Time and the price impact of trades in Australian banking stocks around interest rate announcements

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Abstract

We propose a nonlinear vector-autoregressive model of trade durations, trade attributes (signs and volumes) and returns that incorporates the dynamic interdependence amongst these variables and relaxes the exogeneity assumption that is often imposed on durations in previous studies. We employ this new model to examine the role of durations and trade attributes in the price formation process for Australian banking stocks around interest rate announcements. We find that durations are not only correlated but also jointly determined with trade characteristics and returns. Shorter durations increase the price impact and autocorrelation of trades. Transactions executed within one minute around the announcements have shorter durations and larger impact on prices. Conditioning on an average before-announcement history, the cumulative price impact of an unexpected trade is higher (lower) following a negative (positive) duration shock if durations are endogenous, yet it stays unchanged if durations are treated as exogenous. Shocks to durations contribute significantly less to the forecast error variance of returns than do trade attribute shocks. This result suggests that trade durations play a smaller role in explaining price dynamics than trade attributes.

Keywords: Price Impact; Endogenous Duration; Vector Autoregression; Impulse Response; Forecast Error Variance Decomposition; Banking Stocks; Interest Rate Announcements.

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1 Introduction

Research on market microstructure has flourished over the past two decades as a consequence of increased accessibility of high frequency data and significant improvements in computational technologies. One big strand in microstructure studies has focused on identifying factors that influence asset prices and examining how prices evolve in reaction to new information. Previous research has documented that trade attributes, such as direction and volume, and bid-ask spreads are important pieces of information that drive the price formation process (Hasbrouck, 1988, 1991a,b). In particular, unexpected trades result in a persistent impact on security prices; the larger the volume of a trade and/or the wider the bid-ask spread, the bigger the price adjustment.

Time of trade arrivals has also been shown to play an important role in explaining price dynamics. Theoretical studies by Diamond and Verrecchia (1987) and Easley and O'Hara (1992) highlight the informativeness of trade arrival times and their joint determination with the process of trade generation and price formation. Specifically, Diamond and Verrecchia (1987) hypothesize that long time intervals between trades, or, equivalently, low levels of trading activities, are signals of bad news being revealed to the market, which subsequently lead to a decrease in prices. Meanwhile, Easley and O'Hara (1992) relate long trade durations to a lack of news events and show that trading intensity is positively dependent on the proportion of informed investors in the market. Consequently, the longer the time between trades, the narrower the bid-ask spread and the smaller the price adjustment. Dufour and Engle (2000) lend support to these theories by empirically showing that more frequent trade arrivals or shorter trade durations induce not only stronger positive autocorrelation of trade directions but also a quicker convergence of prices to the equilibrium level. Likewise, higher trading intensity leads to higher price volatility (Engle, 2000) and strengthens the positive dependence of price volatility on trade sizes (Xu et al., 2006).

Despite the theoretical suggestion of the joint determination of trade durations and other variables such as prices and trade attributes (e.g. Diamond and Verrecchia, 1987, Easley and O'Hara, 1992), Dufour and Engle (2000), Engle (2000) and Xu et al. (2006) all assume that trade durations are strictly exogenous. That is, the time between trades is assumed to be only dependent upon previous durations but independent of past trajectories of prices and trade attributes. Nevertheless, Dufour and Engle (2000) conduct a formal test of the validity of the strict exogeneity assumption (which is often imposed on durations in previous studies) and find that it is strongly rejected. They suggest that "incorporating [the] feedback effects of returns, trades and volume on time durations may improve the in-sample performance of the model" (p. 2496). Although they do not pursue the relaxation of this assumption, these authors emphasize the importance of endogenizing trade durations since it "could ultimately provide more accurate impulse response functions" (p. 2496), i.e. it could enable a more accurate assessment of the price impact of trades. Motivated by the Dufour and Engle's suggestion, the current paper aims to build a model for returns, trade characteristics (signs and volumes) and durations that relaxes the strong exogeneity assumption of trade durations, and we use this framework to examine how trades impact prices when trade arrival times are endogenous.

