The Impact of HFT on Liquidity and Price Discovery: Evidence from Interest Rate Derivatives

Alex Frino, Michael Garcia, Zeyang Ivy Zhou*

The University of Wollongong, Wollongong, 2522 *Australia*

Abstract

This study investigates the impact of HFT on liquidity and price discovery for interest rate derivatives around scheduled macroeconomic announcements. We employ an exogenous event, the introduction of co-location facilities at the beginning of 2012 by the Australian Securities Exchange, to determine the impact of HFT on liquidity and the lead effects of futures on information release days. Our results demonstrate that HFT increases dramatically for intervals surrounding news announcements after the introduction of co-location, and the increased amount of HFT improves market depth around macroeconomic releases, but the improvement on spread measures is weak for intervals preceding announcement times, when information uncertainty is high. Moreover, we examines price discovery by looking at the lead-lag effects between futures and SWAPs during information releases in pre- and post-colocation periods. We find that co-location increases the speed at which information is incorporated into the futures market, and therefore, strengthens the lead effects of futures on scheduled announcement days.

Keywords: High Frequency Trading, Macroeconomic Announcement, Information, Liquidity, Price Discovery

*Corresponding author. Zeyang Ivy Zhou. Tel: +61 (2) 4221 3088. Email: izhou@uow.edu.au, University of Wollongong, Northfields Ave, Wollongong NSW 2522, Australia.

1. Introduction

A number of studies have investigated asset price dynamics on announcement days across various asset market structures. Typically, they find that the intraday patterns appear to be largely driven by macro announcements across major financial markets, such as interest rate futures markets, index futures markets, treasury markets, commodity futures markets and foreign exchange markets (Ederington & Lee, 1993, 1995: Frino & Hill, 2001; Cai, Cheung & Wong, 2001; Andersen & Bollerslev, 1998).

Most previous empirical studies were conducted over a relatively short time frame, and ignore the developments in trading environment and market structure over time. Over the last decade, financial markets have been transformed due to the introduction and growth of algorithmic trading (AT). AT is commonly defined as “the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission” (Hendershott, Jones & Menkveld, 2011, Page 1). Co-location is an important technology upgrade for algorithmic traders due to the fact that it significantly reduces latency and allows traders to respond more rapidly to information releases (Jiang, Lo & Valente, 2015; Chaboud et al., 2014, Chordia, Green & Kottimukkalur, 2016; Brogaard, Hendershott & Riordan, 2014; Frino et al., 2016). The characteristics of trading are expected to change following the introduction of co-location facilities through various channels. First, the improvement in latency enables algorithmic traders to adjust their prices more rapidly when new information arrives and therefore improves price discovery efficiency. Second, the popularity and usage of algorithmic trading has brought significant changes to the way traders execute their trades. It is commonly recognized that algorithmic traders are inclined to break down a large order into smaller orders in order to minimise market impacts (Keim & Madhavan, 1995). Third, as market makers are able to trade faster following the introduction of co-location, on one hand, the market liquidity might be improved (Brogaard, 2010; Brogaard, Hendershott & Riordan, 2014; Riordan & Storkenmaier, 2012; Frino, Mollica & Webb, 2014; Brogaard, Hagströmer, Nordén, & Riordan, 2015; Hendershott, Jones & Menkveld, 2011). On the other hand, the adverse selection costs may be higher for non-HFT participants (Boehmer, Fong, & Wu, 2014; Kirilenko, Kyle, Samadi & Tuzun, 2014; Chaboud et al., 2014; Rosu, 2016; Cartea & Panelva, 2012). Therefore, it is crucial for researchers and policy makers to understand the behaviour of algorithmic traders, especially how they impact market quality around macro news releases.

There has been a widespread interest in the literature on understanding the potential impact of HFTs on market dynamics. Some have emphasized the possibility of a faster price discovery, an improvement in liquidity and a reduction in volatility; while others have expressed concerns that HFTs may exacerbate volatility, consume liquidity and induce higher adverse selection costs and profit at the expense of non-HFT participants. Brogaard, Hendershott and Riordan (2014) focus on the role of HFTs in price discovery and price efficiency. HFTs are found to improve pricing efficiency by trading in the same direction of permanent price changes and in the opposite direction of transitory pricing errors. In general, HFTs demand liquidity towards the direction of public information, such as macroeconomic announcements, overall market price movements and order book imbalances. Viljoen, Westerholm and Zheng (2014) extend previous literature to the Australian index futures market, and examine the intraday patterns of HFTs. Their results suggest that HFTs are informed and contribute to liquidity and price discovery in the Australian futures market. Their work has laid a solid foundation for future studies that intend to uncover the impact of HFTs on the Australian market. We extend their work by investigating intraday HFT behaviour surrounding schedule information releases, and more importantly, we measure the causal effect of HFT on liquidity through an exogenous event that heightens the level of HFT in the market.

Co-location events provide the best laboratory to isolate the effect of latency on liquidity and price discovery, and also to identify the causal effect of a change in algorithmic trading on liquidity. Co-location provides a faster speed of trading for co-located institutions and allows them to react faster to changes in market conditions. Co-location also stimulates the growth of HFTs in the market. As more market participants are able to trade fast, the competition for speed become more severe. Consequently, the introduction of co-location is expected to improve liquidity by heightening the level of HFTs and encouraging speed competitions among market participants. Co-location event studies in general suggest that the net effect for market quality is moderately positive. Hendershott et al. (2011) isolate the effect of algorithmic trading (AT) on liquidity in NYSE. The automation of quote dissemination was implemented in 2003, and is used as a natural experiment to test whether an increase in AT activity improves liquidity in the US stock market. Their results show that AT improves liquidity and enhances the informativeness of quotes. The finding provides the first empirical evidence on the causality between AT and liquidity; however, the role of latency in improving liquidity and price discovery around macroeconomic releases still remains unclear in the literature.

On February 20, 2012, the Australian Securities Exchange allowed futures traders to co-locate their servers to the exchange data centre. Frino el al. (2014) demonstrate that this technology update provides a heightened level of HFTs in futures markets and also improves market liquidity, evidenced by a lower bid-ask spread and a thicker market depth. Most empirical work suggest that market liquidity is improved when market makers become faster, which is consistent with existing theoretical models. However, opponents of HFT question the traditional view of liquidity provision by limit orders to the market made by high frequency traders, and also suggest that these fast participants have caused excess volatility in the financial markets. There are in general two sets of market makers: exchange-regulated market makers and undesignated market makers. In contrast to exchange-regulated market makers, undesignated market makers do not have the obligation to provide liquidity, i.e. an obligation to quote on both sides of the market. Therefore, they might withdraw from the market when uncertainties increase and conditions get difficult. With unique access to the audit trail data for the E-mini S&P 500 futures contracts, Kirilenko et al. (2014) are able to identify high frequency traders and then investigate their behaviour on May 6, 2010, the day of the “Flash Crash”. They show that HFTs exacerbated the falling market but did not cause the “Flash Crash”. The study finds that HFTs initially provided liquidity to fundamental sellers but subsequently contributed to the selling pressure that precipitated the incident.

