The Impact of the US Stock Market Opens on Price Discovery of Government Bond Futures

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Abstract

We assess price discovery of Government bond futures before and after the US stock market opens. We employ a price discovery model in sequential markets for the 10-year UK Gilt, German Bund, and US Treasury Note futures over the period from 2010 to 2017. We find that price discovery increases in the US, UK, and German futures following the opening of the US stock market, indicating the importance of the US stock market in domestic and international government bond futures. Variance decomposition results suggest that the increase in price discovery in the US and German bond futures is due to trade-related information, while the increase in the UK Gilt futures is due to trade-unrelated information. Analyses during US public holidays confirm our results that the US stock market is vital for price discovery in the international government bond futures markets.

Keywords: Price discovery; Information share; Sequential markets; Government bond futures

JEL Code: C32; G14; G15

1. Introduction

The government bond yield is a cornerstone of modern finance theories. Extant studies suggest that private information plays an important role in the price discovery in the U.S. Treasury markets (Brandt and Kavajecz, 2004; Green, 2004; Pasquariello and Vega, 2007; Jiang and Lo, 2014). In the government bond markets, private information originates from the fact that agents possess heterogeneous abilities to understand the current state of the economic fundamentals, interpret the economy-wide indicators, and estimate the effect of public information release on bond price dynamics (Brandt and Kavajecz, 2004). Although private information is not observable to other market participants, an investor's beliefs and attributes can be inferred through her trading activities. Recent evidence further shows that transactions in the stock market can reveal important information about the macroeconomic fundamentals that are relevant for valuing assets in the bond markets. In particular, Underwood (2009) finds that order flows in the U.S. stock market plays an indispensable role in determining the intraday returns of the U.S. Treasuries.

A unique characteristic of the U.S. stock market is that information is incorporated into prices rather differently at different times of the day. Barclay and Hendershott (2003) document that the U.S. stock prices are more efficient and informative during the trading hours than after hours. The pre-open and post-close periods generate noticeable, but inefficient, price discovery. Although the inter-market linkages between bond and stock markets have been extensively studied, there has been little evidence on how the intraday variations of price discovery in the U.S. stock market can shape the time-varying price discovery in the bond markets. If the U.S. stock market could convey essential information for bond valuations, investors in the government bond market would monitor and infer information from the trades in the stock market. As the price efficiency fluctuates in the U.S. stock market throughout the day, one would expect the price efficiency in the treasury markets might vary substantially together with the U.S. stock market. Given its size and interconnectedness, one may also expect the U.S. stock market to be a vital determinant of the price discovery in the international government bond markets.

In this paper, we examine the role of the U.S. stock market on the time-varying price discovery of global government bond futures. In particular, we examine three distinct but related questions. First, do the prices of the U.S. Treasury futures become more informative when the regular trading hour begins in the U.S. stock market? Second, how does the U.S. stock market contribute to price discovery in international government bond futures? Third, how would the price discovery in these government bond futures differ if the U.S. stock market closes for public holidays?

We follow an event study approach to answer these questions. Specifically, we investigate the price discovery of government bond futures in the 30 minutes intervals immediately before and after 9:30 AM (Eastern Time) when the U.S. stock market opens. We choose the one-hour event window (from 9:00 AM to 10:00 AM) during the opening period because of three reasons. First, within the regular trading hours, variation in the price efficiency and informed trading is relatively modest. However, there is a structural break in the informational efficiency of stock prices and how information is incorporated into stock prices at the open and the close (Admati and Pfleiderer, 1988; Brandt and Kavajecz, 2004). These exogenous shifts make it possible to investigate the spillover effect of the U.S. stock market in global government bond markets. Second, we choose the U.S. market open (9:30 AM) instead of the close (4:00 PM) because major European stock markets (e.g. London and Frankfurt) are still open. This allows us to evaluate the incremental effect of the U.S. stock market. Third, our choice of the event window leave out the effect of news announcements by excluding 8:30 AM when numerous economic news are released.

To properly estimate the treatment effect of the U.S. stock market at the open, we construct a placebo-controlled test based on the statutory holidays similar to Jacobs and Weber (2012). The control group consists of a list of statutory holidays uniquely observed in the United States. We examine the shifts in price efficiency around 9:30 AM when the U.S. stock market closes for holidays. Since the public holidays impose a restriction on the trading activities both before and after 9:30 AM, the exogenous limitation in market participation provides a natural placebo treatment (Frieder and Subrahmanyam, 2004; DellaVigna and Pollet, 2009; Hong and Yu, 2009; Jacobs and Weber, 2012).

We measure price discovery in markets that are sequential in time (e.g. 9:00 AM - 9:30 AM vs 9:30 AM - 10:00 AM). Since trading volume and dealer's quoting behavior might be different across trading hours, studying price discovery across different time of the day is necessary in order to achieve a clean separation of price innovations from different markets (see e.g. Barclay and Hendershott, 2003; He et al. 2009). This setting is different from the case of parallel markets where trading takes place simultaneously in multiple venues.[1] In a parallel-market study, international comparisons of price discovery are often limited to one or two hours of overlapping trading time, i.e. when the closing of one market overlaps with the opening of another. These small overlapping hours may lead to bias against the earlier market traders because they cannot learn from past price movements, unlike the newly-arrived traders from the later market.