Our econometric framework is built upon the general modeling approach of Engle (2000) that decomposes the joint distribution of trade durations and other variables of interest such as returns and trade attributes into the product of the marginal density of durations and the conditional density of the other variables. By incorporating the past histories of returns, trade characteristics and durations into both the marginal and conditional densities, we allow for feedback effects amongst these variables in the joint system. In particular, we follow Hasbrouck (1991a) and Dufour and Engle (2000) in modeling returns and trade characteristics with a vector autoregression (VAR) that is non-linearly related to trade durations. Meanwhile, we model durations in two ways, both of which take into account the dependence of durations on lagged returns and trade characteristics. The first way is to make durations another endogenous variable that evolves according to an autoregressive structure similar to returns and trade attributes in the VAR system, which is a natural extension of Hasbrouck's (1991a) framework to endogenize trade durations. The second way is to employ an autoregressive conditional duration (ACD) model for durations that incorporates past returns and trade characteristics.

There is a small but growing body of literature that accommodates the endogeneity of trade durations in a multivariate system (Grammig and Wellner, 2002, Manganelli, 2005, Renault and Werker, 2011, Pelletier and Zheng, 2013, Renault et al., 2014, Wei and Pelletier, 2015). Unlike these studies whose main objective is to examine the interdependence between duration and volatility (i.e. the second moment of returns), this chapter focuses on the dynamics of the first moment of returns. In addition, our proposed nonlinear VAR model incorporates trade direction, which is shown to be an important determinant of the price formation process (Hasbrouck, 1991a, Dufour and Engle, 2000, Barclay et al., 2003) but which is often excluded from the aforementioned studies due to its binary nature (i.e. trade direction can only take two values: 1 if a trade is a purchase and -1 if it is a sale). Our work also differs from another related work by Russell and Engle (2005) in that instead of studying discrete tick-size price changes with an autoregressive conditional multinomial model, we examine returns - a widely-used and *continuous* relative measure of price changes which facilitates comparison amongst stocks of different capitalizations.

We apply the proposed model to study the role of durations and trade attributes in the process of price formation for Australian banking stocks. In addition, we investigate how the Reserve Bank of Australia (RBA) interest rate announcements affect the arrival time and the price impact of trades in these stocks. Effectively, the release of monetary policy news is treated as an exogenous event to the joint framework on which we condition our analysis. We focus on banking stocks because they are liquid and very sensitive to interest rate news. With the joint model, we examine several important issues in the microstructure literature. The first issue relates to theoretical predictions about the endogeneity of trade durations and their informativeness about price dynamics (e.g. Easley and O'Hara, 1992). Specifically, are durations correlated with prices and trade attributes, and if so, how? Also, how do trade durations affect the adjustment of security prices to new information? The second issue concerns how the occurrence of exogenous news events such as RBA announcements affect the trade generation and price formation processes. Do interest rate announcements intensify the trading frequency and the price impact of trades? The third issue compares the relative importance of durations and trade attributes (signs and volumes) to price dynamics. Although there are theoretical justifications and empirical evidence of the informativeness of both trade arrival times and trade attributes about price adjustment, there is little guidance, either theoretical or empirical, on which of the two possess a bigger informational content. In this paper, we empirically investigate whether durations or trade characteristics play a dominant role in explaining the behavior of prices.

Our study contributes to the literature in several ways. First, we provide a general model to study the dynamics of returns jointly with durations and trade characteristics that relaxes the strict exogeneity of durations that is often assumed in previous studies. We find that durations are not only correlated but also jointly determined with trade attributes and returns, supporting

Easley and O'Hara's (1992) theory. Specifically, while larger price adjustments tend to increase future trade durations (which is consistent with Admati and Pfleiderer (1988), Grammig and Wellner (2002)), larger past trading volumes tend to shorten the durations of incoming transactions (which supports Easley and O'Hara (1992), Manganelli (2005), Nowak and Anderson (2014)). In conformance with Dufour and Engle (2000), shorter durations strengthen the price impact and the positive autocorrelation of trades.