Scheduled announcements represent a very different informational environment relative to normal trading days, and therefore understanding the consequences of these releases is important to ensure market integrity. The speed of trading has increased substantially in the recent decade, due to the group of high frequency traders who seek to enhance speed by investing in technology upgrades and co-locating their trading servers next to stock exchanges. HFTs may be able to make profits from their speed advantage through rapidly responding to scheduled news releases. The market reaction time to new information may be significantly shortened for HFTs as a result of their advantage in consistency and speed.

Jiang, Lo and Valente (2015) examine HFTs in the U.S. treasury market around major macroeconomic announcements. The study shows that HFT activity substantially increases following news releases and generally improves price efficiency. However, HFT seems to damage market liquidity by widening bid-ask spreads before news releases and weakening market depth following the releases. Chaboud et al. (2014) study the impact of HFTs in the foreign exchange market around macroeconomic news releases. The study finds that HFTs improve the price discovery process through rapidly incorporating new information into prices and eliminating arbitrage opportunities in the market place. Although computer trades tend to be correlated, the study finds no evidence that HFTs lead to excessive volatility in the foreign exchange market. Scholtus, Dijk and Frijns (2014) also examine the market responsiveness to the U.S. macroeconomic releases in the S&P 500 ETF. Unlike previous studies, focus of this work is to determine whether speed is crucial for news based trading strategies. The authors find that the profitability of news based strategies is significantly reduced following a 300 milliseconds delay. And the impact of speed is more evident for days with high volatility or influential news. Positively, HFTs increase quoted depth at the best level and push up trading volume in the minute immediately after the announcement time. Negatively, HFTs deteriorate volatility and reduce the amount of the overall market depth. Furthermore, HTFs reduce quoted half-spreads throughout the order book, and increases quoted half-spreads at the top of the order book.

Earnings announcements are also scheduled releases and represent a period of time with high information asymmetry. Zhang (2013) examines the role of HFTs in reacting to extreme price changes as well as to firm-specific news in the U.S. stock market. He examines whether HFT order flows impact the stock market returns more significantly relative to non-HFT order flows. The results show that HFTs dominate the price discovery for the short time horizon. However, in the longer run, non-HFTs contribute to more price discovery than HFTs. Another public concern emerges from the argument that a financial market is unfair and favours those with access to advanced speed. Frino et al. (2017) shows algorithmic traders react much faster and more accurately to earnings announcements than non-algorithmic traders using Australian equity market data. Specifically, non-algorithmic volume imbalance leads algorithmic volume imbalance in the pre-announcement period and the lead-lag relation is reversed in the post-announcement period. Frino el al. (2017) examine 1-minute intervals surrounding earnings announcements in Italian stock market and find that bid-ask spread widens and market depth falls following earnings announcements in the pre-AT period and no evidence of a significant fall in market depth in the post-AT period. As futures markets have different participants, speeds of trading, market structures and trading rules relative to equity markets, it is important to assess how HFTs affect liquidity, under different latency environments, around new information releases for futures markets. In our study, we first confirm intraday patterns, in relation to announcements, vary under different levels of HFTs; we then extend Frino el al. (2017) by isolating the effect of latency on liquidity for each interval surrounding announcements. We provide the first empirical evidence on the causal relation between HFT and liquidity for each 5-minute window around scheduled macro releases.

Extant literature suggest that HFTs play an important role in the price discovery process in a more general form. Brogaard et al. (2014) deconstruct the price movements of 120 U.S. stocks into permanent (information) and temporary (pricing errors) components and investigate the role of HFT in explaining each type of price change. They find that HFT’s trading volume enhances price discovery by trading in the same direction of permanent price changes and in the opposing direction of transitory price changes, for both volatile and non-volatile periods. Benos and Sagade (2013) provide evidence of the impact of HFTs on market quality, in particular price discovery measures for the U.K. stock market. They analyse the behaviour of HFTs and their impact on four U.K. stocks in a randomly selected one-week period, and find that elevated price volatility leads to increased HFT activity. Furthermore, the authors demonstrate that in general HFTs have a higher information-to-noise ratio than non-HFTs, with some instances where the contribution to information by HFTs is accompanied by a large absolute noise. In our study, we examines price discovery by looking at the lead-lag effects between futures and SWAPs during information releases in pre- and post-colocation periods. We find that co-location increases the speed at which information is incorporated into the futures market, and therefore, strengthens the lead effects of futures on scheduled news release days.

The outline of this paper is as follows. Section 2 provides an overview of the most actively traded futures contracts in Australia and identifies major Australian macroeconomic announcements. In section 3, data and the research design is outlined. Section 4 presents the descriptive statistics on SWAPs and BABs futures, and reports regression results on price discovery and the causality between HFT and liquidity, and Section 5 presents concluding remarks.

2. Data

2.1 Futures Data

All trading data on interest rate futures are sourced from Thomson Reuters Tick History (TRTH) database. The data obtained from TRTH are transaction & quotation data including: (1) the best bid price, (2) the best ask price, (3) the best bid size, (4) the best ask size, (5) trade price, and (6) volume of trade; and end of day data including: (1) open interest, and (2) trading volume for each contract on each trading day. To select the most active futures contract, the data sample only includes contracts with the highest trading volume for each day. The following filters have been applied to remove outliers in the dataset: days on which less than 10 contracts transacted, and observations with bid-ask spreads smaller than the minimum tick are excluded.

2.2 Macroeconomic Announcements Data

This analysis examines HFT behaviour and market quality around macroeconomic announcements over a four-year sample period centred around the introduction of co-location on February 20, 2012. All pre-scheduled macro-economic news announcements are collected from the Australian Bureau of Statistics (ABS). As the normal day trading hours for 90-day Bank Accepted Bills futures are from 8:50 a.m. to 4:30 p.m., with a focus on 11:30 am announcements, this analysis is not affected by the pre-market opening and closing phases.

A 1-hour window is considered around announcement time extending from 30 minutes pre- to 30 minutes post- the release time of 11:30 am. For the case that multiple news releases occur at the same announcement time on the same day, this analysis only selects the one with the highest impact factor[1] across all those that are released simultaneously. There are, in total, 552 macroeconomic releases selected over a four-year sample period.

The first step in the sample selection process is to identify “major” macroeconomic announcements. Following Frino and Hill (2001), this analysis selects the types of announcements with a significant impact on market volatility for BABs futures as “major” announcements. Following McInish and Wood, volatility is calculated as the standard deviation of the quote midpoint during each one-minute interval as follows:

$$QTESD_t = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 t_i}{\sum_{i=1}^{n} t_i}} \qquad (1)$$

[1] The impact factor is a number defined by Bloomberg and attached to each type of macroeconomic announcements. It measures how sensitive the market is to each type of announcements.

Q_i is the last quote midpoint observed on or before *i*; $\bar{Q}$ is the average quote price during interval *t*; t_i is the amount of time Q_i is alive during interval *t*.

