, regardless of the direction. There is no evidence for an asymmetric response of price volatility to positive versus negative price changes. We hypothesize that many dealers submit orders on both sides of the market, i.e., perform a market–making function, so the direction of the price change does not have much of an impact on the price uncertainty, only the magnitude does. Large price swings may be indicative of important news that intuitively could result in an increased divergence of opinions among market participants. Lastly, concerning depth volatility, we document a significant news impact curve function (both the magnitude and asymmetric effects) only up to the second or third tier. Beyond that, value changes do not seem to matter.

We also estimate a specification with the NIC controlling for announcement effects. Although not reported here, the results are consistent with our basic findings.

4.5 Effect of Liquidity Demand

In this section, we examine the effect of liquidity demand, as indicated by the volume of market orders, on the limit order book. First and foremost, trading provides the means for price discovery and accordingly is expected to affect price volatility. Trading consumes depth in the book, can stimulate additional liquidity supply (e.g., Biais, Hillion, and Spatt (1995)), or can change the distribution of depths across price levels. Typically we would expect a negative impact due to the consumption effect, but the stimulus effect might also come into play. Nevertheless, either effect would have the same impact on the volatility of depth.

As shown in Table 6, the estimated effect of trading volume (θ_3) on subsequent market depth is positive, especially for tiers at or near the market, suggesting that liquidity is supplied at a faster rate than it is consumed and supporting to some extent the hypothesis that trading demand might help attract additional liquidity supply. As expected, the variability of depth increases with trading volume, but this effect shows up at the first tier only.

In addition, trading activity does not significantly affect subsequent price volatility at the first tier, but rather increases price volatility only at other tiers. This result still holds after we control for announcement effects. The empirical facts documented earlier, with first tier price volatility and trading volume exhibiting strikingly similar patterns over time and over the course of a trading day, can be relied upon in interpreting the model estimates. Apparently, trading and price volatility at the inside tier are contemporaneously related so that once we control for lagged volatility, lagged trading volume has little incremental explanatory power. Beyond the first tier, however, trading volume still shows its relevance in predicting subsequent price volatility, indicating that the effect of trading activity travels to the outer tiers' price volatility with a lag.

5 Liquidity and Volatility During Flights to Safety

We now turn to an analysis of the Treasury market during flight–to–safety episodes. Prior research mainly focuses on understanding the motives of such flights, e.g., whether investors are seeking the high quality and/or high liquidity of Treasury securities. Evidence seems to favor the liquidity motive for flights. For example, Beber, Brandt, and Kavajecz (2009) show that euro–area bond investors chase liquidity rather than credit quality during times of market stress. Likewise, Longstaff (2004) documents a liquidity premium in Treasury securities, as large of 15% of their values. However, the question of whether the sought–after liquidity is actually there when it is needed the most remains. Addressing this question is the main objective of this section.

5.1 Identification of Flights to Safety

We first describe how flights to safety are identified. It is widely observed, and agreed, that a flight to safety occurs when investors withdraw in droves from risky asset markets and move to safe/liquid asset markets. A common flight to safety is the flow out of equity markets and into the Treasury market. Such a flight is often accompanied by an extreme negative equity return concurrent with an extreme positive Treasury return. This is the basis for the identification of flight–to–safety episodes proposed by Baele, Bekaert, Inghelbrecht, and Wei (2012) – an approach that we adopt in this paper.

Specifically, let r_T and r_E be the daily return on the relevant on–the–run Treasury note and the S&P 500 index respectively.[16] σ_T and σ_E correspond to their sample return volatility. The flight–to–safety dummy, FTS is defined as:

$$FTS = \mathbf{1}_{r_E < -\kappa\sigma_E} * \mathbf{1}_{r_T > \kappa\sigma_T}$$

where κ is the parameter for the severity of the flight.

We examine three different levels of κ, i.e., 1, 1.5, 2 – which we will refer to as "light", "moderate" and "severe" flights. Table 7 shows the dates of these flights, as well as the total count of flights for each security and each severity level. With 1,124 trading days in the sample period from January 2006 through the second quarter of 2010, the light, moderate and severe flights occur on approximately 6%, 2–3% and 0.8–1.2% of the days respectively. The last quarter of 2008 contains a disproportionately large number of flights. In particular, the majority of the severe flights happen in the aftermath of the Lehman bankruptcy, especially on September 15, 29 and October 6 of 2008 when severe flights to safety occur in all three securities. The identification of moderate FTS episodes in the 2– and 5–year notes also picks up August 9, 2007, which marks the beginning of the crisis.

It is worth noting that using the returns on the 5– and 10–year notes helps identify slightly more FTS episodes than when the 2–year note returns are used. Light and moderate flights

[16] We use the daily on–the–run "dirty" prices for the 2–, 5– and 10–year notes from Bloomberg in computing the relevant daily Treasury return for the identification of flights. It is worth noting that there is a discontinuity in price of any given on–the–run Treasury note series on those days when a security goes off–the–run and a new issue becomes on–the–run. To take care of these discontinuities, we first compute daily returns separately for each issue, and then splice together the returns over only the on–the–run period of each issue. The notes are on-the-run from the day following their auction through the day of the following auction (for that maturity).

tend to happen most frequently with the 5–year note, whereas for severe flights, the 10–year note returns pick up the highest frequency of such episodes. One possible explanation is that the Fed lowered rates to the zero bound, thereby anchored the 2–year, creating a more stable pattern for the shorter maturity. Indeed, flights to the 2–year note seem to occur mostly in the earlier period of the sample which is less affected by the zero bound.

5.2 How Different Are Flight–to–Safety Days?

We compare order book depth, trading volume, price volatility and depth volatility on FTS days with non–FTS days and find them to be markedly different. The comparison across the three Treasury notes sheds light onto which one is affected by these episodes the most. For the discussion below, we use moderate FTS days, i.e., days when the Treasury return exceeds 1.5 times its sample volatility and the S&P 500 return falls below -1.5 times its sample standard deviation.

In terms of trading volume, the average daily figure for the 2–year note on FTS days is over $57 billion whereas the number on non–FTS days is only nearly $34 billion. On a typical non–FTS day, selling pressure dominates buying pressure, with a net selling volume of $652 million. This reverses to an average net buying volume of $945 million on FTS days. Likewise, the number of trades is almost double the typical non–FTS level, and the reversal in the net number of trades is more dramatic than is the case with the volume of trades.[17] The average trade size, being 4.35 on FTS days as compared to 4.65 on other days, suggests that market participants submit smaller sized orders than usual on FTS days.

The 5– and 10–year notes also have higher trading volume on FTS compared to non–FTS days, but to a lesser extent than the 2–year note. As with the 2–year note, we observe net selling pressure in the 5– and 10–year notes on non–FTS days, about $465 and $321 million respectively. However, both notes show changes on FTS days that are less dramatic than those for the 2–year note. For the 10–year note, net volume reverses (as with the 2–year note) so that there is net buying averaging $338 million on FTS days. For the 5–year note, net selling is weaker on FTS days, averaging $222 million, but net volume remains negative.

Differences between FTS and non-FTS days for the 5– and 10–year notes are more striking when we look at the number of trades as opposed to trading volume, as is the case with the 2-year note. That is, the overall increase in activity is greater on FTS days when looking

[17] We note that the number of trades is not the same as the number of market orders. When a market order is executed against multiple limit orders, the system records each of them as one trade. Thus a market order can correspond to multiple trades. Nevertheless, the number of trades and volume of trades collectively provide a complete picture of trading activity in the market.

at the number of trades, and the net number of trades flips from negative (i.e., net selling pressure) on non–FTS days, to positive (i.e., net buying pressure) on FTS days for the 5– as well as the 10–year note.

These pieces of evidence together suggest that there is a higher level of trading demand on FTS days, particularly on the buy side, as we would expect to be the case when the Treasury market absorbs the flow of investors fleeing risky asset markets. The differences are especially striking when looking at the number of trades, suggesting that order sizes are smaller on FTS days. The 2–year note appears to be especially affected by flights to safety.

Even more striking evidence from our analysis is that market depth, representing the ex ante liquidity supply (or the willingness to provide liquidity), is much lower on FTS days, as shown in Figure 6. In particular, the order book for the 5– and 10–year notes on FTS days thins out to a greater extent than that for the 2–year note. This lack of willingness to post limit orders spreads over all price tiers, and not just the first tier where depth could naturally be lower if the trading rate exceeded the limit order submission rate.

We in turn examine the behavior of volatility to understand better how the book on FTS days could thin out so much. Both volatility measures are much higher on FTS days, especially price volatility. The evidence seems supportive of our conjecture that, despite the strong demand for liquidity, dealers become more conservative with their liquidity supply on FTS days when the market is highly volatile. They provide less depth to reduce adverse execution risk and allow themselves increased flexibility to respond to the highly volatile market conditions on these days.

5.3 Liquidity and Volatility Dynamics and Flights to Safety

We now turn to our econometric framework to explore whether the dynamics of liquidity and volatility change on FTS days. In particular, we allow for the FTS dummy to affect both the level as well as the persistence of liquidity and volatility. For this section, we use a univariate MEM specification for each of the liquidity and volatility variables in order to expose the FTS effect cleanly on each variable's dynamics. Specifically, each variable's conditional mean equation takes the following form:

$$\mu_t = \omega + \alpha X_{t-1} + \beta \mu_{t-1} + c\,FTS_t + c_\alpha FTS_t X_{t-1} + c_\beta FTS_t \mu_{t-1}.$$

Under this specification, the coefficient c captures the level effect of FTS, while c_α and c_β captures the change in the dynamics of the modeled variable. We estimate this equation for market depth (presented in Table 9) and price volatility (presented in Table 10) for each security and each of the three levels of FTS severity corresponding to three thresholds adopted for κ (1, 1.5, 2).

In general, flights seem to have more of an effect on the dynamics than the level, given that the depth series have been diurnally adjusted to remove intraday regularities. c_α is the coefficient on the interaction between the relevant FTS dummy and the past market depth, hence it captures the marginal impact of news on market depth on FTS days. c_α is mostly negative and significant, suggesting that on those days when flights occur, the immediate past realization of market depth has lower predictive value for depth at the next interval. On the other hand, c_β tend to be somewhat positive on these days, essentially indicating that market participants place greater importance on the historical path of market depth than on just its most recent realization in predicting the next level of market depth. Therefore, while the persistence of depths on FTS days does not significantly differ from that on non–FTS days, the composition has changed that gives less weight to the impact of news on market depth. With respect to the level effects, the 2–year note shows a somewhat lower depth level on FTS days, especially at the inside bid and ask, whereas the evidence is more mixed with the other two notes.