To measure price discovery in sequential non-overlapping markets, we follow the framework of Wang and Yang (2011) and define the information share of a particular market as its share in the total variance of the efficient price in a trading day. The basic logic of this framework is similar to Hasbrouck (1995) where information flow is measured by the variation

[1] There is an abundance of cross-market price discovery studies in Government bond futures including Mizrach and Neely (2008), Chen and Gau (2010) and Fricke and Menkhoff (2011). These studies employ the common price discovery measures such as the Hasbrouck (1995) information share and the Gonzalo and Granger (1995) permanent-transitory decomposition.

in the efficient price of an asset. However, unlike Wang and Yang (2011), we do not use an integrated variance with reduced noise component to compute the information share.[2] Instead, we extract the efficient price directly from transaction prices using a state space model for intraday price dynamics (Brogaard et al., 2014; Hendershott and Menkveld, 2014). The advantage of this state space model is that it decomposes the observed price process into permanent component (representing information) and transitory component (representing pricing errors). This decomposition enables us to separate the informed from the non-informed trading and examine what drives the price discovery in these futures.

Using transaction-level data over the period January 1, 2010, to June 30, 2017, we apply our model to the three most liquid 10-year government bond futures: the US Treasury Note, the German Bund, and the UK Gilt. We estimate the model daily using Kalman Filter technique and compute information shares from the efficient price obtained from the model. Our findings show information share increases for all three futures contracts following the open at 9:30 AM, indicating the importance of the US stock market in domestic and international government bond futures. Our variance decomposition shows that the order flow contributes to the improved price efficiency for U.S. Treasuries futures and German Bund futures, which suggests that information comes from trade-related sources. However, for the UK Gilt futures, the shift in price efficiency is more likely to come from non-trade related sources. When we look at the transitory impact of trades, it reduces significantly for U.S. Treasuries futures, but insignificant for the German Bund and UK Gilt futures. As a placebo test, we find no changes in the price discovery around 9:30 AM on U.S. holidays. Overall, our results show that the opening of the US stock market is vital for price discovery in the international government bond futures markets.

[2] Wang and Yang (2011) use the two-scales (TS) estimator of Zhang et al. (2005) to reduce the impact of the noise term on the estimation of the integrated variance. They explain that the variance of the efficient price estimated using the mean of the TS estimator unambiguously outperforms the realized variance in out-of-sample forecasting comparisons.

Our paper is at the interaction of two strands of literature. First, our paper relates to the study of the linkages between two asset classes - stock and bond. Connolly et al. (2005) examine the time-varying correlation between stock and bond market returns. Fleming et al. (1998) argue that information flow can create cross-market volatility spillovers between the stock and bond markets. Chordia et al. (2005) investigate the linkages of liquidity in the stock and Treasury bond markets. Underwood (2009) document that aggregate order imbalances in the U.S. stock market contain important information about the intraday returns of the U.S. Treasury market. Instead, our paper focus on the linkage of price efficiency between the bond and stock markets.

Second, our research is also related to the studies on the intraday variations in price discovery. Barclay and Hendershott (2003) compare the price discovery during and outside of exchange trading hours in the U.S. stock market. Numerous studies also examine the around-the-clock price discovery in the foreign exchange market (Cai et al., 2008 Wang and Yang, 2011; Gau and Wu, 2017), in the stock futures market (Taylor, 2011), in the credit default spread market (Avino et al., 2015), in the U.S. Treasuries market (Fleming, 1997; He et al., 2009) and in the European sovereign debt market (Dufour and Nguyen, 2013). Our paper adds to this strand of literature by analyzing the cross-assets spillover effect of the price efficiency.

We structure the remainder of this paper as follows. Section 2 details the model we use to estimate price discovery in sequential markets. Section 3 describes the data sources and summary statistics. Section 4 reports the empirical findings. Finally, section 5 concludes.

2. Methodology

2.1. Measuring price discovery in sequential markets

Market microstructure theory assumes that an asset has an efficient price. This unobserved efficient price represents the underlying value of an asset conditional on all available public information. As such, we often acknowledge that the observed price of a security, p_t, can be decomposed into an efficient price, m_t reflecting new information on economic fundamentals, and a noise term, s_t, resulting from transitory factors:

$$p_t = m_t + s_t. \tag{1}$$

The efficient price, m_t is a random-walk and is driven by information that would result in a permanent price change. In a traditional price discovery setting where a single asset is traded in two parallel markets, the observed prices in both markets share a common efficient price and can be expressed in the following form:

$$\binom{p_{1,t}}{p_{2,t}} = \iota m_t + \binom{s_{1,t}}{s_{2,t}} \tag{2}$$

where ι is a (2×1) unit vector. In this case, price discovery is often measured using the Hasbrouck (1995) *information share*, which is the proportion of variance contributed by one market with respect to the variance of the innovations in the common efficient price, m_t shared by the two markets.

We apply the same analogy for measuring price discovery in sequential markets. Specifically, we measure the information share of a particular period interval as its share in the total variance of the efficient price over the full period in consideration, where information flow during period interval i is measured by the variance of $\Delta m_{i,t}$. Hence, in the case of sequential markets, the information share of a period i can be defined as

$$IS_i = \frac{var(\Delta m_{i,t})}{var(\Delta m_t)} = \frac{var(\Delta m_{i,t})}{var(\Delta m_{1,t}) + var(\Delta m_{2,t})}, \quad i = 1,2. \tag{3}$$

IS_i can be calculated on a daily basis provided that we know $var\left(\Delta m_{i,t}\right)$. Since $var\left(\Delta m_{i,t}\right)$ is unobservable, it poses a challenge for estimating price discovery in sequential markets. In the next section, we propose using the state space model to estimate $var(\Delta m_t)$.