The following regression, similar to the methodology used by Fleming and Remolona (1997), is estimated to determine "major" announcements:

$$QTESD_t = a_{0j} + \sum_{k=1}^{K} a_k D_{kt} + e_t \qquad (2)$$

where $QTESD_{jt}$ is the price volatility during the one-minute interval following announcements on day *t*. D_{kt} is a dummy variable that is equal to 1 if announcement *k* is made on day *t* and 0 otherwise. A positive and significant a_{kj} coefficient would indicate announcement type *k* has a significant impact on market volatility. On the other hand, a zero/insignificant a_{kj} coefficient indicates announcement *k* has little influence on market volatility.

The regression model is estimated on 552 announcement days for three interest rate futures. Regression coefficient estimates are reported in Appendix Table A-1. This analysis selects announcements that are significant at the 5% level for BABs futures as the "major" releases. On this basis, the selected eight types of announcements are: BoP Current Account Balance, Private Capital Expenditure, Consumer Price Index, Gross Domestic Product, Producer Price Index, Trade Balance, Retail Sales, Building Approvals, Trade Balance and Unemployment Rate.

2.3 SWAPs Data

Over-the-Counter (OTC) quote data for the Australian 1-year interest rate swap is also collected from TRTH on a 1-minute intraday basis for a four-years period around the implementation of co-location from 2 March 2010 to 19 February 2014. This data includes indicative bid and ask quotes supplied by approved dealers and contributors. Data for interest rate swap and futures contracts is collected for the daytime trading session when both markets are open for trading from 8:28 am to 4:30 pm.

3. Research Design

This section presents the research design used to test the hypotheses developed in this paper. First, HFT proxies and market quality metrics are defined. The section then describes the 2 Stage Least Square (2SLS) regression model employed to evaluate the causality between the intensity of HFT and market quality around macro-economic announcements, with the introduction of co-location facilities as the instrumental variable. Last this section reports the modelling process for price discovery.

3.1 High Frequency Trading Proxy

The SEC document lists several characteristics commonly attributed to HFT including:

> *(1) the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders; (2) the use of co-location services and individual data feeds offered by exchanges and others to minimize network and other types of latencies; (3) very short time-frames for establishing and liquidating positions; (4) the numerous orders that are cancelled shortly after submission; and (5) ending the trading day as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night)*[2].

During the sample period February 20, 2011 – February 20, 2013, the Australian futures market experienced significant improvements in the speed of trading and dramatic growth in HFT, stimulated by the introduction of co-location facilities on February 20, 2012. As HFTs cannot be explicitly identified in the Australian futures data which remains an anonymous market, this analysis employs message traffic to measure HFT. The HFT proxy is then used to quantify the change in the extent of HFT in the Australian interest rate futures market.

Message traffic includes new order submissions, modifications and cancellations. This analysis sources the market depth data from TRTH to aggregate such information. In this analysis, message traffic is defined as the sum of changes in the order book for each minute interval. The larger the message traffic is; the more active the high frequency traders are.

$$Message\ Traffic_{it} = \ The\ Number\ of\ Records\ on\ Market\ Depth_{it} \quad (3)$$

To measure liquidity, this analysis uses time weighted quoted spread (TWQS), time weighted relative spread (TWRS) and time weighted depth (TWDD), at each 5-minute interval from 30 minutes before to 30 minutes after announcements. Further trading volume, volatility and the number of trades for the pre- and the post- announcement periods are also measured. Volatility is proxied by the difference between the highest and the lowest price for each future contract at each minute interval (Parkinson, 1980), where price is defined as the midpoint of the best bid and ask for each quote update. Midpoints of the best quotes, rather than trade prices, are adopted for the calculation of volatility as they mitigate complications associated with the "bid-ask bounce".

[2] See Page 4 https://www.sec.gov/marketstructure/research/hft_lit_review_march_2014.pdf

$$Volatility_{it} = \ln(\frac{High_{it}}{Low_{it}}) \quad (4)$$

3.2 Liquidity Measures

3.2.1 Bid-Ask Spread

The relative bid-ask spread is defined as

$$Relative\_BAS = \frac{Best\_Askprice - Best\_Bidprice}{(Best\_Askprice + Best\_Bidprice)/2} \quad (5)$$

$$Quoted\_BAS = \frac{Best\_Askprice - Best\_Bidprice}{Minimum\ Tick} \quad (6)$$

The time weighted bid-ask spread for each 5-minute interval is defined as follows:

$$TWBAS = \sum_{n=0}^{N} \left(\frac{BAS_i(t_{i+1} - t_i)}{T - T_0}\right) \quad (7)$$

3.2.2 Depth

The level 1 depth is computed for every quote as:

$$Depth = (\mathrm{Best\_AskSize} + \mathrm{Best\_BidSize})/2 \quad (8)$$

Similarly, the time weighted depth for each 5-minute interval is defined as:

$$TWDD = \sum_{n=0}^{N} \left(\frac{Depth_i(t_{i+1} - t_i)}{T - T_0}\right) \quad (9)$$

3.3 The Impact of HFT on Market Liquidity: Two-Stage Least Squares Regression

Most previous studies adopt an ordinary least squares (OLS) model which assumes that errors in the dependent variable are not correlated with independent variables. However, the relationships tested in this paper are bidirectional between dependent and independent variables, i.e. HFT proxies and liquidity variables could be endogenously determined. In such case, an OLS model no longer provides optimal estimates, and a two-stage least-squares (2SLS) regression is required to establish the causality between dependent and independent variables. The first stage regression uses an instrumental variable, the introduction of co-location, to compute estimated values of HFT activity. The co-location service reduces the response time between HFT and the exchange. It thus enables HFT to react faster to information releases, but it does not have any other direct impact on market liquidity, which fulfils the conditions of being an instrument variable. The second stage then uses those predicted HFT values to estimate a linear regression model of the market liquidity variables (dependent variables). Given that the predicted HFT activity is resulted from co-location facilities that are uncorrelated with the errors, the results of the 2SLS are optimal.

This section outlines the 2SLS regression analysis used to examine the two hypotheses tested in this paper. The first hypothesis states that the introduction of co-location facilities by an exchange leads to significantly greater trading activity by high frequency traders. On February 20, 2012, the Australian Securities Exchange (ASX) allowed market participants to co-locate their computer servers in the same room as the exchange server where the trading system operates. This analysis focuses on HFT around macro news releases and defines the 15-minute interval prior to the announcement as the pre-announcement period and the 15-minute interval following the announcement as the post-announcement period. Following Hendershott, Jones and Menkveld (2011), the following regression model is estimated for each 5-minute interval surrounding announcement time, for 90-day Bank Accepted Bills:

$$HFT_t = \alpha \quad + \beta * colo_t + \delta_1 * bad\_news_t + \delta_2 * |Surprise| + \varepsilon_t \tag{10}$$

where HFT_{it} refers to high frequency trading proxy, Message_Traffic; $colo_{it}$ is a dummy variable that takes the value of 1 for the period after the introduction of co-location on February 20, 2012 and 0 for the period prior to the co-location; $volatility_{it}$ measures price movements at each 5-minute interval. Following Chordia et al (2015) and Balduzzi et al (2001), this analysis computes post-announcement returns as the percentage mid-quote change from the release time to the 5-minute following announcements. $|surprise|_d$ is defined as the absolute post-announcement returns on each news day; bad_news_{it} is a dummy variable that takes the value of 1 if the post-announcement return is negative and 0 otherwise.