We now describe the effects of flights on price volatility. Consistent with evidence presented earlier, the level of price uncertainty is significantly higher on flight–to–safety days, although statistical significance seems to diminish with the severity of flights − a direct consequence of a much lower number of observations with the most severe flights to safety. Examining the effects of flights on the dynamics of volatility via the estimates for c_α and c_β, we can see that the news impact coefficient c_α is usually not significantly different from that on non–flight days, except for the positive news impact on volatility at some outer price tiers. The other coefficient c_β often has opposite sign to c_α. Similar to the evidence with depth, we also find that while volatility does not exhibit a significantly different level of persistence on flight–to–safety days, there has been a shift in the relative importance of the news impact coefficient on volatility especially at some of the outer price tiers.

6 Conclusion

In this paper, we propose a new class of dynamic order book models for the purpose of exploring the micro dynamics of depth, price volatility and depth volatility in the inter–dealer market for the 2–, 5– and 10–year U.S. Treasury notes. Our models are based on the multiplicative error framework introduced by Engle (2002). This class of models offers important advantages that are highly suited to the modeling of the Treasure limit order book. Zero or very low values of market depths are not uncommon, particularly around economic announcements and during the crisis. Likewise, intraday volatility is often zero during quiet times of the day. The MEM guarantees the prediction of non–negative depths and volatility measures and allows us to integrate liquidity and volatility into a unified framework from which their dynamic interactions can be studied. It also goes beyond the log linear framework in that it allows for more flexible and realistic probability distributions. Additionally, by modeling the limit order book in a similar fashion to asset price volatility models, we can capitalize on the vast literature in the latter to tailor our model specifications in ways that can capture the dynamics between liquidity and volatility as closely as possible.

In addition to the novel use of the MEM framework to model the dynamics of the limit order book, we also introduce the notion of realized volatility of depth, which is parallel in concept to realized volatility of price. Furthermore, apart from testing market microstructure hypotheses, our proposed class of models can be used for the purpose of forecasting liquidity and managing liquidity risk.

Our empirical analysis examines market depth and volatility around economic announcements, through the crisis and during flight–to–safety episodes. Consistent with earlier studies on the impact of economic announcements, we document an important stylized fact that depths tend to disappear before announcements but return shortly thereafter, together with a surge in trading activity and a jump in price volatility which takes an hour or so to fade away. We offer additional facts about the Treasury market over the crisis not previously documented, that is, the order book thins out substantially over the crisis, coupled with an elevated level of price volatility, although trading activity does not decline substantially until the second half of the crisis.

Our models' key finding is that price volatility and depth at the first price tier exhibit a negative relationship, which runs in both directions. This negative feedback effect becomes more pernicious during the crisis when both of these variables are evidently more persistent. This helps explain spells of liquidity deteriorating as volatility increases, and conversely, liquidity improving as volatility decreases, especially observed during the crisis. Last but not least, our study of the Treasury market during flights to safety shows that market depth is substantially lower despite the higher demand for trading on these days. The inflows of trading interest and the accompanied rise in price uncertainty may necessitate greater market monitoring and reduce dealers' incentive to supply liquidity via limit orders.

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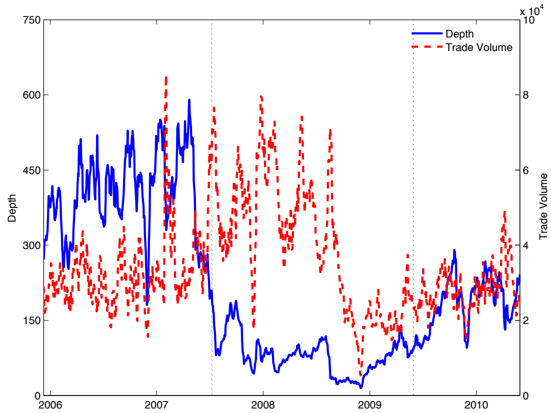
Table 1: Summary Statistics of Depth and Volatility

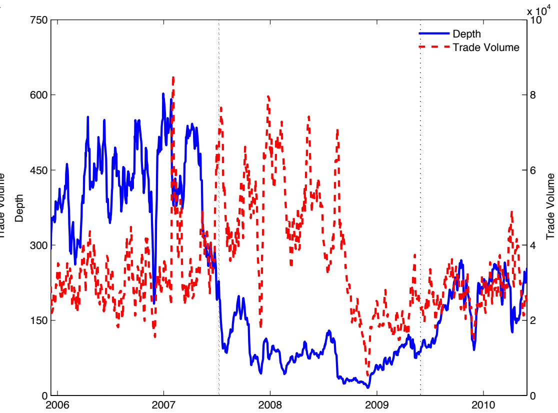
		Depth						Price Volatility						Depth Volatility					
		Before Crisis		Crisis		After Crisis		Before Crisis		Crisis		After Crisis		Before Crisis		Crisis		After Crisis	
		Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD	Mean	StD
2Y	Ask5	287.0	131.0	69.8	56.2	180.9	106.9	2.9	3.0	6.8	4.2	3.4	2.9	0.9	12.9	2.9	10.1	1.1	9.8
	Ask4	338.7	150.8	86.7	65.5	226.5	123.3	2.9	2.9	6.6	3.6	3.4	2.8	1.1	14.3	2.8	9.5	1.2	14.1
	Ask3	473.7	219.5	116.8	84.2	284.4	143.5	2.9	2.8	6.5	3.3	3.4	2.7	1.7	19.7	2.9	12.0	1.1	15.5
	Ask2	647.2	296.9	143.0	105.4	325.5	190.9	2.8	2.8	6.5	3.3	3.4	2.7	1.2	14.8	2.6	8.6	1.7	20.6
	Ask1	399.4	285.8	80.9	81.6	187.1	143.9	2.8	2.8	6.5	3.2	3.4	2.7	13.0	69.2	16.6	43.5	11.5	46.9
	Bid1	418.2	292.8	82.4	84.1	189.3	137.6	2.8	2.8	6.4	3.2	3.4	2.7	13.1	69.7	16.7	46.7	10.7	44.4
	Bid2	676.4	302.2	146.0	107.6	327.7	165.0	2.8	2.8	6.5	3.2	3.4	2.7	1.0	11.3	2.5	8.4	1.1	6.8
	Bid3	498.0	225.5	120.7	88.8	293.0	145.2	2.9	2.8	6.5	3.3	3.4	2.7	1.6	18.3	2.8	9.1	0.9	6.8
	Bid4	355.1	155.9	89.2	67.8	233.2	125.3	2.9	2.9	6.6	3.6	3.4	2.8	1.0	8.9	2.7	8.8	0.9	4.9
	Bid5	298.0	134.0	72.3	59.1	187.0	110.4	2.9	3.0	6.9	4.4	3.4	2.9	0.8	8.4	2.8	8.5	0.9	4.2
5Y	Ask5	67.2	38.5	21.4	19.8	50.7	32.9	6.2	6.1	14.1	14.3	9.1	7.1	2.1	9.5	5.5	10.0	2.4	5.9
	Ask4	83.9	45.4	26.1	22.2	62.4	36.9	6.0	4.9	13.0	9.8	8.8	5.2	2.6	11.4	5.6	9.8	2.0	5.5
	Ask3	139.4	75.8	36.4	29.5	70.3	40.0	5.9	4.1	12.1	6.6	8.7	4.3	3.3	17.4	5.0	9.8	1.9	5.0
	Ask2	164.6	85.2	41.4	33.8	65.7	38.8	5.8	3.6	11.6	4.9	8.6	3.8	2.6	13.5	5.1	9.9	3.1	7.7
	Ask1	72.6	57.9	21.4	22.9	28.0	25.5	5.8	3.3	11.4	4.3	8.5	3.5	15.0	36.5	20.2	36.7	19.2	37.5
	Bid1	73.0	58.0	21.7	23.9	28.5	25.9	5.8	3.3	11.4	4.3	8.5	3.6	15.1	37.3	20.3	35.9	18.8	36.8
	Bid2	165.1	83.8	42.0	34.4	66.8	39.4	5.8	3.5	11.5	4.8	8.6	3.7	2.6	13.6	5.1	9.7	3.0	7.0
	Bid3	140.6	75.4	36.9	30.2	71.1	40.2	5.9	4.0	12.0	6.4	8.6	4.1	3.3	17.6	5.1	10.4	1.9	5.1
	Bid4	86.6	46.2	26.1	22.1	62.8	36.8	6.1	5.1	13.0	10.0	8.7	5.0	2.5	10.6	5.8	10.0	2.0	4.6
	Bid5	69.7	39.3	21.3	19.8	51.3	32.7	6.2	5.8	14.0	13.3	8.9	6.2	2.0	8.7	5.8	10.4	2.4	5.7
10Y	Ask5	67.3	34.8	22.7	17.5	42.8	23.8	11.4	8.1	22.7	18.5	16.4	9.1	1.3	4.1	3.7	6.6	2.2	4.0
	Ask4	80.2	39.3	26.9	19.7	53.4	27.0	11.3	7.3	21.5	14.0	16.3	7.8	1.6	5.2	3.7	6.1	1.8	3.3
	Ask3	127.3	67.2	37.0	27.5	61.2	30.3	11.2	6.8	20.4	9.9	16.1	7.1	2.9	10.1	3.7	6.7	1.7	3.7
	Ask2	166.3	76.3	45.2	34.7	56.6	30.1	11.1	6.4	19.8	8.0	16.1	6.8	2.1	9.7	3.5	7.3	2.6	5.3
	Ask1	71.8	55.4	22.1	23.6	24.3	20.7	11.1	6.3	19.5	7.2	16.0	6.6	15.2	36.8	17.1	29.2	15.1	27.5
	Bid1	72.5	56.2	22.6	24.6	24.7	21.2	11.1	6.3	19.4	7.1	16.0	6.5	15.7	37.5	17.4	29.9	14.8	25.5
	Bid2	167.0	75.2	46.1	36.3	56.9	29.6	11.2	6.3	19.6	7.5	16.0	6.6	2.0	9.0	3.6	7.6	2.6	5.9
	Bid3	127.0	65.5	37.4	28.1	61.4	30.4	11.2	6.5	20.0	8.8	16.1	6.9	2.8	9.0	3.8	7.3	1.6	3.6
	Bid4	81.4	39.5	27.5	20.3	53.6	27.2	11.3	7.0	21.1	12.7	16.2	7.7	1.5	4.3	3.7	6.7	1.8	3.5
	Bid5	69.4	35.5	23.1	17.9	42.9	24.1	11.4	7.6	22.4	17.3	16.4	8.7	1.3	3.9	3.8	7.5	2.3	4.0

This table presents summary statistics of displayed depths, price volatility and depth volatility at the best five bid and ask prices for the 2–, 5– and 10–year Treasury notes for the period 2006–2010Q2. Depths are measured in millions of dollars. Realized volatility of price is calculated as the square root of the five–minute sum of squared second-to-second price changes. Prices are reported in 256ths of a point and the realized price volatility inherits the same unit of measurement. Realized volatility of depth is calculated as the square root of the five–minute sum of squared second-to-second depth changes, and standardized by the depth level at the beginning of the five–minute interval. The summary statistics are reported separately for three sub periods: 1) Before Crisis (January 2006–August 8, 2007), 2) Crisis (August 9, 2007–June 2009), and 3) After Crisis (July 2009–June 2010).