Second, we provide evidence that monetary policy announcements affect the trading intensity and the price impact of trades in banking stocks. Our work differs from most existing studies that investigate how financial markets react to interest rate news because (i) we study how the news impacts trading frequency, in addition to how it impacts returns; and (ii) our study is conducted using tick-by-tick transaction data which helps avoid a loss of information that might bias the analysis (Engle, 2000, Russell and Engle, 2005), whereas most previous studies employ data of lower frequencies such as 5 minutes (e.g. Smales, 2012), daily (Bomfim, 2003, Gasbarro and Monroe, 2004, Kim and Nguyen, 2008), or monthly (Bernanke and Kuttner, 2005, Diggle and Brooks, 2007, Bjørnland and Leitemo, 2009). Using a dataset for major Australian banking stocks, we find that trades transacted within one minute around the RBA announcements have shorter durations and larger impacts on prices. Conditioning on an average history prior to the RBA announcements, the cumulative price impact of an unexpected trade is higher (lower) when the trade occurs faster (slower) if durations are endogenous, yet it stays unchanged if durations are treated as exogenous. The latter result highlights the importance of endogenizing trade durations, confirming Dufour and Engle's (2000) suggestion that allowing for the endogeneity of time between trades could provide a more accurate picture of how trades drive prices.

Third, to the best of our knowledge, this is the first study to compare the relative informativeness of durations and trade attributes (signs and volumes) about the price formation process. Using the generalized forecast error variance decomposition (GFEVD) proposed by Lanne and Nyberg (2016), we find that shocks to durations contribute significantly less to the forecast error variance (FEV) of returns than other trade attribute shocks. The relative importance of duration shocks to returns is less than 9% while that of other trade attribute innovations is typically above 50%. The contributions of both shocks to the returns' FEV are larger on days with interest rate releases, and that of duration shocks is also larger when durations are endogenously modeled. The results suggest that although they carry important informational content about prices (Easley and O'Hara, 1992, Dufour and Engle, 2000), trade durations play a minor role in explaining the price dynamics compared to trade attributes (signs and volumes).

Our findings are potentially of interest to market participants and policy makers because they shed light on how quickly new information, for example interest rate news, is processed and how, how this news is disseminated and incorporated into security prices, as well as how policy-making influences this information dissemination process. In addition, as price impact is known to be the biggest component of trading cost (Keim and Madhavan, 1996, 1998), our findings have relevant practical implications for designing optimal strategies that minimize the cost of trading in financial markets.

The rest of the paper is organized as follows. Section 2 introduces a nonlinear VAR framework for trade arrival times, trade attributes and returns advocated in this study. It also discusses how the information content of monetary policy announcements is incorporated into the model. Section 3 describes the data. Model estimates and further analyses such as impulse response and forecast error variance decomposition for Australian banking stocks are presented in Section 4, and Section 5 concludes.

2 A joint model of durations, trade attributes and returns

Transactions data are conventionally characterized by a sequence of their arrival times that follow a point process and the associated quantities called "marks" that are revealed to the market at those times (Engle, 2000, Manganelli, 2005, Russell and Engle, 2005). Marks are typically a vector of random variables such as the price, the direction and the volume of a transaction which, together with the trade's arrival time, are assumed to be jointly determined by some unknown data generating process (DGP). In order to estimate the true joint distribution, Engle (2000) factorizes it into the product of the conditional density of the marks and the marginal density of the arrival time, and then proposes a model for each component density. This approach has been widely utilized in various market microstructure studies such as Grammig and Wellner (2002), Manganelli (2005), and Russell and Engle (2005).

To formulate the idea of Engle (2000) statistically, let $T_t = z_t - z_{t-1}$ be the time interval, measured in seconds, between two successive transactions, where z_t denotes the time at which the t-th trade is executed. At time z_t, market participants observe a vector of marks y_t. Each pair (T_t, y_t) is assumed to follow a joint distribution $f(T_t, y_t|\mathcal{I}_{t-1}; \mu)$, where $\mathcal{I}_{t-1}$ denotes the past information and μ is a vector of parameters underlying the joint process. Engle (2000) decomposes the joint density $f(T_t, y_t|\mathcal{I}_{t-1}; \mu)$ as

$$f(T_t, y_t|\mathcal{I}_{t-1}; \mu) = g(y_t|T_t, \mathcal{I}_{t-1}; \mu_y) \times h(T_t|\mathcal{I}_{t-1}; \mu_T), \tag{1}$$