The primary variable of interest is β as it captures the impact of co-location facilities on HFT. A positive and significant β indicates the introduction of co-location has significantly lifted the level of HFT activity in the interest rate futures market around macro-economic announcements. This research design enables examinations of the first hypothesis (H_1), which tests whether technological upgrades at ASX leads to an increase in HFT surrounding information releases.

$$H_{1Null}: Coloation\ reduces\ HFT\ in\ the\ market, i, e, \beta < 0;\ or\ colocation\ has\ no\ impcat\ on\ HFT, i.e. \beta = 0$$

$$H_{1Alt}: Colocation\ increases\ HFT\ in\ the\ market, i, e, \beta > 0$$

The second objective of this paper is to understand the impact of an elevated level of HFT on market liquidity surrounding information releases. Following Hendershott, Jones and Menkveld (2011), the second stage regression in (11) examines the causal relation between HFT and market quality by employing an exogenous instrument, the co-location dummy variable. A good instrument needs to fulfil two conditions: firstly, the instrument is not correlated to market quality metrics, and secondly, the instrument is highly correlated with HFT proxies. The introduction of co-location facilities satisfies these two conditions and provides a natural experiment to evaluate the amount of market liquidity affected by the heightened level of HFT due to a latency reduction.

$$LIQ_t = \alpha \quad + \beta * \widehat{HFT}_t + \delta_1 * volatility_t + \delta_2 * bad\_news_t + \delta_3 * |Surprise| + \varepsilon_t \qquad (11)$$

where LIQ_t refers to level 1 depth, level 3 depth, relative bid-ask spread% and quoted spread in ticks for each 5-minute interval on day *t*; $\widehat{HFT}_t$ is the predicted HFT value from the stage 1 regression, LN(Message_Traffic), for each announcement day *t*; $volatility_t$ measures 5-minute price volatility, %LN(High/Low) for each announcement day *t*; bad_news_t is a dummy variable that takes the value of 1 for bad announcement days and 0 otherwise; $|surprise|_t$ is defined as the absolute post announcement return for each announcement day, *t*. Consistent with the extant literature that examines market liquidity around news releases, this analysis controls for volatility, announcement surprise, announcement classification, the pre- and the post- announcements and seasonal patterns associated with minute intervals that are within 5 minutes to the release time. As documented in Chaboud, Wright and Chernenko (2008), scheduled macroeconomic announcements are associated with spikes in trading volumes that tend to occur even though the announcements are in line with market expectations. Therefore, this analysis includes all major announcements days in the sample, rather than just the days with announcement shocks.

The principal objective is a significant β as it captures the impact of increased level of HFT on market quality around information releases. A positive and significant β for dollar depth indicates that the increased level of HFT improves market depth at the first level. Meanwhile, a negative and significant β for bid-ask spread measures indicates that the elevated level of HFT improves market liquidity by reducing bid-ask spreads. This research design enables examinations of the second hypothesis (H_2), which examines the impact of HFTs on market liquidity surrounding macro news releases.

$$H_{2Null}: HFT\ has\ no\ impact\ on\ market\ liquidity, i.e. \beta = 0; or\ HFT\ reduces\ market\ liquidity, i.e. \beta < 0\ for\ depth\ measure\ and\ \beta > 0\ for\ spread\ measures$$

$$H_{2Alt}: HFT\ improves\ market\ liquidity, i.e. \beta > 0\ for\ depth\ measure\ and\ \beta < 0\ for\ spread\ measures$$

3.4. Modelling Price Discovery

Based on previous literature, we implement a lead/lad model similar to Sims (1972) and Frino, Walter and West (2000) to investigate the impact of co-location on the price discovery relationship between the swap and futures markets on information announcement days. Coefficients of the lead/lag model are estimated by regressing various measures of 1-minute swap prices against lagged, contemporaneous and leading 1-minute futures prices as follows:

$$\Delta S_t = \alpha + \sum_{k=-20}^{20} \beta_{t+k} \Delta F_{t+k} + u_t \qquad (12)$$

where ΔS_t is the change in the swap price over interval *t*, ΔF_t is the change in the futures price over interval *t*, and u_t is the random error term.[3] Under Equation (1), the futures market leads the swap market when coefficients of lagged futures prices (k < 0) are significant while coefficients of lead futures prices (k > 0) are insignificant. Alternatively, the swap market leads the futures market, when coefficients of lagged futures prices (k < 0) are insignificant while coefficients of lead futures prices (k > 0) are significant. In addition, using a Wald test, Hypothesis-1 (H1) examines that the sum of the first ten lead coefficients (i.e., k=+1 to k=+10) are equal to zero (H1: $\sum_{k=1}^{10} \beta_{t+k} = 0$). Similarly, Hypothesis-2 (H2) examines that the sum of the first ten lag coefficients (i.e., k=-1 to k=-10) are equal to zero (H2: $\sum_{k=-1}^{-10} \beta_{t+k} = 0$).

[3] We ignore the 20 minutes before and after trading breaks to avoid comparing prices across market breaks as in Frino, Walter and West (2000).

4. Empirical Results

4.1 Descriptive Statistics

In this section, descriptive statistics are presented for BABs futures and SWAPs. The statistics are based upon data in the four-year period from February 20, 2010 to February 19, 2014, coinciding with a 48-month event window centred on the introduction of co-location facilities in the Australian futures market. This analysis primarily focuses on time intervals surrounding macro-economic announcements; therefore Panel C is calculated based on the 1-hour window surrounding announcements, with a 30-minute pre- and a 30-minute post- event window. The analysis splits the sample into two periods by the co-location date as the pre- and the post- co-location periods, and computes summary statistics for each interest rate derivative for each co-location period. Several market quality metrics are computed and compared between the pre and the post co-location periods. Table 1 reports the average number of trades, volatility, level 1 quoted depth and quoted bid-ask spread in the pre and the post co-location periods. The table also reports the mean difference between the two co-location groups, as well as the t-statistics for the null hypothesis that the mean values between the two groups are the same.

Table 1 reports message traffic increased significantly for BABs futures following the introduction of co-location, and no significant change is observed in the number of quotes for SWAPs, which makes sense as OTC market is not directly benefited from the co-location facilities. A significant reduction in Volatility is observed following co-location for both BABs and SWAPs. Turning to liquidity measures, depth improves significantly for BABs and spread improves for SWAPs across all panels, following the introduction of co-location. A significant reduction on the quoted spread is observed for BABs in Panel A, C and D.

In summary, descriptive statistics reported in Table 1 provide preliminary evidence that liquidity improves and volatility reduces following the introduction of co-location for both SWAPs and BABs futures.