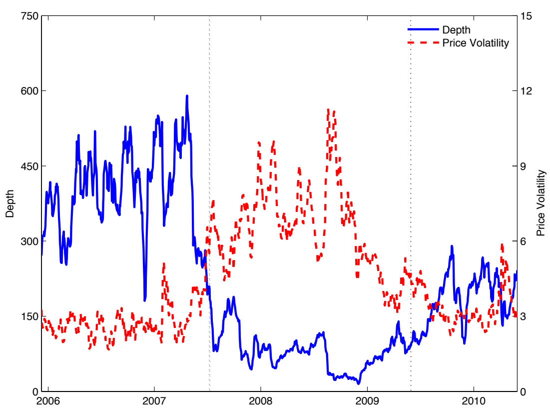
Figure 1: Daily Liquidity and Volatility at First Price Tier of 2–Year Treasury Note



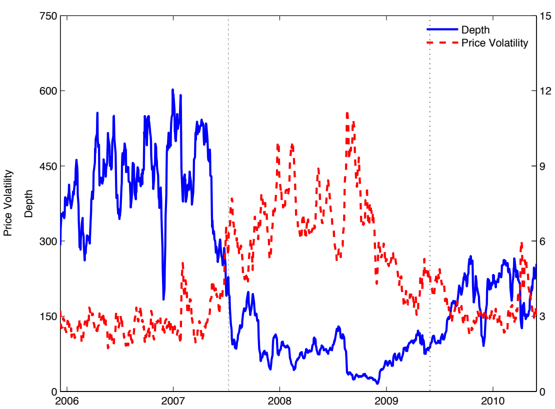
(a) Ask: Depth & Trade Volume



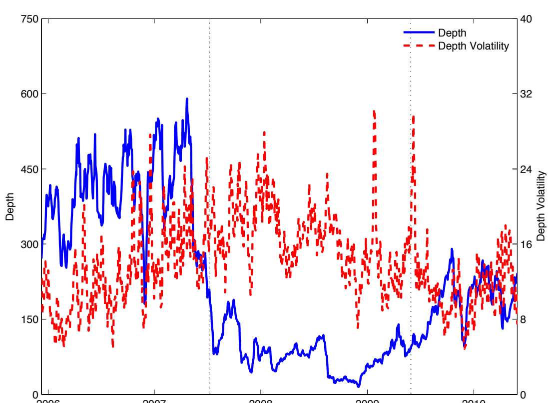
(b) Bid: Depth & Trade Volume



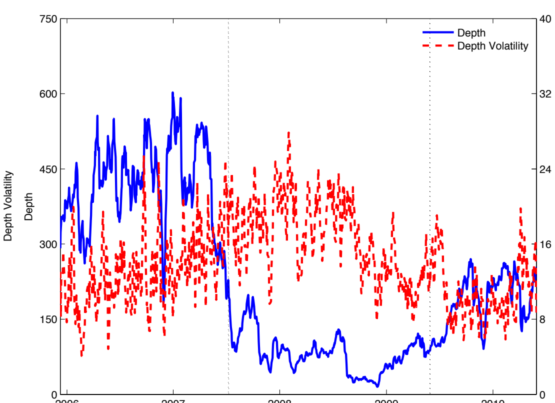
(c) Ask: Depth & Price Vol.



(d) Bid: Depth & Price Vol.



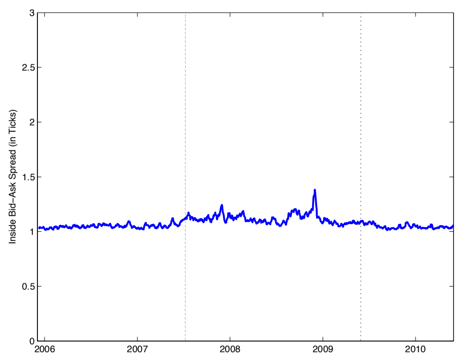
(e) Ask: Depth & Depth Vol.



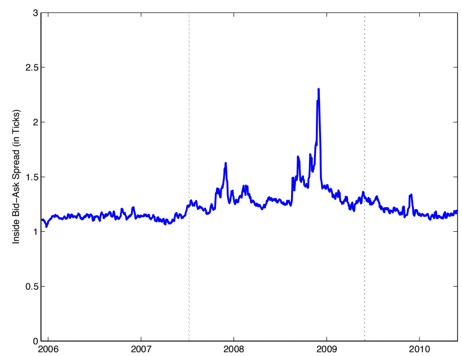
(f) Bid: Depth & Depth Vol.

This figure shows the 2–year Treasury note's daily average market depth, total trading volume, price volatility and depth volatility at the first price tier, using BrokerTec order book data over the period 2006–2010Q2. Two vertical dotted lines mark the beginning (August 9, 2007) and ending (June 30, 2009) of the crisis. The series are smoothed using a 5–day moving average for better viewing of the trend.

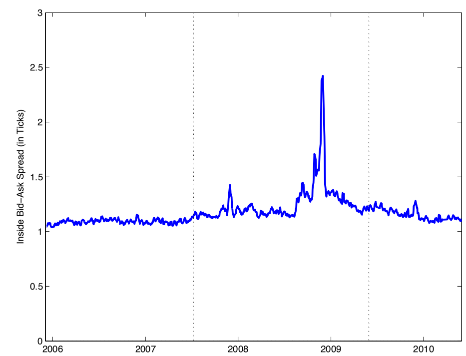
Figure 2: Daily Bid–Ask Spread at First Price Tier



(a) 2–Year Treasury



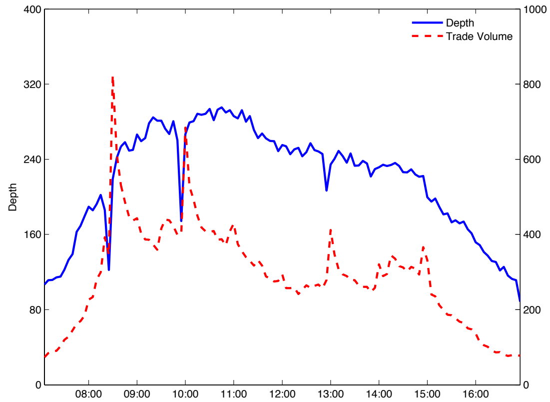
(b) 5–Year Treasury



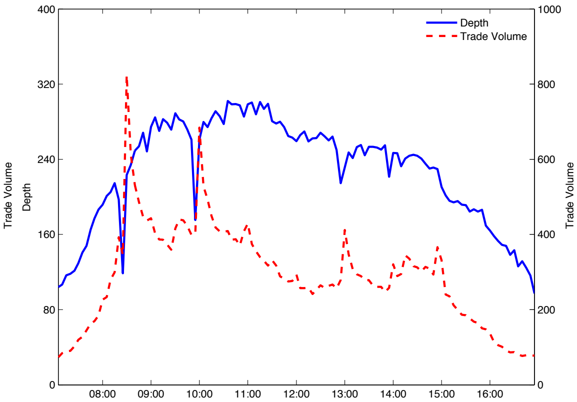
(c) 10–Year Treasury

This figure shows the daily average bid–ask spread at the first price tier for the 2–, 5– and 10–year Treasury notes, using BrokerTec order book data over the period 2006–2010Q2. The spread is standardized by the relevant tick size, i.e. 1/128th of a point for the 2– and 5–year notes, and 1/64th of a point for the 10–year note. Two vertical dotted lines mark the beginning (August 9, 2007) and ending (June 30, 2009) of the crisis. The series are smoothed using a 5–day moving average for better viewing of the trend.

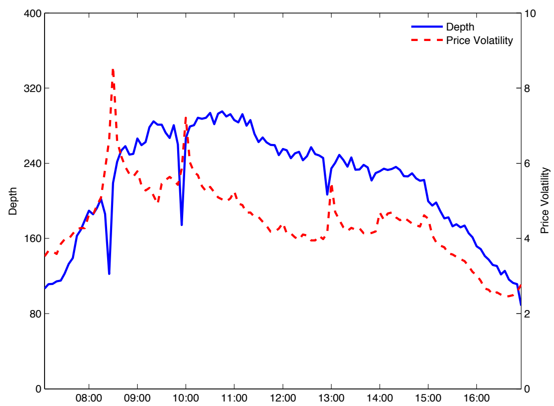
Figure 3: Intraday Patterns of Liquidity and Volatility at First Price Tier of 2–Year Treasury Note



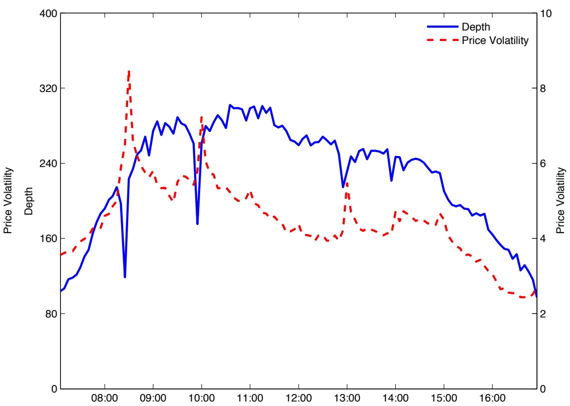
(a) Ask: Depth & Trade Volume



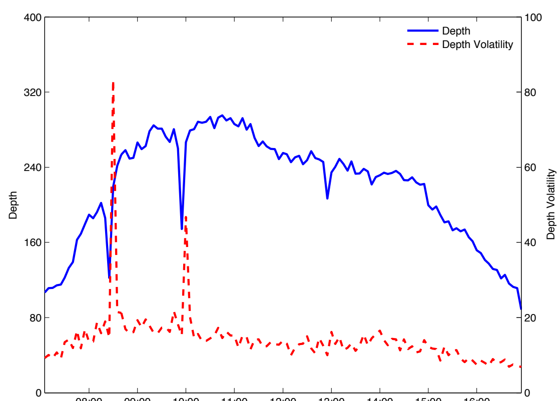
(b) Bid: Depth & Trade Volume



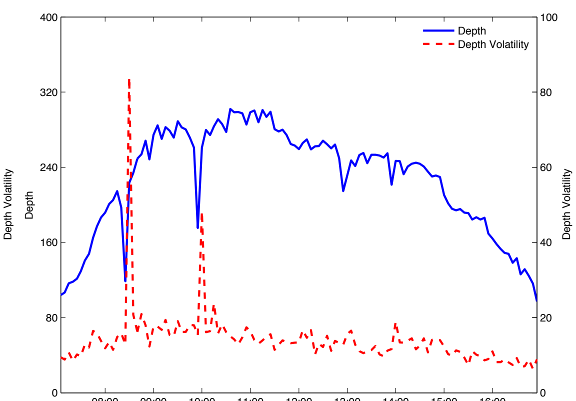
(c) Ask: Depth & Price Vol.