2.2. State Space Model

To obtain the efficient price m_t, we estimate a state space model similar to Brogaard et al. (2014) and Hendershott and Menkveld (2014). We start by decomposing the futures price into two components, a non-stationary price process that captures the evolution of the efficient price, and a transitory process that captures temporary deviations from the efficient price. In this section, we focus on the mechanics of the state space model. Further details on the methodology are provided in Appendix 1.

Recall the expression for prices in Equation (1), where m_t is the unobserved efficient price of the asset. This efficient or permanent price component is modeled as a random walk with respect to the arrival of information, where information can come from public news shocks or private information.[3] Hence, the efficient price process can be written as

$$m_t = m_{t-1} + \lambda \hat{O}_t + \varepsilon_t, \tag{4}$$

where $\hat{O}_t$ is the surprise in order flow (in the number of contracts) of the t^{th} transaction in a given day, and ε_t captures the arrival of news that is not related to trade. The price impact of the surprise in order flow is captured by λ, and can be seen as a measure of private information

[3] Like Brogaard et al. (2014), we do not include a drift term in the efficient price process as sampling is done in transaction time. At this high-frequency, the price drift would be extremely small.

held by traders in Treasury futures. We capture the surprise in order flow by taking the residuals of an autoregressive model of signed order flow.

For the transitory component, we assume trades can exert a temporary price pressure that pushes the price temporarily away from the efficient price. This happens through the signed order flow O_t, and to capture persistence in the price pressure, we model the transitory component as an AR(1) process, i.e.,

$$s_t = \phi s_{t-1} + \theta O_t + \eta_t, \tag{5}$$

where ϕ captures the persistence in the price pressure, θ captures the effect of order flow on the transitory component and η_t captures shocks to the temporary component. Similar to Brogaard et al. (2014) and Hendershott and Menkveld (2014), we assume that the innovations in the efficient price process and the transitory components are independent, i.e. $Cov(\varepsilon_t, \eta_t) = 0$. This can be done because we include order flow in both the efficient price process as well as the transitory component. This inclusion eliminates the correlation between the innovations of the permanent and transitory components. Presenting these equations together, we estimate the following state space model:

$$\begin{cases} p_t = m_t + s_t \\ m_t = m_{t-1} + \lambda \hat{O}_t + \epsilon_t. \\ s_t = \phi s_{t-1} + \theta O_t + \eta_t \end{cases} \tag{6}$$

Given that the permanent component of the price process follows a random walk, we initialize the Kalman Filter using a diffuse prior. Estimation of the model is done each day using maximum likelihood via the Kalman Filter.

3. The Government Bond Futures Market and Data

Our sample covers the period January 1, 2010 to June 30, 2017 and we focus on the three most actively traded 10-year government bond futures in the world: the UK 10-year Gilt (with a ticker symbol FLG), the German 10-year Bund (FGBL), and the US 10-year Treasury Bond (TY) Futures.[4] They are electronically traded on the Intercontinental Exchange (ICE), the Eurex Exchange (EUX), and the Chicago Board of Trade (CBOT), respectively.[5] These futures contracts have four maturities per year: March, June, September, and December. Each contract is for 100,000 of the local currency. On each trading day, various maturities are traded with different levels of activity. We focus on the nearby contracts as they are the most liquid, which should allow for a more accurate assessment trading activity. Each contract is rolled over to the second-nearby contract when the volume of the second-nearby contract exceeds the volume of the front-end contract.

Trading hours of these futures contract vary, as shown in Panel A of Table 1. Referring to the timing in GMT (winter), the FLG contracts have the least hours of activity, trading only from 08:00am to 18:00pm. The FGBL contracts have slightly longer trading hours from 06:00am to 20:05pm. The TY contracts have the longest hours of trading from 23:00pm to 22:00pm the next day. Panel B shows the opening hour for the local stock market, namely the London stock exchange, the Frankfurt stock exchange, and the New York stock exchange. We focus on the opening hour of the New York stock exchange as it occurs at 14:30pm GMT (winter), the time at which all the above futures are actively traded.

[4]These 10-year contracts have been the subject in many studies on Treasury securities such as Gwilym et al. (2005), Brandt et al. (2007), Fricke and Menkhoff (2011) and Kanas (2014). For instance, Fricke and Menkhoff (2011) explain that the German Bund possesses a benchmark status and is often regarded as the single most important asset in the Euro bond markets to reflect the flow of news into this market more accurately than other assets. Kanas (2014) explains that the UK long gilt futures is the most liquid and popular futures contract traded in LIFFE (now ICE).

[5] The German 10-yr Bund futures are also traded on ICE, but is fairly illiquid.

INSERT TABLE 1 HERE

We obtain transaction-level data for prices, volume and bid-ask quotes from Thomson Reuters Tick History maintained by the Securities Industry Research Centre of Asia-Pacific. These data contain all activity observed at the top of the limit order book which includes transactions and revisions in the bid and ask prices, time-stamped to the nearest millisecond. We treat multiple trades that are executed at the exact same time as one trade, as these typically reflect a trade that is initiated by one market participant but executed against the limit orders of multiple market participants. In such cases, we use the value-weighted average price and aggregate the traded volume. Trade classification into a buyer- or seller-initiated trades is made on the basis of the prevailing quotes prior to the trade. A trade is classified as a buyer- (seller-) initiated if it is above (below) the midquote. For trades that occur at the midquote, we employ the tick rule and compare the current price with the previous price.