TABLE 1

Descriptive Statistics of 1-Year SWAPs and BABs Futures

This table documents summary statistics of liquidity variables over the period 12 months before and 12 months after the implementation of co-location on the ASX. This table reports volatility, level 1 depth, quoted bid-ask spread, message traffic/number of quotes for the pre and post co-location periods. The mean difference between the pre and post groups is computed and reported in the "Difference" column. T-Statistics are reported next to the "Difference" for the null hypothesis that the values between the pre and post groups are the same. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level.

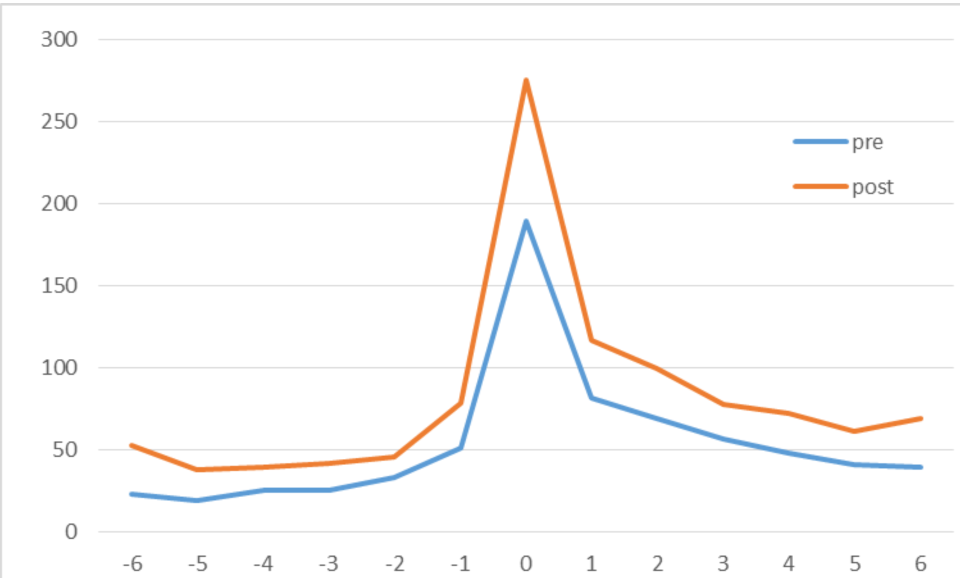
	1-year Interest Rate Swaps			90-day Bank Accepted Bills Futures			
	# Quotes	Volatility	Quoted Spread	Message	Volatility	Quoted Spread	Level 1 Depth
Panel A. All Days							
Pre	289.47	0.016	4.34	2337.60	0.01	1.023	1328.00
Post	286.81	0.009	3.02	3785.20	0.01	1.013	1989.10
Difference	-2.66	-0.006	-1.32	1447.60	0.00	-0.010	661.10
t-stat	-0.18	-10.60***	-30.98***	13.23***	-3.61***	-6.16***	7.83***
Panel B. Announcement Days							
Pre	338.88	0.023	4.25	2616.90	0.02	1.024	1306.80
Post	476.92	0.017	3.23	4191.60	0.01	1.019	1948.00
Difference	138.05	-0.006	-1.01	1574.70	-0.01	-0.005	641.20
t-stat	4.03***	-3.00***	-12.51***	6.89***	-2.08**	-1.480	3.74***
Panel C. Announcement Days (News Release Window)							
Pre	77.28	0.017	4.41	705.70	0.02	0.006	1106.70
Post	119.64	0.012	3.00	1068.50	0.01	0.005	1754.70
Difference	42.36	-0.005	-1.41	362.80	-0.01	0.000	648.00
t-stat	3.73***	-2.93***	-8.51***	3.93***	-1.96**	-2.61***	3.75***
Panel C. Non - Announcement Days							
Pre	282.37	0.013	4.20	2056.00	0.01	1.021	1392.70
Post	327.93	0.009	3.16	3522.40	0.01	1.011	2189.80
Difference	45.56	-0.004	-1.03	-1466.40	0.00	-0.010	797.20
t-stat	1.50	-5.39***	-11.57***	-6.55***	-3.17***	-3.25***	4.15***

4.2 The Impact of Co-location on High Frequency Trading

We first compute the average number of order book updates (message traffic) for each minute interval surrounding the announcement time. Figure 1 displays the message traffic surrounding macro news releases from 30 minutes before to 30 minutes after the announcement time for BABs futures, and compares the HFT activity between pre- and post-co-location periods. As seen in the figure, the introduction of co-location has significantly increased the level of HFT for intervals before and after the announcement time. For both pre-colo and post-colo periods, HFT activity increases 5 minutes prior to the announcement time and peaks in the 5-minute following the release time. After the initial surge, message traffic gradually declines but stays relatively high for the next 30 minutes.

Figure 1
High Frequency Trading: Message Traffic Proxy

Figure 1 graphs the HFT behaviour surrounding macro news releases from 30 minutes before to 30 after the announcement time for BABs futures, where the blue line indicates the pre-colo period and the orange line indicates the post-colo period. HFT is proxied by message traffic for each 5-minute interval. The event window extends 2 years pre to 2 years post the co-location date.



We then assess the causal impact of co-location on HFT. Specifically, we estimate equation (10) for HFT proxy to evaluate hypothesis H_1. Table 2 reports coefficient estimates on message traffic for each 5-minute interval surrounding announcements.

As reported in Table 2, the introduction of co-location stimulates HFT activity, as evidenced by a positive and significant coefficient on the co-location dummy variable. This finding is consistent across all intervals. Turning to announcement surprise, HFT is positively correlated with the degree of a surprise, i.e. the higher the announcement surprise, the greater the presence of HFT; however, this may attribute to the higher trading volume associated with the announcement surprise. The negative coefficients on Bad_News as reported in Table 2 indicate that the level of HFT reduces when market condition is not optimistic. The reduction is significant in the 5-minute interval preceding announcement time.

TABLE 3

The Impact of Co-Location on High Frequency Trading

This table reports regression results on the impact of co-location on HFT on macro announcement days. This analysis only focuses on the 1-hour window around news releases. The following regression model is estimated for each 5-minute interval surrounding announcement time, T, for 90-day Bank Accepted Bills:

$$HFT_t = \alpha \quad + \beta * colo_t + \delta_1 * bad\_news_t + \delta_2 * |Surprise| + \varepsilon_t$$

HFT_t is the high frequency trading proxy, LN(Message_Traffic), for each announcement day t; $colo_t$ is a dummy variable that takes the value of 1 for the period after the introduction of co-location on February 20, 2012 and 0 otherwise; bad_news_t is a dummy variable that takes the value of 1 for bad announcement days and 0 otherwise; $|surprise|_t$ is defined as the absolute post announcement return for each announcement day, *t*. The event window extends 2-year pre to 2-year post the co-location date. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level.