(d) Bid: Depth & Price Vol.



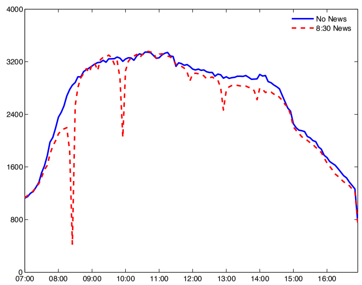
(e) Ask: Depth & Depth Vol.



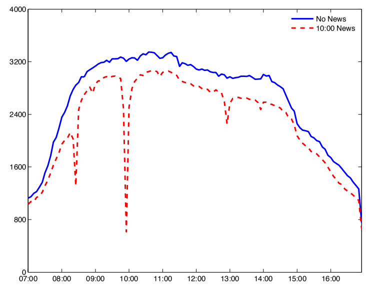
(f) Bid: Depth & Depth Vol.

This figure shows the 2–year Treasury note's intraday patterns of market depth, price volatility and depth volatility at the first price tier, using BrokerTec order book data over the period 2006–2010Q2.

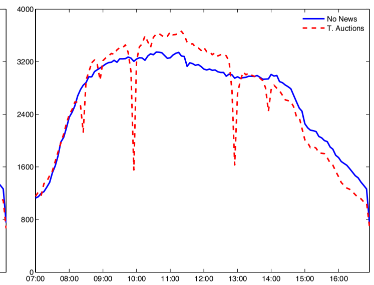
Figure 4: 2–Year Treasury Note's Depth, Trading Volume and Price Volatility on Days With and Without Key Announcements



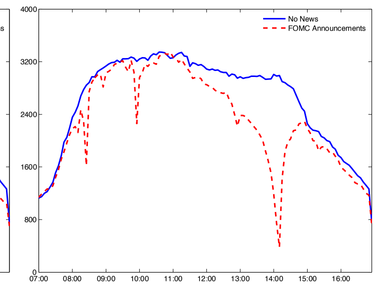
(a) Depth–8:30 News



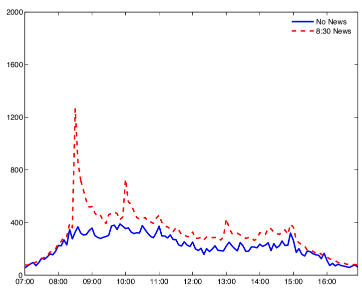
(b) Depth–10:00 News



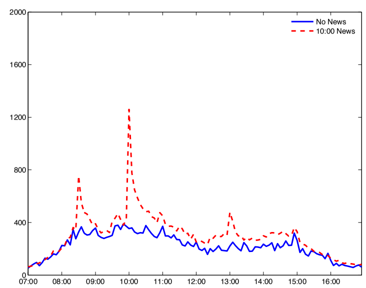
(c) Depth–Treasury. Auction



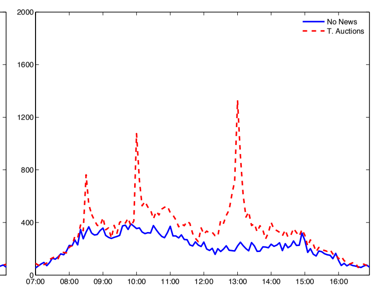
(d) Depth–FOMC Ann.



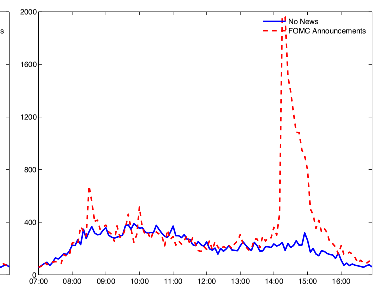
(e) Trade–8:30 News



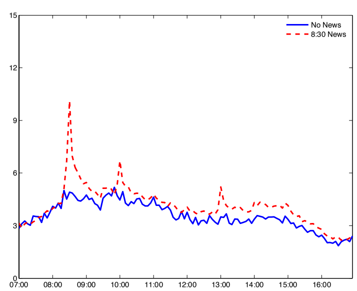
(f) Trade–10:00 News



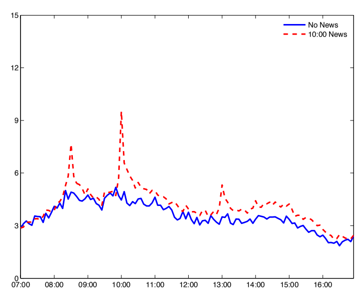
(g) Trade–Treasury Auction



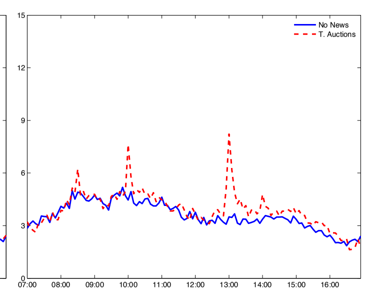
(h) Trade–FOMC Ann.



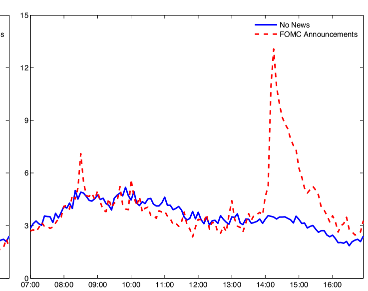
(i) Price Vol. – 8:30 News



(j) Price Vol.–10:00 News



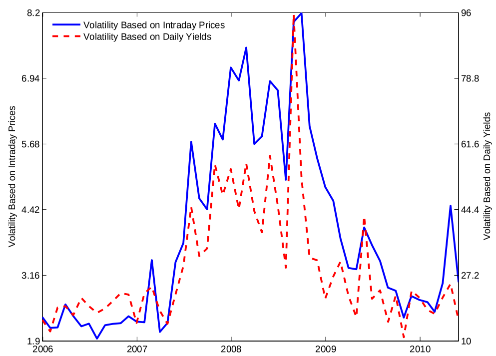
(k) Price Vol.–Treasury Auction



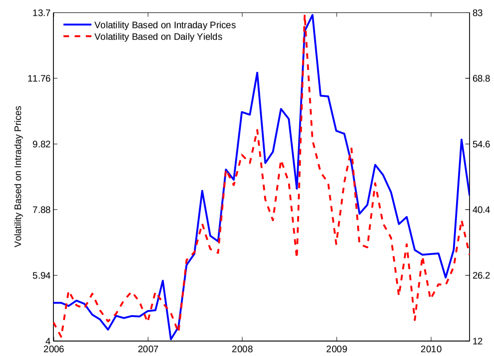
(l) Price Vol.–FOMC Ann.

Intradaily pattern of depth, trading volume and price volatility on announcement days and non–announcement days, using BrokerTec data over the period 2006–2010Q2. Depth is the total market depth ($Million) at the best five bid and ask prices. Trade is the five–minute total volume of trades ($Million). Price volatility is the five–minute realized volatility of the best bid ask mid–point. Treasury auction results are announced shortly after the 13:00 auction close on auction days, and FOMC rate decision announcements are typically made around 14:15.

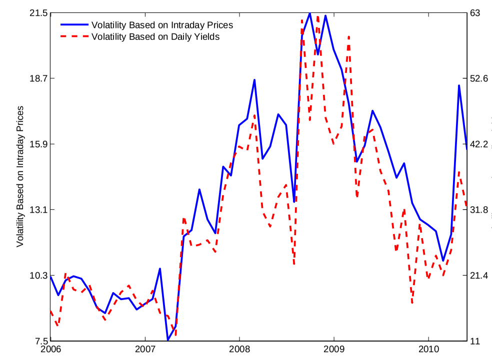
Figure 5: Comparison of Realized Volatility Measures: Price Changes or Yield Changes?



(a) 2–Year Treasury Note



(b) 5–Year Treasury Note



(c) 10–Year Treasury Note

This figure plots realized volatility computed from intraday price changes (‘RV of price’) compared with that computed from daily yield changes (‘RV of yield’) over the period 2006–2010Q2. Specifically, the RV of price is computed for each five–minute interval as the square root of the sum of squared second–by–second price changes. The figure shows the monthly average of this five–minute volatility measure using the left scale where one unit equals one 256th of one percent of par value. The RV of yield for each month is the square root of the realized variance of yield, the latter of which is computed as the sum of squared daily yield changes over the month. It is shown on the right scale where one unit equals one basis point of yield. Daily on–the–run Treasury yields are from Bloomberg.

Table 2: Liquidity and Volatility Dynamics: Baseline Estimates for 2–Year Treasury Note

	Ask5	Ask4	Ask3	Ask2	Ask1	Bid1	Bid2	Bid3	Bid4	Bid5
DEPTH ($X^{(1)}$)										
ω_1	0.005	0.000	0.006	0.006	0.015	0.014	0.001*	0.007	0.009	0.013
α_1	0.341	0.314	0.286	0.291	0.111	0.114	0.286	0.293	0.330	0.348
β_1	0.651	0.679	0.705	0.701	0.877	0.874	0.708	0.698	0.659	0.638
γ_2	0.004	0.008	0.001*	0.002	-0.005	-0.004	0.003	−0.000*	−0.001*	−0.001*
γ_3	0.001*	-0.000	0.002	0.001	0.003	0.002	0.002	0.003	0.003	0.003
RVP ($X^{(2)}$)										
ω_2	0.216	0.215	0.220	0.209	0.154	0.202	0.237	0.230	0.223	0.199
α_2	0.239	0.234	0.230	0.229	0.209	0.234	0.241	0.240	0.241	0.241
β_2	0.600	0.605	0.609	0.610	0.678	0.613	0.585	0.590	0.591	0.599
γ_1	-0.032	-0.033	-0.038	-0.029	−0.023*	-0.023	-0.042	-0.039	-0.036	-0.022
γ_3	0.001	0.001	0.001	0.002	−0.002*	-0.002	0.002	0.001	0.001	0.002
RVD ($X^{(3)}$)										
ω_3	0.364	0.468	0.634	0.633	0.561	0.431	0.525*	0.429	0.418	0.334
α_3	0.685	0.505	0.350	0.520	0.012	0.023	0.644*	0.435	0.486	0.696
β_3	0.215	0.143	0.137	0.023	0.018	0.072	0.074*	0.257	0.245	0.221
γ_1	−0.064*	−0.076*	-0.145	-0.077	-0.062	-0.033	−0.076*	−0.087*	−0.083*	−0.036*
γ_2	0.131*	0.252	0.357	0.411	0.874	0.974	0.216*	0.236	0.140	0.044*

This table shows estimates for the baseline model with no covariates for the 2–year Treasury note. The model is estimated jointly for depth ($X^{(1)}$), price volatility ($X^{(2)}$) and depth volatility ($X^{(3)}$). Each conditional mean equation is specified as: $\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)}$. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level, based on Newey West robust standard errors.