where $g(\cdot)$ denotes the conditional density of the marks y_t given the current trade duration T_t, and $h(\cdot)$ denotes the marginal density of T_t. Prior studies in the literature have primarily focused on modeling the $h(\cdot)$ function only (e.g. Engle and Russell, 1998, Bauwens and Giot, 2000, Knight and Ning, 2008, Xu et al., 2011). A few studies that accommodate joint modeling typically assume that trade durations are strictly exogenous (e.g. Engle, 2000, Dufour and Engle, 2000, Xu et al., 2006). In other words, these studies assume that the past information set $\mathcal{I}_{t-1}$ in the $h(\cdot)$ function only includes lagged trade durations but excludes the information from previous marks, even though these studies allow both past durations and marks to be included in the $g(\cdot)$ function.

We relax this strict exogeneity of trade durations by incorporating the past trajectories of durations and marks into both $g(\cdot)$ and $h(\cdot)$ functions, which explicitly allows for the dynamic interdependence between the variables. The decomposition (**??**) assumes that there is instantaneous Granger-causality running from T_t to y_t while the latter does not contemporaneously Granger-cause the former. This is because T_t measures the time interval between the $(t-1)$-th and the t-th transactions and thus potentially conveys relevant information that has been accumulated during the time period (Easley and O'Hara, 1992), while y_t is only realized once the t-th trade is completed. Therefore, the parameterization (**??**) appears natural and plausible.

This study aims to develop a joint modeling framework for tick-by-tick returns or quote revisions, trade characteristics (signs and volumes) and trade durations, based on which the effects of the interest rate announcements on the role of durations and trade characteristics in explaining the price dynamics will be examined. Thus, the marks of interest include (i) quote revision r_t, defined as the natural logarithmic change in the midquote price following the t-th trade and quoted in basis points (bps), i.e. $r_t = 10000 * (\ln(q_{t+1}) - \ln(q_t))$, where q_t is the midpoint of the bid and ask quotes immediately before the t-th trade,[1] (ii) trade sign x_t^0, which equals 1 (-1) for buyer- (seller-) initiated transactions, and (iii) signed volume v_t, defined as the signed natural logarithm of the ratio of the actual share volume (V_t) of the t-th trade to the prevailing quoted depth ($depth_t$) at the best opposite-side quote immediately before that trade,[2] i.e. $v_t = x_t^0 \ln(V_t/depth_t)$. The use of the volume to depth ratio, rather than the actual share volume, is motivated by work of Chan and Fong (2000), Engle and Lange (2001), Brogaard et al. (2015), and Pham et al. (2017), who show that for a given share volume, trades have a bigger impact on prices if the prevailing depths prior to these trades are smaller (i.e. if the market is less liquid). Thus, a trade is considered big if it has a large volume to depth ratio, and this measure not only incorporates the effects of trade sizes, but also market liquidity. We need to model the conditional density of the marks $g(\cdot)$ and the marginal density of trade durations $h(\cdot)$ to capture the joint distribution of the variables of interest, and these are discussed in the next subsections.

2.1 Modeling returns and trade attributes given trade durations

Building on Hasbrouck (1991a) and Dufour and Engle (2000), the current study models the joint dynamics of quote revisions, trade signs and signed volumes, conditional on trade arrival times (i.e. $g(y_t|T_t, \mathcal{I}_{t-1}; \mu_y)$ where $y_t = (r_t, x_t^0, v_t)'$), with the following VAR framework:

$$\begin{aligned} r_t &= \alpha^r + \beta^r \text{open}_t + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \left\{ \sum_{i=1}^{p} a_i^r r_{t-i} + \lambda^r \text{open}_t x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})] x_{t-i} \right\} + u_t^r, \\ x_t &= \alpha^x + \beta^x \text{open}_t + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \left\{ \sum_{i=1}^{p} a_i^x r_{t-i} + \lambda^x \text{open}_{t-1} x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})] x_{t-i} \right\} + u_t^x, \end{aligned} \tag{2}$$

where $x_t = (x_t^0, v_t)'$; open_t is a dummy variable that equals 1 for trades executed within the first 30 minutes of a trading day, and 0 otherwise; α's, β's, b's, a's λ's, γ's, and δ's are conformable matrices of coefficients. This VAR framework is similar, but not identical to the original Dufour and Engle (2000) specification, which only investigates returns r_t and trade signs x_t^0 and includes components in braces of equation (2). The extension of the original Dufour and Engle (2000) VAR system to incorporate trading volume is motivated by the findings of Easley and O'Hara (1987),