	Co-location	Bad_News	|Surprise|
[T-30, T-25]	0.6013***	-0.0577	0.3256
	(3.44)	(-0.33)	(0.28)
[T-25, T-20]	0.5654***	-0.1614	0.5769
	(3.69)	(-1.06)	(0.60)
[T-20, T-15]	0.4406***	-0.0249	0.9901
	(2.95)	(-0.17)	(1.06)
[T-15, T-10]	0.4495***	-0.0742	0.6313
	(3.23)	(-0.54)	(0.73)
[T-10, T-5]	0.4058***	-0.0073	2.0524**
	(3.01)	(-0.05)	(2.43)
[T-5, T]	0.4154***	-0.2668**	0.6178
	(3.23)	(-2.09)	(0.77)
[T, T+5]	0.4764***	-0.0846	0.5394
	(2.62)	(-0.47)	(0.47)
[T+5, T+10]	0.4267**	-0.0097	1.4417
	(2.41)	(-0.06)	(1.31)
[T+10, T+15]	0.4280**	-0.1127	2.2168*
	(2.29)	(-0.61)	(1.90)
[T+15, T+20]	0.3576**	-0.0752	1.7954
	(1.94)	(-0.41)	(1.56)
[T+20, T+25]	0.4448**	-0.1242	2.2254**
	(2.56)	(-0.72)	(2.05)
[T+25, T+30]	0.3591**	-0.1019	2.3063**
	(2.17)	(-0.62)	(2.23)

4.3 The Impact of High Frequency Trading on Market Liquidity

After identifying a strong positive correlation between HFT and co-location, this section examines the impact of a heightened level HFT on market liquidity for both the pre- and the post- announcement periods. Further this section determines the directional causality between HFT and market liquidity using co-location as an instrumental variable.

Figure 2 compares liquidity responses to public information arrivals between the pre-colo and the post-colo periods. Figure 2 shows that Level 1 depth reduces before the announcement time, almost simultaneously for both periods, and reaches the bottom of the curve in the 5-minute preceding the release time. The patterns are similar between the two sample periods; however, the level of depth is higher in the post-colo period consistently throughout the announcement times. Based on the quoted spread measure, liquidity is higher for the post-colo period at the exact announcement time and remains similar between the two periods for intervals preceding and following the release time.

Figure 2
Liquidity: Depth, Relative Spread and Quoted Spread

Figure 2 graphs the market liquidity measures surrounding macro news releases from 30 minutes before to 30 after the announcement time for BABs futures, where the blue line indicates the pre-colo period and the orange line indicates the post-colo period. The event window extends 2 years pre to 2 years post the co-location date. Figure 2-1 depicts the Level 1 depth for each 5-minute interval. Figure 2-2 depicts the average relative spread (Bid-Ask Spread %) for each 5-minute interval. Figure 2-3 depicts the average quoted spread (Bid-Ask Spread Ticks) for each 5-minute interval.