Table 3: Liquidity and Volatility Dynamics With Announcement Effects for 2–Year Treasury Note

	Ask5	Ask4	Ask3	Ask2	Ask1	Bid1	Bid2	Bid3	Bid4	Bid5
DEPTH ($X^{(1)}$)										
ω_1	0.032	0.032	0.012	0.010	0.017	0.017	0.007*	0.013	0.016	0.029
α_1	0.165	0.357	0.316	0.336	0.112	0.118	0.317	0.313	0.361	0.192
β_1	0.795	0.618	0.670	0.649	0.873	0.867	0.671	0.672	0.623	0.785
γ_2	-0.001	-0.007	−0.000*	0.003*	-0.005	-0.005	0.002*	−0.002*	−0.002*	-0.008
γ_3	0.003	0.001	0.001	0.001	0.002	0.002	0.001*	0.002	0.002	0.001
θ_1	-0.147	-0.079	-0.056	-0.095	-0.157	-0.114	-0.090	-0.099	-0.059	-0.092
θ_2	0.123	0.139	0.259	0.280	0.200	0.077	0.287	0.304	0.303	0.315
θ_3	0.088	0.143	0.014*	0.005*	0.051*	0.128	−0.001*	0.035*	0.002*	0.256
RVP ($X^{(2)}$)										
ω_2	0.179	0.619	0.796	0.188	0.164	0.183	0.209	0.200	0.192	0.173
α_2	0.217	0.704	0.371	0.216	0.184	0.222	0.227	0.225	0.224	0.221
β_2	0.641	0.083	0.000*	0.635	0.692	0.635	0.614	0.620	0.623	0.634
γ_1	-0.024	-0.096	-0.094	-0.026	-0.025	-0.021	-0.035	-0.031	-0.028	-0.019
γ_3	0.001*	-0.001	0.004	0.002	-0.001	-0.002	0.002*	0.001*	0.002	0.002
θ_1	1.175	0.967	0.674	0.592	0.282	0.519	0.598	0.721	0.907	1.123
θ_2	0.543	1.350	0.862	0.635	0.838	0.678	0.626	0.568	0.533	0.560
θ_3	-0.917	-0.272	−0.165*	-0.672	-0.728	-0.587	-0.661	-0.666	-0.744	-0.891
RVD ($X^{(3)}$)										
ω_3	0.505	0.322	0.484	0.445	0.540	0.411	0.408	0.310	0.327	0.108
α_3	0.551	0.434	0.395	0.505	0.022	0.029	0.463	0.378	0.438	0.258
β_3	0.156	0.350	0.272	0.201	0.021	0.083	0.255	0.435	0.372	0.728
γ_1	-0.077	-0.054	-0.116	-0.056	-0.060	-0.031	-0.067	-0.071	-0.065	-0.025
γ_2	0.020	0.031	0.069	0.049	0.791	0.898	0.044	0.027	0.004	-0.021
θ_1	3.265	0.468	0.224	0.222	0.056	-0.195	0.405	0.191	0.490	3.320
θ_2	31.622	38.731	41.688	55.011	13.568	11.733	40.250	33.868	25.131	3.944
θ_3	-5.611	-13.968	-11.939	-11.615	-0.631	-1.407	-10.738	-15.354	-9.844	-0.620

This table shows estimates for the model with announcement effects for the 2–year Treasury note. The model is estimated jointly for depth ($X^{(1)}$), price volatility ($X^{(2)}$) and depth volatility ($X^{(3)}$). Each conditional mean equation is specified as: $\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta' \mathbf{Z}_{t-1}$, where $\mathbf{Z}$ represents other covariates. $\mathbf{Z} = (prenews2, prenews1, news)$ where $prenews2$ is the dummy for the second to last five–minute interval before announcements, $prenews1$ is the dummy for the five–minute interval before announcements and $news$ is the dummy for the five–minute interval containing announcement time. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level, based on Newey West robust standard errors.

Table 4: Liquidity and Volatility Dynamics With Crisis Period and Announcement Effects for 2–Year Treasury Note

	Ask5	Ask4	Ask3	Ask2	Ask1	Bid1	Bid2	Bid3	Bid4	Bid5
DEPTH ($X^{(1)}$)										
ω_1	0.089	0.044	0.000*	0.009*	0.046	0.036	0.007*	0.018	0.031*	0.054
α_1	0.351	0.370	0.386	0.411	0.183	0.179	0.404	0.408	0.383	0.151
β_1	0.559	0.574	0.610	0.574	0.773	0.786	0.584	0.573	0.579	0.796
γ_2	-0.012	0.008	0.002*	0.003*	-0.007	-0.006	0.002*	−0.002*	-0.007	-0.005
γ_3	0.002	−0.000*	0.002	0.002	0.003	0.003	0.001	0.002	0.006	0.000
θ_1	−0.040*	−0.030*	0.007	−0.003*	-0.035	-0.026	−0.004*	−0.008*	−0.012*	-0.035
θ_2	-0.033	-0.039	-0.052	-0.097	-0.136	-0.091	-0.095	-0.106	-0.032	-0.088
θ_3	−0.009*	−0.008*	0.271	0.305	0.212	0.076	0.306	0.331	0.257	0.137
θ_4	0.023*	0.055	−0.006*	−0.028*	0.020*	0.105	−0.033*	0.005*	0.172	0.090
θ_5	0.091	−0.009*	-0.124	-0.138	-0.111	-0.108	-0.170	-0.149	0.014*	0.056
θ_6	−0.027*	0.045*	0.116	0.142	0.147	0.135	0.173	0.156	0.010*	-0.016
RVP ($X^{(2)}$)										
ω_2	0.213	0.438	0.032	0.218	0.215	0.220	0.227	0.230	0.231	0.221
α_2	0.230	0.416	0.149	0.233	0.236	0.244	0.240	0.244	0.243	0.242
β_2	0.599	0.326	0.040	0.588	0.591	0.580	0.578	0.570	0.570	0.575
γ_1	-0.014	-0.074	0.480	-0.013	-0.010	-0.010	-0.017	-0.016	-0.016	-0.011
γ_3	0.001*	-0.000	0.317	0.002*	-0.002	-0.002	0.002*	0.001*	0.001*	0.001*
θ_1	-0.122	0.006	-0.039	-0.146	-0.144	-0.151	-0.136	-0.146	-0.140	-0.133
θ_2	1.137	0.270	1.275	0.554	0.441	0.471	0.565	0.678	0.863	1.077
θ_3	0.514	1.331	2.015	0.606	0.651	0.634	0.603	0.543	0.515	0.540
θ_4	-0.885	0.709	−0.099*	-0.695	-0.578	-0.608	-0.687	-0.680	-0.733	-0.847
θ_5	0.017*	-0.176	0.226	-0.028	-0.031	-0.043	−0.026*	-0.028	−0.005*	0.009*
θ_6	0.077	0.101	0.120	0.146	0.146	0.164	0.135	0.143	0.113	0.091
RVD ($X^{(3)}$)										
ω_3	0.341	0.337	0.488	0.494	0.487	0.420	0.443	0.319	0.332	0.316
α_3	0.461	0.473	0.444	0.535	0.046	0.046	0.488	0.358	0.480	0.569
β_3	0.346	0.335	0.258	0.183	0.071	0.111	0.231	0.445	0.362	0.296
γ_1	-0.044	-0.049	-0.116	-0.062	-0.054	-0.033	-0.071	-0.064	-0.067	-0.024
γ_2	0.036	0.043	0.073	0.077	0.789	0.907	0.072	0.042	0.002	0.002
θ_1	-0.123	-0.045	0.000*	-0.085	0.000*	-0.093	-0.045	-0.099	0.006	-0.137
θ_2	0.729	0.450	0.211	0.230	0.062	-0.178	0.401	0.192	0.485	0.978
θ_3	22.863	38.497	41.866	53.526	12.800	11.137	39.401	33.544	24.597	18.279
θ_4	-8.537	-13.682	-11.575	-10.592	-0.530	-0.907	-9.791	-15.777	-9.594	-6.085
θ_5	0.020	-0.097	-0.101	-0.119	-0.034	-0.026	-0.108	0.036	-0.098	-0.135
θ_6	0.021	0.016	0.006	0.009	-0.056	-0.057	0.010	0.010	0.014	0.155

This table shows estimates for the model with crisis period and announcement effects for the 2–year Treasury note. The model is estimated jointly for depth ($X^{(1)}$), price volatility ($X^{(2)}$) and depth volatility ($X^{(3)}$). Each conditional mean equation is specified as: $\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta' \mathbf{Z}_{t-1}$, where $\mathbf{Z}$ represents other covariates. $\mathbf{Z} = (DC, prenews2, prenews1, news, DC * X^{(i)}, DC * \mu^{(i)})$ where DC is the dummy for the crisis period, defined to be from August 9, 2007 through June 30, 2009, $prenews2$ is the dummy for the second to last five–minute interval before announcements, $prenews1$ is the dummy for the five–minute interval before announcements and $news$ is the dummy for the five–minute interval containing announcement time. $(\theta_5 + \theta_6)$ shows the effect of the crisis period on the persistence of $X^{(i)}$. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level, based on Newey West robust standard errors.

Table 5: Liquidity and Volatility Dynamics With News Impact Curve for 2–Year Treasury Note

	Ask5	Ask4	Ask3	Ask2	Ask1	Bid1	Bid2	Bid3	Bid4	Bid5
DEPTH ($X^{(1)}$)										
ω_1	0.000	0.000	0.006	0.004	0.016	0.013	0.001*	0.007	0.007	0.012
α_1	0.240	0.306	0.287	0.291	0.111	0.114	0.287	0.296	0.333	0.350
β_1	0.752	0.689	0.704	0.701	0.877	0.874	0.708	0.696	0.658	0.638
γ_2	0.004	0.007	0.001*	0.001*	-0.005	-0.004	0.002	−0.001*	−0.002*	−0.002*
γ_3	0.001	0.000	0.002	0.001	0.003	0.002	0.002	0.003	0.003	0.003
θ_1	0.003	-0.000	0.002	0.002	-0.001	0.001*	0.000*	-0.001	0.000*	−0.000*
θ_2	-0.003	0.000	-0.003	-0.002	0.001	−0.000*	0.000*	0.003	0.002	0.002
RVP ($X^{(2)}$)										
ω_2	0.219	0.220	0.225	0.213	0.216	0.206	0.242	0.235	0.227	0.202
α_2	0.230	0.225	0.220	0.218	0.221	0.222	0.229	0.229	0.231	0.233
β_2	0.593	0.598	0.601	0.602	0.599	0.605	0.578	0.581	0.584	0.594
γ_1	-0.033	-0.034	-0.039	-0.029	-0.027	-0.024	-0.043	-0.040	-0.037	-0.023
γ_3	0.001	0.001	0.001	0.002	-0.002	-0.002	0.002	0.001	0.001	0.001
θ_1	0.007	0.007	0.007	0.008	0.010	0.008	0.010	0.010	0.009	0.006
θ_2	0.001*	0.002*	0.002	0.001*	−0.000*	0.003	−0.000*	−0.001*	−0.001*	0.001*
RVD ($X^{(3)}$)										
ω_3	0.365	0.469	0.615	0.656	0.455	0.422	0.525	0.442	0.420	0.334
α_3	0.682	0.502	0.348	0.525	0.020	0.037	0.643	0.430	0.483	0.692
β_3	0.219	0.144	0.144	0.000	0.090	0.066	0.064	0.242	0.245*	0.221
γ_1	−0.065*	−0.076*	-0.141	-0.079	-0.051	-0.032	-0.075	−0.087*	−0.083*	−0.036*
γ_2	0.144*	0.255	0.303	0.339	0.833	0.836	0.155	0.232*	0.143*	0.040*
θ_1	0.007*	0.015*	0.068	0.058	-0.064	0.181	0.042	−0.015*	−0.015*	−0.014*
θ_2	−0.034*	−0.033*	-0.070	-0.021	0.155	-0.206	0.002*	0.048*	0.028*	0.035*