Table 2 presents statistics for trading activity during the 30 minutes period before and after the US stock market opens. It reports the total trades, trading volume, percentage quoted spread (in bps), the volume order imbalance and volatility (measured as the standard deviation of returns). As can be seen, the total number of trades and trading volume increase across all futures, indicating an increase in trading activity following the opening of the US stock market. The average percentage quoted spread increase, while the volume order imbalance increase, particularly for TY and FGBL contracts. This observation suggests that there are more buy-initiated trades following the US market open, which may indicate some degree of information-driven trades. As expected, volatility also increases, given the increase in trading activity during this period.

INSERT TABLE 2 HERE

4. Empirical Results

This section reports the empirical estimation of the information shares before and after the US stock market opens. The first subsection reports the estimated information shares based on the variance of the efficient price. The second subsection reports the results from variance decomposition. We then extend our analysis by comparing our findings during US public holidays.

4.1. Price discovery around US stock market opens

The model in Section 3 is estimated daily for each futures. To compute the surprise in order flow, $\hat{O}_t$, we estimate an autoregressive model, where the optimal lag length is determined based on the Akaike Information Criterion (AIC). The daily variance for market i is $var(\Delta m_{t,i}), i = 1,2,3$, is the return variance of the efficient price m_t from Equation (5). The daily information share may be defined as $IS_{i,t} = var(\Delta m_{t,i}) / \sum_{i=1}^{3} var(\Delta m_{t,i})$.

In Table 3, we report the results for the information share, IS. Turning first to Panel A, we observe that price discovery for TY, FGBL and FLG increase by 12.2%, 7.4% and 9.1%, respectively, following the opening of US stock market. The results are consistent across various event windows, including the 20 minutes (Panel B) and 30 minutes period window (Panel C). These results suggest that prices of these futures become more informative as trading in the stock market begins.

INSERT TABLE 3 HERE

4.2. Variance decomposition

We are particularly interested in investigating the informativeness of trades in each sequential market. We employ variance decomposition model similar to Brogaard et al. (2014) and Hendershott and Menkveld (2014) to decompose prices into two components: a permanent price process that captures the evolution of the efficient price, and a transitory process that captures temporary deviations from the efficient price.

4.2.1. Permanent price process

In this section, we start our discussion with the permanent price process. Given the definition of the efficient price process in Equation (5), we can perform a decomposition of the variance of this process as:

$$Var(\Delta m_t) = \lambda^2 Var(\hat{O}_t) + Var(\varepsilon_t). \tag{7}$$

Equation (7) suggests that variance of the efficient price is determined by trade-related and trade-unrelated information. We are interested in determining the contribution of trade to the total variance of the efficient price given as $\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$.

In Table 4, we report the results of Equation (7). We report the average parameter estimates and the Newey-West corrected t-statistics. The first row in each panel reports the variance of the (log) difference of the efficient price, obtained from the state space model. The second row reports the variance of trade-related information while the third row reports the variance of trade-unrelated information. The fourth row presents the proportion of variance that is contributed by the trade-related information.

INSERT TABLE 4 HERE

Turning first to Panel A, we observe that variance for the US Treasury Note futures (TY) increases significantly following the US stock market opens. We find that variance coming from both trade-related and trade-unrelated information increase significantly during this period. As a result, the relative contribution of trades to changes in the efficient price increases by 0.7% following the stock market open. In Panel B, we show the results for the German Bund futures (FGBL). Similar to Panel A, we observe that price variance is higher after. Variance from trades increases by 0.002 and variance from trade-unrelated information also increase by 0.002. On average, the contribution of trade to the variance of the efficient price increase by 0.6%. Panel C reports the results for the UK Gilt Futures (FLG). We find that variance from trade-unrelated information is significantly higher than the increase in variance from trade-related information. This observation may suggest that the role of trades is rather minimal in this market.

4.2.2. Transitory price process

Similar to the variance decomposition of the efficient price, we also perform a variance decomposition of the transitory part of the price process. Since the transitory part is already stationary, we can compute the variance of the transitory part directly from Equation (6), i.e.,

$$Var(s_t) = \phi^2 Var(s_{t-1}) + \theta^2 Var(O_t) + Var(\eta_t). \tag{8}$$

Equation (8) shows that the variance of the transitory process has three components, a component due to the persistence in the pricing error, a component due to trade, and another component due to random noise. We are interested in determining the contribution of trade to the total variance of the pricing error. The percentage contribution of trade is given as $\theta^2 Var(O_t)/Var(s_t)$.

In Table 5, we report the results of Equation (8). The first row in each panel reports the variance of the pricing error, obtained from the state space model. The second, third and fourth rows are the component of variance due to the persistence in the pricing error, trade, and random noise, respectively. The final row is the proportion of pricing error variance that is contributed by the trades.

INSERT TABLE 5 HERE

In Panel A, we observe that variance of pricing error for the US Treasury Note futures (TY) is significantly higher following the US stock market opens. The majority of this variance comes from the trade-unrelated or noise, whereas trades contribute around 40.2%. The results for the German Bund futures presented in Panel B are similar to Panel A. In particular, the variance of the transitory process is higher following the US market open. Panel C shows the result for the UK Gilt futures (FLG). Here, we do not observe significant changes in the variance of the transitory price components.