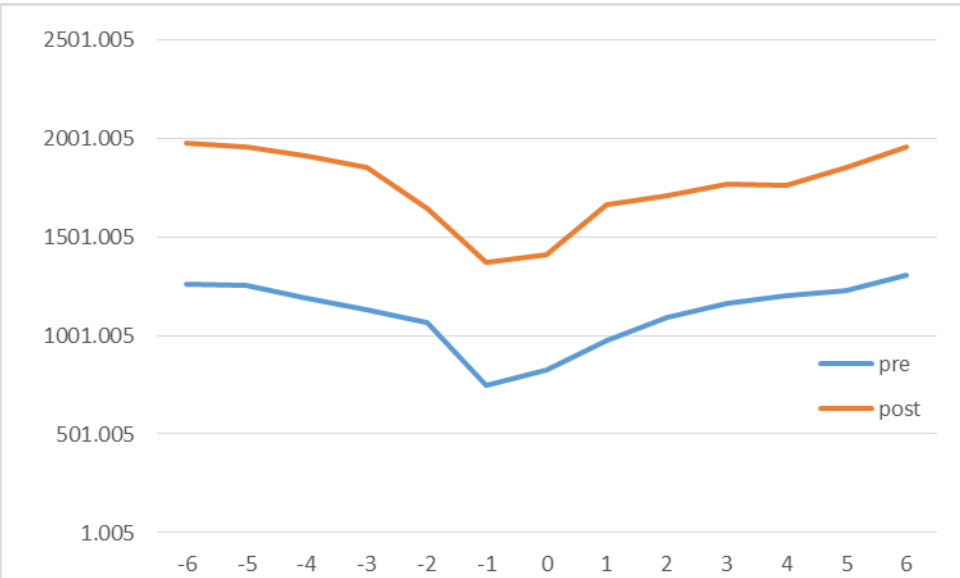


Figure 2-1

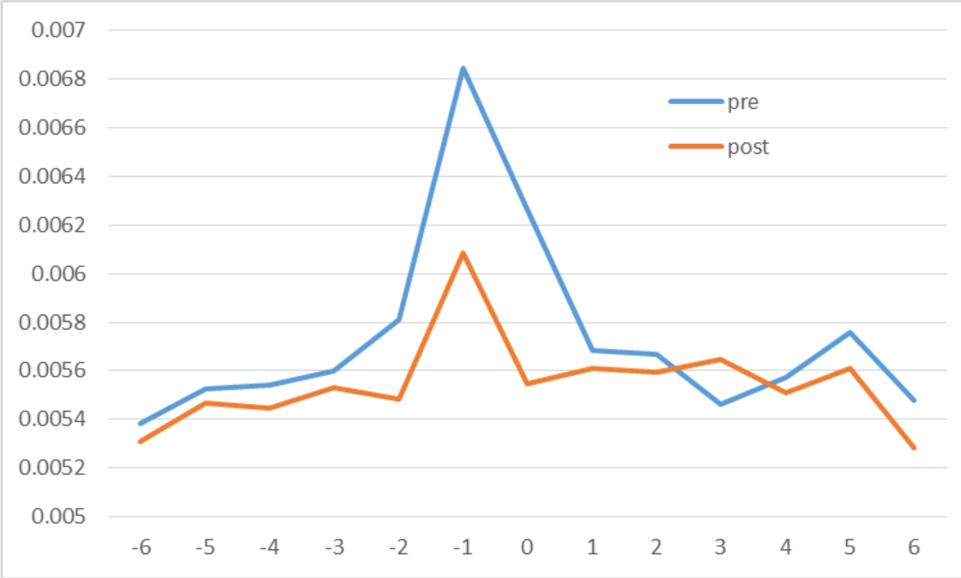


Figure 2-2

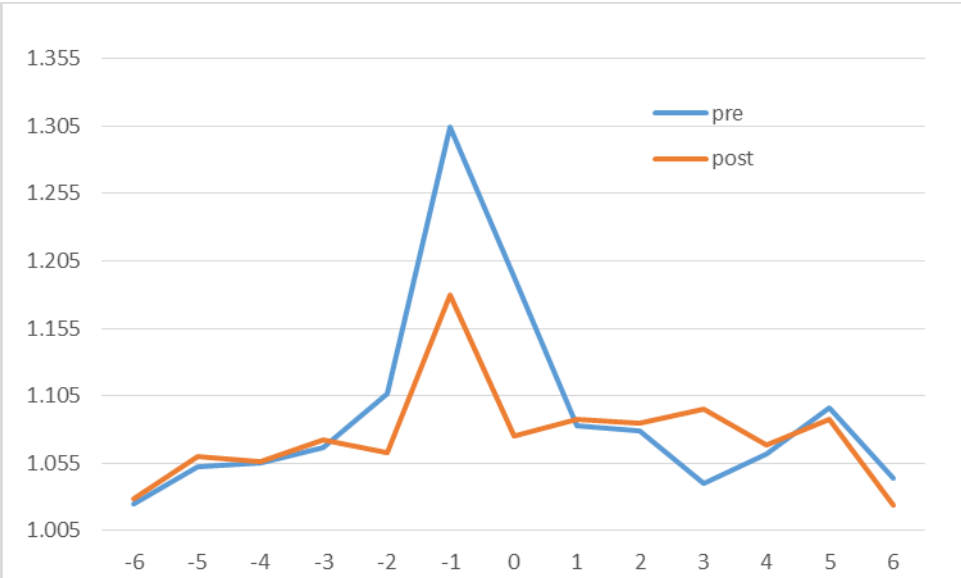


Figure 2-3

Table 3 presents coefficient estimates of equation (11) and reveals a positive correlation between HFT and depth, and a negative correlation between HFT and measures of bid-ask spreads. Depth is positively correlated with HFT for all 5-minute intervals. The correlation is strongly significant for all intervals. This finding suggests that HFT significantly reduces market depth for intervals surrounding scheduled information releases.

The second column summarises regression results on relative spread. A reduction on relative spread is observed following a heighted level of HFT, but it is only significant for the interval immediately following news releases. This order book movement is less significant than that observed for market depth. Results on the quoted spread are similar with those reported on the relative spread, but with a lower degree of significance. In aggregate, results reported in Table 3 confirms that the increased level of HFT, resulted from co-location, causes an improvement in market depth for the intervals around macroeconomic announcements. However, such improvement is not significant for spread measures for intervals preceding announcements or after 5 minutes of the release time.

TABLE 3

The Impact of High Frequency Trading on Market Liquidity

This table reports regression results on the two-stage-least-squares (2SLS) regression analysis which examines the impact of HFT on market liquidity on macro announcement days. This analysis only focuses on the 1-hour window around news releases. The first stage regression model is documented in Table 3 and the second stage regression is estimated for each 5-minute interval surrounding announcement time, *T*, and for each liquidity measure:

$$LIQ_t = \alpha \quad + \beta * \widehat{HFT}_t + \delta_1 * volatility_t + \delta_2 * bad\_news_t + \delta_3 * |Surprise| + \varepsilon_t$$

LIQ_t refers to level 1 depth, level 3 depth, relative bid-ask spread% and quoted spread in ticks for each 5-minute interval on day *t*; $\widehat{HFT}_t$ is the predicted HFT value from the stage 1 regression, LN(Message_Traffic), for each announcement day *t*; $volatility_t$ measures 5-minute price volatility, %LN(High/Low) for each announcement day *t*; bad_news_t is a dummy variable that takes the value of 1 for bad announcement days and 0 otherwise; $|surprise|_t$ is defined as the absolute post announcement return for each announcement day, *t*. Coefficients on HFT are reported for each liquidity measure. The event window extends 2-year pre to 2-year post the co-location date. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level.

	Depth Level 1	Relative Spread (%)	Quoted Spread (Ticks)
[T-30, T-25]	0.5634**	-0.0001	0.0088
	(2.04)	(-0.64)	(0.28)
[T-25, T-20]	0.6179**	-0.0001	0.0212
	(2.15)	(-0.15)	(0.28)
[T-20, T-15]	0.9750**	-0.0002	0.0147
	(2.23)	(-0.30)	(0.14)
[T-15, T-10]	0.8699**	-0.0001	0.0169
	(2.11)	(-0.24)	(0.15)
[T-10, T-5]	0.8385*	-0.0008	-0.1000
	(1.73)	(-1.13)	(-0.75)
[T-5, T]	0.7942*	-0.0015	-0.2379
	(1.77)	(-1.55)	(-1.29)
[T, T+5]	0.6181***	-0.0011***	-0.1797**
	(2.53)	(-2.62)	(-2.31)
[T+5, T+10]	0.8143**	-0.0002	0.0140
	(2.02)	(-0.25)	(0.10)
[T+10, T+15]	0.8327**	-0.0001	0.0234
	(1.95)	(-0.18)	(0.16)
[T+15, T+20]	1.0018**	0.0007	0.1931
	(1.94)	(-0.69)	(0.88)
[T+20, T+25]	0.7792**	-0.0001	0.0333
	(2.02)	(-0.13)	(0.31)
[T+25, T+30]	0.9004*	-0.0004	-0.0086
	(1.64)	(-0.43)	(-0.05)

4.4. The Impact of Co-location on Price Discovery

Panel A of Table 4 shows that when the lead-lag model is estimated on announcement days during the two-years period before co-location, four lagged futures prices (k=-1 to k=-4) are significantly positive, which implies that the futures market leads the swap market by up to four minutes. Additionally, coefficients on two lead futures prices (k=+1 to k=+2) are significantly positive at the 0.01 level, suggesting a two minutes feedback from the swap market to the futures market. These results demonstrate that the futures market leads price discovery on announcement days during the period before co-location. When the lead-lag model is estimated on announcement days during the two-years period after co-location, two additional lag futures prices (k=-5 and k=-6) become significantly positive, implying that the lead of the futures market increases after co-location. These findings indicate that co-location increases the speed at which information is incorporated into the futures markets, and therefore, strengthening the lead of the futures market on macroeconomic information releases when there is an increase of informed trading and information asymmetry in the market.