This table shows estimates for the model with a news impact curve for the 2–year Treasury note. The model is estimated jointly for depth ($X^{(1)}$), price volatility ($X^{(2)}$) and depth volatility ($X^{(3)}$). Each conditional mean equation is specified as: $\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta' \mathbf{Z}_{t-1}$, where $\mathbf{Z}$ represents other covariates. $\mathbf{Z} = (|Ret|, |Ret| * \mathbf{1}_{Ret<0})$ is the news impact curve and a function of the five–minute return Ret. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level, based on Newey West robust standard errors.

Table 6: Liquidity and Volatility Dynamics With Trading Volume Effects for 2–Year Treasury Note

	Ask5	Ask4	Ask3	Ask2	Ask1	Bid1	Bid2	Bid3	Bid4	Bid5
DEPTH ($X^{(1)}$)										
ω_1	0.015	0.000	0.007	0.007	0.020	0.019	0.003*	0.009	0.012	0.013
α_1	0.189	0.253	0.287	0.292	0.112	0.116	0.288	0.295	0.330	0.348
β_1	0.797	0.744	0.703	0.698	0.872	0.867	0.705	0.693	0.653	0.635
γ_2	−0.005*	0.003*	−0.001*	0.000*	-0.010	-0.010	0.001*	-0.004	-0.004	-0.003
γ_3	0.002*	0.001*	0.002	0.001	0.003	0.002	0.002	0.003	0.002	0.003
θ	0.001*	−0.001*	0.002	0.002	0.004	0.004	0.002	0.004	0.005	0.004
RVP ($X^{(2)}$)										
ω_2	0.213	0.213	0.221	0.207	0.193	0.100	0.372	0.227	0.221	0.193
α_2	0.207	0.201	0.193	0.191	0.181	0.100	0.277	0.202	0.205	0.211
β_2	0.597	0.601	0.606	0.608	0.636	0.800	0.427	0.588	0.591	0.599
γ_1	-0.037	-0.038	-0.046	−0.035*	−0.029*	−0.022*	-0.067	-0.043	-0.042	-0.023
γ_3	0.000*	0.001	0.001	0.001*	−0.002*	−0.001*	0.001	0.001	0.001	0.002
θ	0.036	0.038	0.041	0.040*	0.033*	0.029*	0.024	0.039	0.036	0.031
RVD ($X^{(3)}$)										
ω_3	0.374	0.483	0.615	0.656	0.430	0.352	0.531	0.439	0.419	0.338
α_3	0.687	0.510	0.341	0.521	0.014	0.024	0.645	0.439	0.486*	0.697
β_3	0.213*	0.140	0.158	0.019	0.030	0.061	0.075	0.252*	0.245*	0.220*
γ_1	−0.065*	−0.077*	−0.151*	-0.080	-0.047	−0.026*	−0.076*	−0.088*	−0.083*	−0.037*
γ_2	0.135*	0.261	0.343	0.426	0.804	0.885	0.225	0.246*	0.140*	0.048*
θ	−0.012*	−0.020*	0.014*	-0.027	0.160	0.167	−0.014*	−0.014*	−0.000*	−0.007*

This table shows estimates for the model with trading volume for the 2–year Treasury note. The model is estimated jointly for depth ($X^{(1)}$), price volatility ($X^{(2)}$) and depth volatility ($X^{(3)}$). Each conditional mean equation is specified as: $\mu_t^{(i)} = \omega_i + \alpha_i X_{t-1}^{(i)} + \beta_i \mu_{t-1}^{(i)} + \sum_{j \neq i} \gamma_j X_{t-1}^{(j)} + \theta' \mathbf{Z}_{t-1}$, where $\mathbf{Z}$ represents other covariates. $\mathbf{Z} = qV$, where qV is the volume of trading initiated by the opposite side, e.g., for tiers on the Ask side, $qV =$ buyer–initiated trading volume. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level, based on Newey West robust standard errors.

Table 7: Flight–to–Safety Episodes During 2006–2010Q2 Period

	Light FTS			**Moderate FTS**			**Severe FTS**		
Date	2–Year	5–Year	10–Year	2–Year	5–Year	10–Year	2–Year	5–Year	10–Year
02/27/2007	X	X	X	X	X	X	X		
03/13/2007	X	X							
07/26/2007	X	X	X						
08/03/2007	X	X	X	X	X				
08/09/2007	X	X	X	X	X				
08/28/2007	X	X							
09/07/2007	X	X	X						
10/19/2007	X	X	X	X					
11/01/2007	X	X	X	X	X	X			
11/07/2007	X	X		X	X				
11/19/2007	X	X	X						
11/21/2007	X	X	X						
11/26/2007	X	X	X						
12/11/2007	X	X	X	X	X	X			
01/04/2008	X								
01/08/2008		X							
01/15/2008	X	X	X						
01/17/2008	X	X	X		X	X			
01/25/2008	X	X	X						
02/05/2008	X	X	X	X	X		X		
02/29/2008	X	X	X	X	X	X			
03/06/2008	X	X	X						
03/14/2008	X	X							
03/19/2008	X	X	X	X	X	X			
04/11/2008	X	X	X						
05/07/2008	X	X							
06/06/2008	X	X	X	X	X	X			
06/11/2008	X	X							
06/26/2008	X	X		X	X				
07/02/2008	X								
07/09/2008	X	X	X						
07/24/2008	X	X	X						
07/28/2008	X	X	X						
08/07/2008	X	X	X						
08/25/2008	X	X	X						
09/04/2008	X	X	X						
09/09/2008	X	X	X	X	X	X	X		
09/15/2008	X	X	X	X	X	X	X	X	X
09/17/2008	X			X			X		
09/29/2008	X	X	X	X	X	X	X	X	X
10/02/2008	X	X	X	X	X	X	X	X	
10/06/2008	X	X	X	X	X	X	X	X	X
10/15/2008	X	X	X	X	X	X	X	X	
10/21/2008	X	X	X		X				
10/22/2008	X	X	X	X	X	X			X
10/24/2008	X								

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Table 7 – *Continued from previous page*

	Light FTS			**Moderate FTS**			**Severe FTS**		
Date	2–Year	5–Year	10–Year	2–Year	5–Year	10–Year	2–Year	5–Year	10–Year
11/12/2008	X	X	X		X				
11/14/2008		X	X			X			
11/17/2008			X						
11/19/2008		X	X		X	X		X	X
11/20/2008	X	X	X		X	X			X
12/01/2008	X	X	X		X	X		X	X
12/04/2008	X	X	X			X			
12/09/2008	X	X	X						
12/11/2008	X		X						
12/18/2008		X	X						
01/09/2009	X	X							
01/12/2009			X						
01/14/2009		X	X						
02/10/2009	X	X	X	X	X	X		X	X
02/17/2009	X	X	X		X	X		X	X
02/27/2009	X	X							
03/02/2009	X	X	X	X	X	X		X	X
03/05/2009		X	X		X	X			X
03/30/2009		X							
04/14/2009		X	X						
04/20/2009		X	X			X			
05/11/2009	X	X	X						
06/15/2009			X						
06/22/2009	X	X	X						
07/02/2009		X							
08/17/2009		X	X						
10/01/2009	X	X	X		X	X			
10/30/2009	X	X	X		X	X			
02/04/2010	X	X	X						
04/16/2010		X	X						
04/27/2010	X	X	X						
04/30/2010			X						
05/04/2010		X	X						
05/06/2010	X	X	X		X	X			X
05/14/2010		X	X						
05/20/2010		X	X		X	X			X
06/04/2010	X	X	X		X	X		X	X
06/22/2010			X						
06/29/2010			X						
No. of FTS days	64	74	69	22	33	29	9	11	14

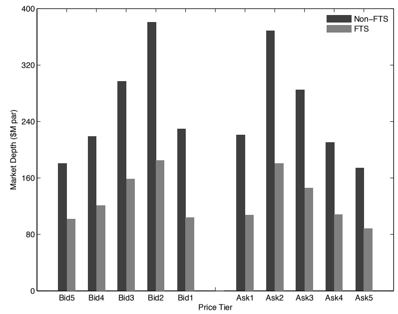
This table presents flights to safety (FTS) over the period 2006–2010Q2. Flights are identified by a large positive return on the Treasury note and a large negative return on the S&P500 index. Light FTS episodes are based on a 1 standard deviation threshold, moderate FTS on a 1.5 standard deviation threshold and severe FTS on a 2 standard deviation threshold.

Table 8: Average Daily Trading Volume and Number of Trades on FTS and non–FTS days

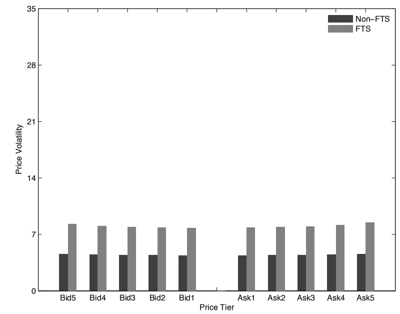
	2–Year Treasury Note		5–Year Treasury Note		10–Year Treasury Note	
	Non–FTS	FTS	Non–FTS	FTS	Non–FTS	FTS
Trading Volume ($M of Par)	33,775	57,425	30,627	39,946	25,971	31,440
Buyer–Initiated Volume	16,561	29,185	15,081	19,862	12,825	15,889
Seller–Initiated Volume	17,214	28,240	15,546	20,084	13,146	15,551
Net Volume (Buy - Sell)	-652	945	-465	-222	-321	338
Number of Trades	7,264	13,190	12,532	18,419	12,041	17,602
Number of Buy Trades	3,580	6,767	6,194	9,267	5,963	8,934
Number of Sell Trades	3,683	6,423	6,338	9,151	6,078	8,668
Net Number of Trades (Buy - Sell)	-103	344	-144	116	-116	266

This table shows the average daily trading volume and number of trades on days with a flight to safety ("FTS") and days without such an episode ("non–FTS"), using BrokerTec trade data for the 2006–2010Q2 period. Flights are identified by a large positive return on the Treasury note and a large negative return on the S&P500 index, based on a 1.5 standard deviation threshold. Daily trading volume is the total volume exchanged during the 7:00-17:00 time period. Similarly, daily number of trades is the total number of order executions during the same time period.