4.3. Price discovery during public holidays: A Placebo Test

In the previous sections, we examined the price discovery before and after the openings of U.S. stock market. As a robustness test, we assess price discovery during US public holidays. This test is akin to the placebo test based on public holidays in Jacobs and Weber (2012).

The United States, similar to many other countries, has several public holidays that limit business activities in the domestic financial markets, but not in other countries. For example, the Thanksgiving day observed in the United States might temporarily curb market participation in the US financial markets, but not trading activities in other countries such as the U.K. and Germany (Frieder and Subrahmanyam, 2004; DellaVigna and Pollet, 2009; Hong and Yu, 2009; Jacobs and Weber, 2012). The exogenous variation in market participation in the geographic dimension can help us measure the role of the U.S. stock market in shaping the observed variation in price discovery around 9:30am Eastern Time. If the opening of the U.S. stock market is indeed the cause of our observed increase in price discovery, we should expect no such effect when the U.S. stock market is closed during public holidays.

To achieve our goals, we first compile a list of statutory holidays in the United States, United Kingdom and Germany. As required by our empirical design, we exclude the public holidays observed in multiple markets concurrently such as the New Year's Day, the Christmas, and the Good Friday/Easter Monday. In the end, for each year between 2010 and 2017, we identify five holidays uniquely observed in the U.S.: Martin Luther King, Day, Presidents' Day, Memorial Day, Independent Day, and Thanksgiving Day. In total, we have 49 days on which the stock markets are closed.

Table 6 presents the summary statistics for the placebo test. It shows the average number of trades, trading volume, quoted spread, order imbalance in value, and volatility on U.S. public holidays. First, the trading activities, measured by the number of trades and trading volume, fall considerably during the holidays. The average trading volume is 4,399.5, 4,166, 16,285.5 during the U.S. holidays for TY, FLG and FGBL, respectively[6]. They represent an approximately 93%, 54%, and 61% drop in trading volume respectively. The decline in trading activities is much more noticeable for U.S. Treasuries and largely comparable between U.K and German government bond futures. Second, during the U.S. holidays, the differences between pre- and post-9:30am periods are modest. The test statistics from two-sample t-tests,

[6] The average trading volume is computed as the average volume before and after U.S. market opens. For example, the average volume for TY is (3966+4833)/2 = 4399.5 during U.S. holidays, which equals to a 93% drop from the average daily volume 68814 ((53224+84404)/2).

which compare the mean between the two sample periods, are mostly insignificant for TY and FGBL futures and moderately significant for FLG futures. Compared to Table 2, this suggests that the U.S. equity market indeed triggers a positive shock in the trading activities in the government bond futures market. Lastly, other market characteristics such as volatility, bid-ask spread, order imbalance, and price remain stable during the U.S. public holidays. In summary, Table 5 highlights the fact that investors often briefly refrain from actively trading in the bond futures market in the post-9:30am period during U.S. statutory holidays. Such inattention of investors generates disproportionately large reductions in the trading volume and the number of transactions in the post-9:30am period.

INSERT TABLE 6 HERE

Table 7 displays the estimated information share from the state space model. We first estimate our state space model for the pre- and post- U.S. stock market open periods separately. Then, we compare the estimated coefficients between these two sub-samples. Unlike the results in Table 3, Table 7 reveals that the information share experiences little variation around the US market open. This suggests that after tuning down the information flow from U.S. stock market due to U.S. public holidays, the observed increase in information share around 9:30 am in the previous sections disappears.

INSERT TABLE 7 HERE

Table 8 and Table 9 present variance decomposition results from the state space model. Since the information share remains constant around 9:30am (Eastern Time), the variance compositions naturally exhibit a similar pattern. For FGBL and FLG, most of the decomposed variance terms stay unchanged around 9:30 am. The variance decomposition of the permanent price process in Table 8 suggests that the drop in the information share of FGBL shown in Table 7 is mainly driven by the term $Var(\varepsilon_t)$. This implies that the decrease in information share is determined by non-trade related sources. Taking together, these findings highlight the importance of the U.S. stock market in the price discovery process of government bond futures. After the opening of the U.S. stock market at 9:30am (Eastern Time), price discovery of government bond futures improves; however, the effect vanishes when the U.S. stock market closes for statutory holidays.

INSERT TABLE 8 AND 9 HERE

5. Conclusion

We assess price discovery of Government bond futures before and after the US stock market opens. We employ a price discovery model in sequential markets for the 10-year UK Gilt, German Bund, and US Treasury Note futures over the period from 2010 to 2017. We estimate the model daily using Kalman Filter technique and compute information share from the efficient price obtained from the model. Our findings show information share increases for all three futures contracts following the open at 9:30 AM, indicating the importance of the US stock market in domestic and international government bond futures. Our variance decomposition shows that order flow contributes to the improved price efficiency for U.S. Treasuries futures and German Bund futures, which suggests that information comes from trade-related sources. However, for the UK Gilt futures, the shift in price efficiency is more likely to come from non-trade related sources. As a placebo test, we find no changes in the price discovery around 9:30 AM on U.S. holidays. Overall, our results show that the opening of the US stock market is vital for price discovery in the international government bond futures markets.

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Appendix 1. State Space Model

This appendix elaborates the state space model used in our study. A similar model is used in Brogaard et al. (2014), Hendershott and Menkveld (2014) and Fernandez-Perez et al. (2018).