TABLE 4

The Lead/Lag Relationship Between Swap and Futures Prices on Announcement Days

Panel A: Coefficients from lead/lag OLS regression

	Before Co-location		After Co-location	
	Coefficient	T-statistic	Coefficient	T-statistic
Intercept	0.0000	0.00	0.0000	0.09
$\boldsymbol{\beta}$ t+10	-0.0051	-0.42	0.0089	1.15
$\boldsymbol{\beta}$ t+9	-0.0063	-0.52	0.0061	0.78
$\boldsymbol{\beta}$ t+8	0.0009	0.08	0.0061	0.79
$\boldsymbol{\beta}$ t+7	-0.0091	-0.76	-0.0013	-0.17
$\boldsymbol{\beta}$ t+6	0.0131	1.09	0.0135	1.74
$\boldsymbol{\beta}$ t+5	0.0153	1.28	0.0140	1.81
$\boldsymbol{\beta}$ t+4	0.0215	1.79	-0.0012	-0.16
$\boldsymbol{\beta}$ t+3	-0.0095	-0.79	0.0030	0.21
$\boldsymbol{\beta}$ t+2	0.0356	2.97***	0.0200	2.58***
$\boldsymbol{\beta}$ t+1	0.0673	5.56***	0.0522	6.73***
$\boldsymbol{\beta}$ t	0.4144	34.30***	0.3152	40.68***
$\boldsymbol{\beta}$ t-1	0.1877	15.53***	0.2176	28.09***
$\boldsymbol{\beta}$ t-2	0.0769	6.36***	0.0457	5.90***
$\boldsymbol{\beta}$ t-3	0.0588	4.87***	0.0340	4.39***
$\boldsymbol{\beta}$ t-4	0.0523	4.38***	0.0158	2.04**
$\boldsymbol{\beta}$ t-5	0.0078	0.65	0.0166	2.13**
$\boldsymbol{\beta}$ t-6	0.0213	1.78	0.0249	3.22***
$\boldsymbol{\beta}$ t-7	0.0000	0.00	0.0121	1.57
$\boldsymbol{\beta}$ t-8	0.0166	1.39	0.0115	1.49
$\boldsymbol{\beta}$ t-9	0.0024	0.20	0.0106	1.37
$\boldsymbol{\beta}$ t-10	-0.0034	-0.38	-0.0075	-0.97
Panel B: Hypothesis tests (F-test)				
H1: $\sum_{k=1}^{10} \beta_{t+k}$		7.79***		21.98***
H2: $\sum_{k=-1}^{-10} \beta_{t+k}$		77.01***		137.92***

Note. Table 4 reports the regression coefficients of the lead/lag model on announcement days over the two years period before co-location and two years period after co-location. Panel A presents the coefficients estimated using an OLS regression with 1-minute intraday observations where the dependent and independent variables are the change in the swap price and nearby futures contract price, respectively. Panel B reports the F-statistics of Wald tests on coefficient restrictions for the two hypotheses. ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

On February 20, 2012, ASX introduced co-location facilities to Australian futures markets. A previous study conducted by Frino, Mollica and Webb (2014) provides the first Australian evidence on the impact of co-location on HFT activity and market liquidity. This study extends their work by examining the impact of co-location on HFT around scheduled macroeconomic announcements. Announcement periods represent a sensitive and different informational environment relative to the normal times, and it is important to determine the impact of co-location on HFT for each intervals around scheduled news releases. Furthermore, this analysis examines the causality effect between HFT and market liquidity for intervals surrounding announcement time by employing co-location as an exogenous event to HFT.

Results based on the first hypothesis H_1 demonstrate that HFT activity increases following the introduction of co-location across all intervals around news releases. Furthermore, results based on the second hypothesis H_2 reports that the heighted level of HFT, exhibited in the post co-location period, results in a significant improvement in market depth surrounding macro announcements, however the improvement is not significant for spread measures for intervals preceding announcements or after 5 minutes of the release time. Moreover, we examines price discovery by looking at the lead-lag effects between futures and SWAPs during information releases in pre- and post-colocation periods. We find that co-location increases the speed at which information is incorporated into the futures market, and therefore, strengthens the lead effects of futures on scheduled news release days.

Appendix

This appendix analyses the impact of HFT on market quality, measured by trading volumes and the number of trades; specifically, it compares trading activity between the pre- and the post- co-location periods during announcement times. The pre-colo (extending from February 2010 to February 2012) is defined as the 2-year period prior to the introduction of co-location and the post-colo is defined as the 2-year period (extending from February 2012 to February 2014) following the introduction of co-location. This appendix also visualises market responses to major announcements, which are those with a statistically significant impact on market volatility.

Overall, the selected announcements reported in Table A-1 are similar to those identified in extant literature. The table reports the type of macro announcements, the a_{kj}coefficients on the BABs, the 3-year Government Bond and the 10-year Government Bond respectively, and the frequency of announcement releases. As reported in Table 5-1, 9 of 20 sources of news releases reveal significant a_{kj} coefficients for the BABs, at either 5% or the 1% statistical level. The average impact of significant announcements is 0.0066. Turning to the 3-year Government Bond, results are consistent with the BABs, except announcements of BoP Current Account Balance are not eventful. The average a_{kj} coefficient of significant announcements is 0.0081 for the 3-year Government Bond. In terms of the 10-year Government Bond, further to the 9 news announcements identified for BABs, the release of the NAB Business Confidence index is eventful, 10% significance level. The average impact of significant announcements is 0.0034 for the 10-year Government Bond, which is much larger compared to 0.0001, the average impact of news that are not significant.

TABLE A-1

The Impact of Macro Announcements on Interest Rate Futures

This table presents regression analysis of the impact of macro-economic announcements on the volatility of three interest rate futures contracts. The following regression model is estimated:

$$QTESD_{jt} = a_{0j} + \sum_{k=1}^{K} a_{kj} D_{kt} + e_{jt} \tag{2}$$

where $QTESD_{jt}$ is the volatility proxy for each announcement day; D_{kt} is the dummy variable that equals 1 if announcement k is released on day t and zero otherwise. The a_{kj} coefficients are reported for the 90-day BABs, the 3-year government bond and the 10-year government bond in the second, third and fourth columns respectively. * indicates a_{kj} significant at 10%, ** indicates a_{kj} significant at 5% and *** indicates a_{kj} significant at the 1% level. The announcement type is reported in the first column while the frequency of releases is reported in the last. 11*4 + 9*12

Announcement	***BABs***	***3-Y Bond***	***10-Y Bond***	***Frequency***
Job vacancies	-0.0005	-0.0004	-0.0001	Quarterly
House Price Index	0.0016	-0.0006	0.0005	Quarterly
Dwelling Starts	0.0006	0.0003	0.0001	Quarterly
Average Weekly Wages	-0.0014	-0.0006	-0.0002	Quarterly
BoP Current Account Balance	0.0025**	0.0012	0.0010**	Quarterly
Private Capital Expenditure	0.0032***	0.0044***	0.0024***	Quarterly
Consumer Price Index	0.0161***	0.0189***	0.0078***	Quarterly
Company Operating Profit	-0.0004	-0.0003	0.0008	Quarterly
Gross Domestic Product	0.0067***	0.0092***	0.0053***	Quarterly
Import price index	-0.0007	-0.0009	-0.0003	Quarterly
Producer Price Index	0.0050***	0.0051***	0.0032***	Quarterly
Retail Sales	0.0083***	0.0054***	0.0039***	Monthly
ANZ Job Advertisements	0.0002	0.0000	0.0000	Monthly
NAB Business Confidence	0.0006	0.0006	0.0005*	Monthly
Private Sector Credit	0.0001	0.0009	0.0004	Monthly
Home Loans	0.0005	0.0006	0.0007***	Monthly
Building Approvals	0.0034***	0.0047***	0.0030***	Monthly
Trade Balance	0.0012**	0.0013**	0.0010***	Monthly
Unemployment Rate	0.0134***	0.0157***	0.0086***	Monthly
New Motor Vehicle Sales	-0.0005	-0.0009	-0.0003	Monthly

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