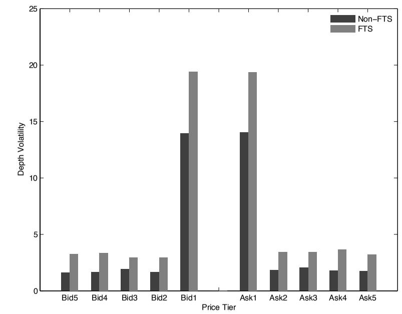
Figure 6: Liquidity and Volatility on FTS and non–FTS days



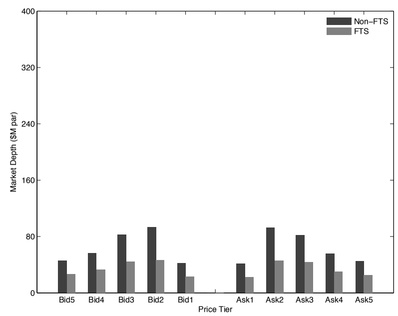
(a) 2Y: Depth



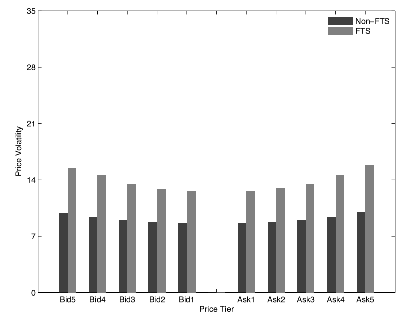
(b) 2Y: Price Volatility



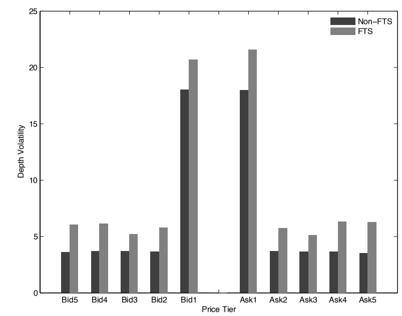
(c) 2Y: Depth Volatility



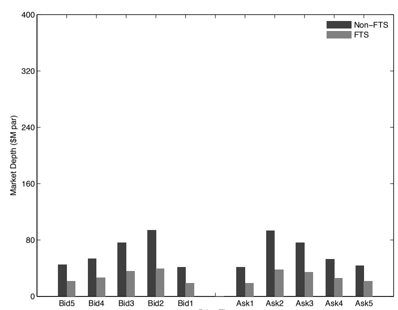
(d) 5Y: Depth



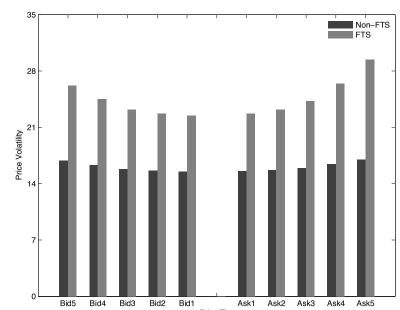
(e) 5Y: Price Volatility



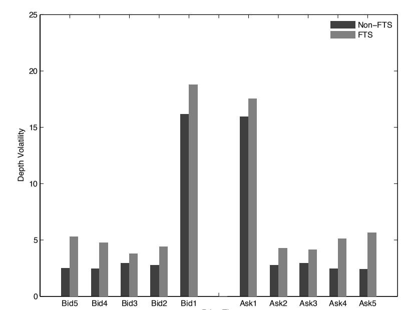
(f) 5Y: Depth Volatility



(g) 10Y: Depth



(h) 10Y: Price Volatility



(i) 10Y: Depth Volatility

This figure shows average market depth, price volatility and depth volatility at a five–minute frequency, on days with a flight to safety (“FTS” – light colored bars) and days without such an episode (“nonFTS” – dark colored bars), using BrokerTec order book data over the period 2006–2010Q2. Flights are identified by a large positive return on the Treasury note and a large negative return on the S&P500 index, based on a 1.5 standard deviation threshold.

Table 9: Liquidity Dynamics With Flight–to–Safety Effect

	2–Year Treasury Note						5–Year Treasury Note						10–Year Treasury Note					
	ω	α	β	c	c_α	c_β	ω	α	β	c	c_α	c_β	ω	α	β	c	c_α	c_β
Panel A: Flight–to–Safety Dummy Based on $\kappa = 1$																		
Ask5	0.027	0.580	0.407	−0.003*	-0.119	0.098							0.030	0.508	0.482	0.000*	-0.076	0.049
Ask4	0.024	0.561	0.430	-0.009	-0.101	0.093	0.043	0.488	0.492	0.003*	-0.067	0.054	0.028	0.502	0.489	−0.002*	-0.086	0.065
Ask3	0.022	0.538	0.456	−0.004*	-0.072	0.060	0.029	0.469	0.527	−0.001*	−0.022*	0.008*	0.021	0.482	0.521	0.001*	−0.039*	0.014*
Ask2	0.022	0.540	0.456	0.003*	−0.035*	0.009*	0.027	0.466	0.533	0.014	−0.037*	−0.009*	0.020	0.495	0.504	0.004*	−0.046*	0.020*
Ask1	0.069	0.364	0.612	-0.021	-0.045	0.035												
Bid1	0.066	0.361	0.616	-0.014	-0.043	0.005*	0.111	0.291	0.660	0.006*	-0.037	−0.025*	0.089	0.306	0.661	−0.004*	−0.022*	-0.029
Bid2	0.020	0.547	0.450	−0.001*	-0.087	0.067	0.030	0.465	0.528	0.004*	-0.048	0.018*	0.021	0.485	0.513	0.001*	-0.046	0.022*
Bid3	0.021	0.538	0.456	−0.002*	-0.068	0.052	0.034	0.472	0.518	0.003*	−0.038*	0.004*	0.021	0.473	0.527	0.006*	−0.038*	0.005*
Bid4	0.025	0.563	0.426	−0.004*	-0.060	0.047*	0.046	0.494	0.483	−0.000*	-0.077	0.043*	0.032	0.502	0.484	0.002*	-0.068	0.041*
Bid5	0.027	0.569	0.417	-0.007	-0.084	0.073	0.046	0.491	0.486	−0.000*	-0.077	0.043	0.033	0.506	0.481	−0.005*	-0.083	0.067
Panel B: Flight–to–Safety Dummy Based on $\kappa = 1.5$																		
Ask5	0.027	0.575	0.411	0.002*	-0.096	0.066*	0.046	0.495	0.484	-0.012	-0.086	0.067	0.030	0.505	0.484	0.004*	-0.080	0.034*
Ask4	0.023	0.557	0.434	−0.006*	-0.085	0.077*	0.044	0.485	0.495	−0.004*	-0.076	0.042*	0.028	0.500	0.490	−0.005*	-0.109	0.082
Ask3	0.022	0.536	0.458	−0.008*	-0.087	0.085	0.029	0.467	0.529	0.004*	−0.025*	−0.007*	0.021	0.481	0.520	0.003*	−0.063*	0.023*
Ask2	0.022	0.537	0.458	0.014	0.037*	−0.074*	0.027	0.466	0.532	0.013	-0.060	0.007*	0.020	0.494	0.505	0.010*	−0.062*	0.013*
Ask1	0.067	0.362	0.614	−0.007*	−0.005*	−0.006*	0.103	0.290	0.666	−0.001*	-0.041	−0.020*	0.091	0.309	0.655	0.007*	−0.033*	-0.055
Bid1	0.064	0.361	0.616	-0.020	-0.091	0.057	0.111	0.289	0.660	0.010*	−0.030*	-0.049	0.088	0.306	0.660	−0.002*	-0.036	−0.045*
Bid2	0.020	0.543	0.453	−0.003*	-0.090	0.070*	0.030	0.463	0.530	0.012	−0.042*	−0.010*	0.021	0.484	0.513	0.004*	-0.068	0.027*
Bid3	0.021	0.537	0.457	0.002*	−0.066*	0.040*	0.034	0.471	0.518	−0.006*	-0.075	0.048*						
Bid4	0.025	0.561	0.427	−0.005*	−0.066*	0.057*	0.046	0.492	0.484	−0.005*	-0.069	0.036*	0.032	0.501	0.484	−0.001*	-0.101	0.064
Bid5	0.026	0.566	0.420	−0.006*	-0.120	0.108	0.046	0.489	0.487	−0.004*	-0.083	0.048*	0.033	0.504	0.482	−0.006*	-0.117	0.088
Panel C: Flight–to–Safety Dummy Based on $\kappa = 2$																		
Ask5	0.026	0.574	0.412	0.006*	-0.155	0.086*	0.046	0.493	0.486	−0.010*	−0.083*	0.035*	0.030	0.504	0.486	0.011*	−0.046*	−0.038*
Ask4	0.024	0.556	0.434	-0.010	-0.164	0.143	0.044	0.485	0.495	0.004*	-0.163	0.071*	0.028	0.498	0.491	−0.006*	-0.101	0.066*
Ask3	0.022	0.535	0.459	−0.009*	-0.103	0.091*	0.029	0.468	0.527	−0.000*	−0.020*	−0.028*	0.021	0.480	0.522	0.013*	−0.050*	−0.038*
Ask2	0.022	0.539	0.456	0.009*	−0.061*	−0.016*	0.028	0.465	0.532	0.027	−0.088*	−0.050*	0.019	0.492	0.508	0.016*	−0.096*	0.015*
Ask1	0.068	0.362	0.614	-0.031	-0.066	0.032*	0.103	0.290	0.665	0.031*	-0.130	−0.078*	0.091	0.309	0.655	0.070*	-0.074	−0.168*
Bid1	0.064	0.360	0.616	-0.037	-0.113	0.090	0.111	0.290	0.659	0.173	−0.068*	-0.412	0.088	0.306	0.660	0.008*	-0.108	−0.027*
Bid2	0.020	0.541	0.455	−0.004*	-0.116	0.083*	0.030	0.462	0.531	0.044	−0.043*	-0.147	0.021	0.484	0.513	0.007*	-0.100	0.034*
Bid3	0.021	0.536	0.458	0.003*	−0.100*	0.055*	0.034	0.470	0.519	0.007*	−0.088*	−0.000*	0.022	0.474	0.525	0.011*	−0.066*	−0.009*
Bid4	0.025	0.560	0.429	−0.001*	−0.001*	−0.031*	0.046	0.491	0.485	0.009*	-0.146	0.035*	0.031	0.498	0.487	0.009*	−0.065*	−0.011*
Bid5	0.027	0.568	0.418	−0.009*	-0.154	0.134	0.046	0.487	0.490	0.029	−0.072*	−0.091*	0.033	0.503	0.483	−0.002*	-0.106	0.052*

This table shows estimates for the model of market depth with a flight–to–safety effect for the 2–, 5– and 10–year Treasury notes. The conditional mean equation is specified as: $\mu_t = \omega + \alpha X_{t-1} + \beta\mu_{t-1} + c\,FTS_t + c_\alpha FTS_t X_{t-1} + c_\beta FTS_t \mu_{t-1}$. FTS is the dummy for flight–to–safety days, defined as those days when the equity return (based on the S&P500) falls below $-\kappa$ times its sample standard deviation while the Treasury note return exceeds κ times the latter's sample standard deviation. The table shows three definitions of FTS corresponding to three levels for κ (1, 1.5, 2). c captures the level effect of FTS on market depth, while c_α and c_β capture the change in the dynamics of market depth on FTS days. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level.