3.1. Model Setup

We would like to estimate the following state space model

$$p_t = m_t + s_t \tag{A.1}$$

$$m_t = m_{t-1} + \lambda \hat{O}_t + \epsilon_t \tag{A.2}$$

$$s_t = \phi s_{t-1} + \theta O_t + \eta_t \tag{A.3}$$

Where ϵ_t is the process noise which is assumed to be drawn from $N(0, Q)$, η_t is the process noise which is assumed to be drawn from$N(O, R)$, O_t and $\hat{O}_t$ are the order flow and surprised order flow, respectively. p_t is the observable price series, m_t is the unobservable fundamental price, s_t is the unobservable transitory price.

3.2. Kalman Filter

Given a setup parameters$(\lambda, \theta, \phi, Q, R)$, the Kalman filter will produce estimates of unknown variablesm_t, s_t. The Kalman Filter is most often conceptualized as two distinct phases: "Predict" and "Update". We define a few variables as follows: (1) priori state estimate, $m_{k|k-1}$, (2) posteriori state estimate, $m_{k|k}$; and (3) posteriori error covariance matrix: $P_{k|k}$.

3.2.1. Step 1: Predict

Predicted a priori state estimate

$$m_{k|k-1} = m_{k-1|k-1} + \lambda \hat{O}_k \tag{A.4}$$

$$s_{k|k-1} = \phi s_{k-1|k-1} + \theta O_k \tag{A.5}$$

Predicted priori estimate covariance

$$P_{k|k-1} = P_{k-1|k-1} + Q \tag{A.6}$$

3.2.2. Step 2: Update

Innovation or measurement pre-fit residual

$$\hat{y}_k = p_k - p_{k|k-1} = p_k - m_{k|k-1} - s_{k|k-1} \tag{A.7}$$

Innovation (or pre-fit residual) covariance

$$S_k = R + P_{k|k-1} \tag{A.8}$$

Optimal Kalman gain

$$K_k = P_{k|k-1} S_k^{-1} \tag{A.9}$$

Updated (a posteriori state estimate

$$m_{k|k} = m_{k|k-1} + K_{k\hat{y}k} \tag{A.10}$$

Updated (a posteriori) estimate covariance

$$P_{k|k} = (1 - K_k) P_{k|k-1} \tag{A.11}$$

Table 1. Trading hours of futures and stock markets

Panel A shows the trading hours of various government bond futures: the UK 10-yr Gilt futures (FLG), the 10-yr German Bund futures (FGBL), and the US 10-yr Treasury Note futures (TY). Panel B reports various stock market opening time.

Futures	Timezone	Local time	GMT (winter)	GMT (summer)
Panel A: Futures market trading hour				
FLG	UTC	08:00am - 18:00pm	08:00am - 18:00pm	07:00am - 17:00pm
FGBL	CET	07:00am - 21:05pm	06:00am - 20:05pm	05:00am - 19:05pm
TY	EST	18:00pm - 17:00pm	23:00pm - 22:00pm	22:00pm - 21:00pm
Panel B: Stock market open time				
London stock exchange	UTC	08:00am	08:00am	07:00am
Frankfurt stock exchange	CET	08:00am	07:00am	06:00am
New York stock exchange	EST	09:30am	14:30pm	13:30pm

Table 2. Trading activity before and after US stock market opens

This table reports trading activity 30 minutes before and 30 minutes after the US stock market opens. It reports the number of trades, trading volume, quoted bid-ask spread, volume order imbalance and the realized volatility (measured as the standard deviation of stock returns). Reported figures are averaged over the sample period from January 2010 to June 2017. Panels A, B and C report trading activity for the US 10-yr Treasury Note futures (TY), the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Before	*After*	*Diff*	*t-stat*
Panel A: TY				
Trade	1,370	2,018	648***	(20.66)
Volume	53,224	84,404	31,180***	(22.35)
QSpread	1.24	1.24	0.0017***	(6.79)
OIBV	-255	482	737***	(2.94)
Volatility	0.381	0.404	0.023***	(14.65)
Panel B: FGBL				
Trade	1,303	1,778	474***	(18.30)
Volume	36,143	49,156	13,013***	(19.25)
QSpread	0.72	0.72	0.0011***	(2.68)
OIBV	-158	158	316***	(2.23)
Volatility	0.301	0.308	0.007***	(7.31)
Panel C: FLG				
Trade	649	878	229***	(19.71)
Volume	8,029	10,402	2,374***	(16.58)
QSpread	0.97	0.98	0.0091***	(7.24)
OIBV	-33	-40	-8	(-0.12)
Volatility	0.468	0.479	0.011***	(7.94)

Table 3. Price discovery before and after US stock market opens

This table reports the average information share 10 minutes (Panel A), 20 minutes (Panel B) and 30 minutes (Panel C) before and after the US stock market opens. Sample period is from January 2010 to June 2017. IS is computed as, for example, $IS_{before} = \frac{var(\Delta m_{before})}{var(\Delta m_{before}) + var(\Delta m_{after})}$, where m_t is the efficient price from Equation (4), obtained from estimating the state space model.