[1]Measuring prices as the mid-point of bid and ask quotes is standard practice in the microstructure literature to circumvent the bid-ask bounce problem (e.g. Hasbrouck, 1988, Manganelli, 2005). The factor of 10,000 enables returns to be measured in basis points.

[2]If the t-th trade is a purchase (sale), $depth_t$ is defined as the number of shares available at the best ask (bid) price right before the trade.

Hasbrouck (1988), O'Hara et al. (2014), among others, that there is a significant price-quantity relationship. Likewise, the inclusion of $|r_{t-i}|$ is to capture the effects of stock volatility on returns and trade attributes (e.g. Xu et al., 2006).

In conformance with Hasbrouck (1991a) and Dufour and Engle (2000), the VAR specification in (2) assumes that conditioning on the time of trade arrivals, there are two sources of information affecting price dynamics. One is the public or trade-unrelated information, u_t^r, and the other is the private information induced by unanticipated trades, u_t^x. These two informational innovations are assumed to have zero means and to be jointly and serially uncorrelated.[3] After observing a new trade, the market maker learns the information conveyed by the trade and then revises the quotes to take into account the new information. Thus, the trade contemporaneously affects the quote revision, but not vice versa. This fact is reflected by the inclusion of the contemporaneous value of x_t in the quote revision equation, and thus it is assumed that $\mathbb{E}(u_t^r u_t^x) = 0$.

As in Dufour and Engle (2000), the VAR setting in (2) allows the impact of trades on prices and future transactions to be nonlinearly dependent upon trade durations. Furthermore, trades transacted at the market open (i.e. first 30 minutes) are allowed to have different impact from those executed later in the trading day. This time-augmented structure enables one to empirically test the theoretical conjectures in the microstructure literature that the arrival times of trades possess an information content that significantly contributes to the price formation and trade generation processes (Diamond and Verrecchia, 1987, Easley and O'Hara, 1992). In the parameterization (2), the effects of trades on the price evolution and the autocorrelation amongst transactions that are contributed by trading intensity are measured by the δ's, while the additional impact of trades executed at the beginning of the trading day is quantified by the λ's. The joint significance of the δ's and λ's will ascertain the informativeness of trade arrival times in driving price dynamics. We also include the indicator variable open_t in each equation to account for additional opening variations that might come from other sources of information other than trades.

[3]That is, $\mathbb{E}(u_t^r) = 0, \mathbb{E}(u_t^x) = 0$, and $\mathbb{E}(u_t^r u_s^r) = 0, \mathbb{E}(u_t^r u_s^x) = 0, \mathbb{E}(u_t^x u_s^{x\prime}) = 0$ for $s \neq t$.

2.2 Modeling trade durations

A critical assumption that Dufour and Engle (2000) impose on their bivariate VAR framework is that trade arrivals are strongly exogenous; that is, the times of trade arrivals are not influenced by the past histories of prices and trade characteristics but only depend on previous arrival times. Although the strict exogeneity assumption of trade durations is often imposed in the duration modeling literature (e.g. Engle 2000, Xu et al. 2006, Xu et al. 2011, Knight and Ning 2008), it is too restrictive. Theoretical frameworks of Diamond and Verrecchia (1987) and Easley and O'Hara (1992) are built on the notion that time durations between trades are correlated with prices and volumes. Other empirical studies also document that returns, volume and volatility are significant predictors of trade durations (Engle and Russell, 1997, Manganelli, 2005, Russell and Engle, 2005, Nowak and Anderson, 2014). Formally testing the strict exogeneity assumption, Dufour and Engle (2000) also provide strong evidence of its rejection, and thus accentuate the importance of relaxing it, even though they do not attempt to do so.