Table 10: Volatility Dynamics With Flight–to–Safety Effect

	2–Year Treasury Note						5–Year Treasury Note						10–Year Treasury Note					
	ω	α	β	c	c_α	c_β	ω	α	β	c	c_α	c_β	ω	α	β	c	c_α	c_β
Panel A: Flight–to–Safety Dummy Based on $\kappa = 1$																		
Ask5	0.143	0.379	0.471	0.098	0.023*	−0.018*	0.129	0.499	0.364	0.194	0.074	-0.172	0.155	0.477	0.357	−0.018*	0.077	0.002*
Ask4	0.143	0.368	0.482	0.110	0.019*	−0.019*	0.131	0.486	0.376	0.076	0.035*	−0.046*	0.145	0.443	0.405	0.012*	0.068	−0.022*
Ask3	0.153	0.371	0.470	0.123	0.006*	−0.013*	0.143	0.465	0.386	0.059	0.024*	−0.015*	0.147	0.440	0.408	0.036*	0.045*	−0.018*
Ask2	0.165	0.378	0.451	0.140	0.022*	−0.037*	0.149	0.450	0.395	0.081	0.060*	−0.065*	0.156	0.434	0.406	0.019*	0.058*	−0.021*
Ask1	0.155	0.368	0.471	0.117	0.009*	−0.015*	0.149	0.447	0.399	0.117	0.050*	−0.090*	0.163	0.431	0.403	0.082	0.039*	−0.053*
Bid1	0.152	0.367	0.475	0.165	0.019*	−0.061*	0.158	0.453	0.384	0.105	0.049*	−0.080*	0.171	0.438	0.389	0.124	0.005*	−0.056*
Bid2							0.161	0.466	0.369	0.111	0.096	-0.130	0.155	0.437	0.407	0.128	0.046*	-0.103
Bid3	0.151	0.370	0.474	0.145	0.016*	−0.044*	0.145	0.465	0.387	0.056*	0.005*	−0.001*	0.159	0.445	0.391	0.100	0.004*	−0.038*
Bid4	0.152	0.377	0.465	0.125	0.021*	−0.037*	0.134	0.460	0.401	0.029*	0.035*	−0.014*	0.153	0.459	0.383	0.063*	0.072	−0.077*
Bid5	0.124	0.352	0.517	0.097	0.021*	−0.027*	0.120	0.465	0.407	0.026*	0.080	−0.058*	0.155	0.471	0.365	0.048*	0.087	-0.074
Panel B: Flight–to–Safety Dummy Based on $\kappa = 1.5$																		
Ask5	0.143	0.382	0.471	0.052*	0.002*	0.046*	0.135	0.507	0.351	0.161	0.007*	−0.058*	0.154	0.478	0.358	−0.008*	0.115	−0.020*
Ask4	0.143	0.371	0.483	0.102	0.021*	0.009*	0.132	0.490	0.373	0.070	−0.039*	0.050*	0.146	0.446	0.402	0.024*	0.061*	0.001*
Ask3	0.152	0.373	0.472	0.160	0.038*	−0.042*	0.142	0.468	0.386	0.101	−0.011*	0.004*	0.147	0.443	0.407	0.039*	0.017*	0.034*
Ask2	0.164	0.379	0.453	0.123	0.040*	−0.022*	0.149	0.453	0.395	0.082*	0.079*	−0.074*	0.156	0.437	0.405	−0.006*	0.049*	0.027*
Ask1	0.154	0.370	0.473	0.151	0.020*	−0.025*	0.149	0.450	0.398	0.106*	0.026*	−0.044*	0.163	0.434	0.402	0.110*	0.024*	−0.034*
Bid1	0.152	0.370	0.476	0.152	0.009*	−0.022*	0.157	0.454	0.385	0.137	0.060*	−0.096*	0.171	0.440	0.389	0.220	−0.007*	−0.088*
Bid2	0.149	0.369	0.479	0.174	0.020*	−0.043*	0.161	0.470	0.367	0.110*	0.157	-0.161	0.155	0.439	0.406	0.227	0.046*	−0.146*
Bid3	0.151	0.373	0.474	0.174	−0.013*	−0.016*	0.146	0.469	0.384	0.052*	−0.037*	0.060*	0.158	0.447	0.392	0.206	0.004*	−0.087*
Bid4	0.151	0.379	0.467	0.091	0.016*	0.006*	0.132	0.460	0.403	0.050*	0.084	−0.064*	0.153	0.461	0.382	0.060*	0.086*	−0.067*
Bid5	0.124	0.354	0.518	0.065*	0.024*	0.003*	0.120	0.467	0.407	0.040*	0.112	−0.090*	0.156	0.474	0.363	0.054*	0.101	−0.067*
Panel C: Flight–to–Safety Dummy Based on $\kappa = 2$																		
Ask5	0.142	0.382	0.473	0.057*	0.026*	0.048*	0.135	0.509	0.350	0.241	−0.010*	−0.050*	0.153	0.479	0.359	−0.037*	0.115*	0.011*
Ask4	0.142	0.372	0.484	0.086*	0.040*	0.023*	0.132	0.492	0.373	0.074*	−0.085*	0.117	0.144	0.445	0.406	−0.036*	0.225	−0.103*
Ask3	0.152	0.374	0.472	0.201	0.092*	−0.082*	0.142	0.469	0.386	0.157*	−0.026*	0.017*	0.147	0.444	0.407	0.053*	0.027*	0.031*
Ask2	0.163	0.380	0.455	0.139*	0.121*	−0.079*	0.149	0.455	0.394	0.057*	0.062*	−0.017*	0.156	0.437	0.406	−0.049*	0.100*	0.022*
Ask1	0.153	0.371	0.474	0.165*	0.054*	−0.038*	0.148	0.452	0.399	0.078*	−0.020*	0.033*	0.163	0.434	0.403	0.099*	0.029*	−0.011*
Bid1	0.151	0.370	0.477	0.137*	0.004*	0.013*	0.157	0.458	0.384	0.242	0.024*	−0.113*	0.171	0.440	0.389	0.317	−0.006*	−0.137*
Bid2	0.149	0.370	0.480	0.139*	0.014*	0.003*	0.160	0.472	0.366	0.261	0.197	-0.269	0.156	0.441	0.404	0.373*	0.015*	−0.195*
Bid3	0.150	0.373	0.475	0.177*	−0.010*	0.007*	0.145	0.469	0.385	0.039*	−0.060*	0.119	0.158	0.448	0.392	0.327	−0.003*	−0.147*
Bid4	0.151	0.380	0.467	0.083*	0.050*	0.000*	0.133	0.462	0.402	0.033*	0.086*	−0.034*	0.153	0.463	0.380	0.064*	0.052*	−0.026*
Bid5	0.123	0.355	0.518	0.039*	0.024*	0.034*	0.120	0.470	0.404	0.008*	0.104*	−0.035*	0.155	0.475	0.364	0.082*	0.075*	−0.048*

This table shows estimates for the model of realized price volatility with a flight–to–safety effect for the 2–, 5– and 10–year Treasury notes. The conditional mean equation is specified as: $\mu_t = \omega + \alpha X_{t-1} + \beta\mu_{t-1} + c\,FTS_t + c_\alpha FTS_t X_{t-1} + c_\beta FTS_t \mu_{t-1}$. FTS is the dummy for flight–to–safety days, defined as those days when the equity return (based on the S&P500) falls below $-\kappa$ times its sample standard deviation while the Treasury note return exceeds κ times the latter's sample standard deviation. The table shows three definitions of FTS corresponding to three levels for κ (1, 1.5, 2). c captures the level effect of FTS on volatility, while c_α and c_β capture the change in the dynamics of price volatility on FTS days. Estimation uses BrokerTec limit order book data over the period 2006–2010Q2. It is based on five–minute snapshots of the best five price tiers on each side of the market. Note: * denotes insignificance at 5 percent level.

A Economic Announcements

We consider three categories of news that are relevant for the Treasury market: 1) macroeconomic announcements, 2) monetary policy announcements (i.e., FOMC rate decision announcements), and 3) Treasury auction results.

A.1 Macroeconomic Announcements

Included in our analysis are major economic announcements – those that are classified as "Market Moving" indicators by Bloomberg. Data for each announcement's release date and time are from Bloomberg. These announcements include:

Time	Announcement	Frequency
8:30	Employment Report	Monthly
8:30	Consumer Price Index (MoM)	Monthly
8:30	Durable Goods Orders	Monthly
8:30	GDP QoQ (Annualized)	Quarterly
8:30	Housing Starts	Monthly
8:30	Initial Jobless Claims	Weekly
8:30	Personal Income and Outlays	Monthly
8:30	Producer Price Index (MoM)	Monthly
8:30	Retail Sales	Monthly
8:30	Trade Balance	Monthly
9:15	Industrial Production	Monthly
10:00	Existing Home Sales	Monthly
10:00	ISM Manufacturing	Monthly
10:00	New Home Sales	Monthly
10:00	Philadelphia Fed. (after 2008)	Monthly
12:00	Philadelphia Fed. (before 2008)	Monthly

A.2 Monetary Policy Announcements

Included in our analysis are FOMC rate decision announcements. Such announcements occur after regularly scheduled FOMC meetings, of which there are eight per year. During our sample period, announcements after scheduled meetings are made at about 14:15. Announcements can also occur after unscheduled meetings. There were two rate changes announced after unscheduled meetings during our sample period. The announcements after the unscheduled meetings occurred on January 22, 2008 at 8:20 and October 8, 2008 at 7:00. Announcement times are from Bloomberg.

A.3 Treasury Auction Result Announcements

Included in our analysis are auction result announcements for the 2–, 5–, and 10–year notes. Auction results are announced shortly after the 13:00 auction close on auction dates for the relevant security. The 2– and 5–year notes are newly issued every month, while the 10–year note is newly issued every quarter, with reopenings in the following month and – since November 2008 – two months.