	Before	*After*	*Diff*	*t-stat*
Panel A: 10-min before and after				
TY	43.9%	56.1%	12.2%***	(15.08)
FGBL	46.3%	53.7%	7.4%***	(12.41)
FLG	45.4%	54.6%	9.1%***	(11.90)
Panel B: 20-min before and after				
TY	46.3%	53.7%	7.3%***	(12.00)
FGBL	47.5%	52.5%	4.9%***	(10.20)
FLG	46.6%	53.4%	6.7%***	(11.98)
Panel C: 30-min before and after				
TY	47.8%	52.2%	4.3%***	(7.79)
FGBL	48.3%	51.7%	3.3%***	(7.61)
FLG	47.8%	52.2%	4.4%***	(8.75)

Table 4. Variance Decomposition of the permanent price process surrounding US stock market opens

This table reports estimation results from the State Space Model for the permanent price process. It reports estimates for the 30 minutes period before and after the US stock market opens. The model is estimated daily and averaged over the sample period from January 2010 to June 2017. Panels A, B and C report estimates for the US 10-yr Treasury Note futures (TY), the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Units	*Before*	t-stat	*After*	t-stat	*Diff*	t-stat
Panel A: TY							
$Var(\Delta m_t)$	bps^2	0.060***	(55.15)	0.066***	(59.20)	0.006***	(7.22)
$\lambda^2 Var(\hat{O}_t)$	$(bps/contract)^2$	0.028***	(54.25)	0.032***	(57.93)	0.003***	(6.98)
$Var(\varepsilon_t)$	bps^2	0.032***	(46.66)	0.034***	(49.50)	0.003***	(5.40)
$\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$	%	47.2%***	(116.04)	48.0%***	(119.78)	0.7%**	(2.21)
Panel B: FGBL							
$Var(\Delta m_t)$	bps^2	0.043***	(48.75)	0.047***	(44.80)	0.004***	(7.56)
$\lambda^2 Var(\hat{O}_t)$	$(bps/contract)^2$	0.014***	(52.15)	0.015***	(45.52)	0.002***	(6.35)
$Var(\varepsilon_t)$	bps^2	0.029***	(41.04)	0.031***	(39.61)	0.002***	(6.03)
$\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$	%	32.7%***	(78.15)	33.3%***	(84.04)	0.6%*	(1.77)
Panel C: FLG							
$Var(\Delta m_t)$	bps^2	0.112***	(49.97)	0.123***	(49.79)	0.011***	(8.18)
$\lambda^2 Var(\hat{O}_t)$	$(bps/contract)^2$	0.011***	(17.51)	0.012***	(17.57)	0.001**	(1.99)
$Var(\varepsilon_t)$	bps^2	0.101***	(43.83)	0.111***	(43.92)	0.010***	(8.07)
$\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$	%	10.9%***	(19.02)	10.6%***	(19.17)	-0.2%	(-0.82)

Table 5. Variance decomposition of the transitory price process surrounding US stock market opens

This table reports estimation results from the State Space Model for the transitory price process. It reports estimates for the 30 minutes period before and after the US stock market opens. The model is estimated daily and averaged over the sample period from January 2010 to June 2017. Panels A, B and C report estimates for the US 10-yr Treasury Note futures (TY), the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Units	*Before*	t-stat	*After*	t-stat	*Diff*	t-stat
Panel A: TY							
$Var(s_t)$	bps^2	0.132***	(60.21)	0.152***	(65.86)	0.019***	(13.38)
$\phi^2 Var(s_{t-1})$	bps^2	0.021***	(27.28)	0.025***	(29.46)	0.004***	(7.80)
$\theta^2 Var(O_t)$	(bps/contract)^2	0.053***	(62.32)	0.060***	(71.22)	0.007***	(10.10)
$Var(\eta_t)$	bps^2	0.058***	(42.68)	0.066***	(45.52)	0.008***	(11.33)
$\theta^2 Var(O_t)/Var(s_t)$	%	41.4%***	(97.54)	40.7%***	(110.99)	-0.7%**	(-2.05)
Panel B: FGBL							
$Var(s_t)$	bps^2	0.055***	(72.48)	0.059***	(65.57)	0.004***	(6.85)
$\phi^2 Var(s_{t-1})$	bps^2	0.007***	(15.63)	0.009***	(14.85)	0.002***	(4.17)
$\theta^2 Var(O_t)$	(bps/contract)^2	0.021***	(61.76)	0.023***	(54.66)	0.002***	(6.05)
$Var(\eta_t)$	bps^2	0.027***	(75.33)	0.028***	(85.50)	0.001***	(4.04)
$\theta^2 Var(O_t)/Var(s_t)$	%	39.2%***	(78.33)	39.1%***	(76.56)	-0.1%	(-0.26)
Panel C: FLG							
$Var(s_t)$	bps^2	0.082***	(53.23)	0.082***	(49.87)	0.000	(0.40)
$\phi^2 Var(s_{t-1})$	bps^2	0.005***	(14.99)	0.004***	(17.32)	-0.001	(-1.24)
$\theta^2 Var(O_t)$	(bps/contract)^2	0.026***	(31.63)	0.027***	(30.07)	0.001	(1.54)
$Var(\eta_t)$	bps^2	0.051***	(52.26)	0.051***	(47.79)	0.000	(0.31)
$\theta^2 Var(O_t)/Var(s_t)$	%	31.6%***	(51.59)	32.2%***	(50.71)	0.6%	(0.97)