The exogeneity test of Dufour and Engle (2000) suggests that trade durations should be treated as an endogenous variable that needs to be determined concurrently with quote revisions and trade characteristics. A natural way to endogenize durations is to extend the VAR framework in (2) by adding another equation for durations as below:[4]

$$
\begin{aligned}
r_t &= \alpha^r + \beta^r \text{open}_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r \text{open}_t x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^r \ln(T_{t-i}) + u_t^r, \\
x_t &= \alpha^x + \beta^x \text{open}_t + \sum_{i=1}^{p} a_i^x r_{t-i} + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \lambda^x \text{open}_{t-1} x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^x \ln(T_{t-i}) + u_t^x, \\
\ln(T_t) &= \alpha^T + \beta^T \text{open}_{t-1} + \sum_{i=1}^{p} a_i^T r_{t-i} + \sum_{i=1}^{p} b_i^T |r_{t-i}| + \lambda^T \text{open}_{t-1} x_{t-1} + \sum_{i=1}^{p} \left[\gamma_i^T + \delta_i^T \ln(T_{t-i})\right] x_{t-i} + \sum_{i=1}^{p} c_i^T \ln(T_{t-i}) + u_t^T,
\end{aligned}
\tag{3}
$$

where u_t^r, u_t^x and u_t^T are zero-mean, serially uncorrelated disturbances. Lags of durations, $\sum_{i=1}^{p} c_i^T \ln(T_{t-i})$, are included in the duration equation to account for the autocorrelation of durations. They are also incorporated into the quote revision and trade attribute equations to capture the additional effects of durations. In this so-called "*Endo-VAR*" specification, trade duration depends not only upon its lagged values but also upon the past histories of quote changes and trade characteristics according to an autoregressive structure. The *Endo-VAR* model, which provides a natural and nice layout built upon Hasbrouck's (1991a) framework to investigate the joint dynamics of quote

[4] We do not include the dummy variable open_t, but use open_{t-1} instead, in the duration equation because open_t can only be observed simultaneously with T_t, and hence it is unknown given the past information $\mathcal{I}_{t-1}$.

revisions, trade attributes and durations, can be estimated consistently by ordinary least squares (OLS).

An alternative specification of the marginal distribution of trade durations, $h(T_t|\mathcal{I}_{t-1};\mu_T)$, is similar in spirit to an ACD model proposed by Engle and Russell (1998). These authors show that the ACD model works well in capturing the dynamic structure of trade durations such as duration clustering. The ACD model and a wide range of its variations have been utilized intensively in the duration modeling literature (Bauwens and Giot, 2000, Engle, 2000, Fernandes and Grammig, 2006, Pacurar, 2008). In their analysis, Dufour and Engle (2000) also model time durations with an ACD setting. However, by assuming that durations are strongly exogenous, they do not allow the past dynamics of trade attributes and quote changes to enter the conditional duration specification. The current study relaxes this strict exogeneity assumption by allowing for the dependence of time durations on lagged values of quote revisions and trade characteristics within an ACD framework. Specifically, following Engle and Russell (1998) we firstly remove the deterministic intra-day component of durations using a cubic spline $\varphi(t)$.[5] The diurnally adjusted durations, $\widetilde{T}_t = T_t/\varphi(t)$, are then fitted with the following Weibull ACD (WACD) (p_1, p_2) model:

$$\widetilde{T}_t = [\phi_t \Gamma(1+1/\theta)]\,\epsilon_t, \qquad \epsilon_t \overset{iid}{\sim} \text{Weibull}\left(scale = \frac{1}{\Gamma(1+1/\theta)}, shape = \theta \right), \tag{4}$$

$$\mathbb{E}(\widetilde{T}_t|\mathcal{I}_{t-1},\theta) \equiv \phi_t \Gamma(1+1/\theta), \tag{5}$$

$$\ln(\phi_t) = \alpha^T + \sum_{i=1}^{p_1} a_i^T r_{t-i} + \sum_{j=1}^{p_1} b_i^T |r_{t-i}| + \sum_{i=1}^{p_1} \gamma_i^T x_{t-i} + \sum_{i=1}^{p_1} \rho_i \ln(\widetilde{T}_{t-i}) + \sum_{i=1}^{p_2} \zeta_i \ln(\phi_{t-i}) + \lambda^T \text{open}_{t-1}. \tag{6}$$