Table 6. Summary statistics during US public holidays

This table reports trading activity during US public holidays, particularly the 30 minutes period before after the hypothetical US stock market opens. It reports the number of trades, trading volume, quoted bid-ask spread, volume order imbalance and the realized volatility (measured as the standard deviation of stock returns). Reported figures are averaged over the sample period from January 2010 to June 2017. Panels A and B report trading activity for the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Before	*After*	*Diff*	*t-stat*
Panel A: FGBL				
Trade	602	740	139	(1.23)
Volume	15,504	17,067	1,563	(0.67)
QSpread	0.72	0.72	-0.006	(-1.58)
OIBV	296	-118	-414	(-0.54)
Volatility	0.282	0.275	-0.007	(-1.05)
Panel B: FLG				
Trade	290	355	65**	(2.06)
Volume	3,461	4,871	1,411***	(3.26)
QSpread	0.96	0.95	-0.008	(-1.01)
OIBV	-73	-98	-24	(-0.08)
Volatility	0.433	0.436	0.003	(0.36)

Table 7. Price discovery during US public holidays

This table reports the average information share 10 minutes (Panel A), 20 minutes (Panel B) and 30 minutes (Panel C) before and after the hypothetical US stock market opens. Sample period is from January 2010 to June 2017. IS is computed as, for example, $IS_{before} = \frac{var(\Delta m_{before})}{var(\Delta m_{before})+var(\Delta m_{after})}$, where m_t is the efficient price from Equation (4), obtained from estimating the state space model.

	Before	*After*	*Diff*	*t-stat*
Panel A: 10-min before and after				
FGBL	52.4%	47.6%	-4.7%	(-0.84)
FLG	52.4%	47.6%	-4.7%	(-1.05)
Panel B: 20-min before and after				
FGBL	50.9%	49.1%	-1.7%	(-0.36)
FLG	51.7%	48.3%	-3.4%	(-1.03)
Panel C: 30-min before and after				
FGBL	51.9%	48.1%	-3.8%	(-1.37)
FLG	50.6%	49.4%	-1.3%	(-0.35)

Table 8. Variance decomposition of the permanent price process during US public holidays

This table reports estimation results from the State Space Model for the permanent price process. It reports estimates for the 30 minutes period before and after the hypothetical US stock market opens. The model is estimated daily and averaged over the sample period from January 2010 to June 2017. Panels A and B report estimates for the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Units	*Before*	t-stat	*After*	t-stat	*Diff*	t-stat
Panel A: FGBL							
$Var(\Delta m_t)$	bps^2	0.035***	(12.31)	0.032***	(11.67)	-0.003**	(-1.97)
$\lambda^2 Var(\hat{O}_t)$	$(bps/contract)^2$	0.010***	(6.42)	0.010***	(6.36)	-0.001	(-0.77)
$Var(\varepsilon_t)$	bps^2	0.025***	(9.45)	0.023***	(10.10)	-0.002**	(-2.04)
$\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$	%	29.2%***	(8.60)	28.5%***	(10.00)	-0.7%	(-0.38)
Panel B: FLG							
$Var(\Delta m_t)$	bps^2	0.092***	(11.34)	0.091***	(10.61)	-0.001	(-0.15)
$\lambda^2 Var(\hat{O}_t)$	$(bps/contract)^2$	0.014***	(3.19)	0.012***	(3.40)	-0.002	(-0.92)
$Var(\varepsilon_t)$	bps^2	0.078***	(9.44)	0.079***	(9.84)	0.001	(0.15)
$\lambda^2 Var(\hat{O}_t)/Var(\Delta m_t)$	%	15.6%***	(3.53)	14.0%***	(4.28)	-1.6%	(-0.84)

Table 9. Variance decomposition of the transitory price process during US public holidays

This table reports estimation results from the State Space Model for the transitory price process. It reports estimates for the 30 minutes period before and after the hypothetical US stock market opens. The model is estimated daily and averaged over the sample period from January 2010 to June 2017. Panels A and B report estimates for the 10-yr German Bund futures (FGBL) and the UK 10-yr Gilt futures (FLG), respectively. Figures in parentheses are the Newey-West adjusted t-statistics. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

	Units	*Before*	t-stat	*After*	t-stat	*Diff*	t-stat
Panel A: FGBL							
$Var(s_t)$	bps^2	0.047***	(17.67)	0.047***	(21.04)	0.000	(-0.03)
$\phi^2 Var(s_{t-1})$	bps^2	0.006***	(3.69)	0.006***	(3.95)	0.000	(0.30)
$\theta^2 Var(O_t)$	$(bps/contract)^2$	0.017***	(9.04)	0.017***	(8.84)	0.000	(-0.20)
$Var(\eta_t)$	bps^2	0.024***	(14.97)	0.024***	(15.15)	0.000	(0.03)
$\theta^2 Var(O_t)/Var(s_t)$	%	36.3%***	(12.48)	36.3%***	(11.52)	0.0%	(0.02)
Panel B: FLG							
$Var(s_t)$	bps^2	0.080***	(13.51)	0.080***	(13.43)	0.000	(-0.86)
$\phi^2 Var(s_{t-1})$	bps^2	0.005***	(4.28)	0.005***	(6.06)	0.000	(0.32)
$\theta^2 Var(O_t)$	$(bps/contract)^2$	0.027***	(5.03)	0.025***	(5.59)	-0.002	(-0.55)
$Var(\eta_t)$	bps^2	0.046***	(12.91)	0.050***	(14.81)	0.004	(0.97)
$\theta^2 Var(O_t)/Var(s_t)$	%	35.1%***	(6.58)	27.6%***	(6.95)	-7.5%	(-1.38)