We incorporate the opening dummy variable into equation (6) to see if there remains any deterministic opening variation that cannot be fully removed by the diurnalization procedure. Equation (6) explicitly allows for the effects of the past quote changes and trade attributes on durations. Following Bauwens and Giot (2000) and Russell and Engle (2005), we employ a logarithmic variation of the conditional duration equation to ensure the positivity of the conditional expectation of trade durations, especially when additional explanatory variables are included. With this parameterization, the stationarity of the duration series is obtained if and only if $\sum_{j=1}^{p_1} \rho_j + \sum_{j=1}^{p_2} \zeta_j < 1$.

Replacing the duration equation of the *Endo-VAR* model with the WACD(p_1, p_2) model gives us the following *WACD-VAR* system:

[5]The cubic spline we employ is of the form $\varphi(t) = \beta_0 + \beta_1 z_t + \beta_2 z_t^2 + \beta_3 z_t^3 + \sum_{j=1}^{k} \beta_{j+3} \left[(z_t - c_j)^3 \times I_{z_t > c_j} \right]$, where z_t is the clock time of the $t-$th trade, c_j $(j = 1, \cdots, k)$ are the spline knots that we set at 10:30, 11:00, 11:30, 12:00, 12:30, 13:00, 13:30, 14:00, 14:30, 15:00, 15:30, 15:45 since the trading day in our dataset runs from 10:10 to 16:00.

$$
\begin{aligned}
r_t = &\alpha^r + \beta^r \text{open}_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r \text{open}_t x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})] x_{t-i} + \sum_{i=i}^{p} c_i^r \ln(T_{t-i}) + u_t^r, \\
x_t = &\alpha^x + \beta^x \text{open}_t + \sum_{i=1}^{p} a_i^x r_{t-i} + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \lambda^x \text{open}_{t-1} x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})] x_{t-i} + \sum_{i=i}^{p} c_i^x \ln(T_{t-i}) + u_t^x, \\
\widetilde{T}_t = &T_t / \varphi(t) = [\phi_t \Gamma(1 + 1/\theta)] \epsilon_t, \\
\ln(\phi_t) = &\alpha^T + \sum_{i=1}^{p_1} a_i^T r_{t-i} + \sum_{i=1}^{p_1} b_i^T |r_{t-i}| + \sum_{i=1}^{p_1} \gamma_i^T x_{t-i} + \sum_{i=1}^{p_1} \rho_i \ln(\widetilde{T}_{t-i}) + \sum_{i=1}^{p_2} \zeta_i \ln(\phi_{t-i}) + \lambda^T \text{open}_{t-1}.
\end{aligned}
\tag{7}
$$

The estimation of the *WACD-VAR* model is obtained by OLS for the marks (i.e. $(r_t, x_t')'$) and by maximum likelihood for trade durations.

2.3 Modeling the impact of RBA interest rate announcements

Each year, there are eleven scheduled RBA board meetings on the first Tuesday of every month except in January. Since December 2007, the RBA board's decision to change or keep the interest rate has been released to the media at 14:30:00 Australian Eastern Standard Time (GMT + 10) on the same day of the meeting (Smales, 2012). In order to examine how the RBA target rate announcements influence the role of durations and trade attributes in the process of price formation for Australian banking stocks, we modify the *Endo-VAR* model in (3) and the *WACD-VAR* model in (7) to incorporate the information contained by the RBA monetary policy releases. It would be of interest to examine the effects of the *surprise* or *unexpected* component of the news, as in Balduzzi et al. (2001), Kuttner (2001), Andersen et al. (2003), Kim and Nguyen (2008), Smales (2012), among others. In these studies, the unexpected news is calculated as the difference between the actual announcement and the expected component, where the latter is either proxied by the median analyst forecasts (Balduzzi et al., 2001, Andersen et al., 2003) or inferred from interest rate futures prices (Kuttner, 2001, Kim and Nguyen, 2008, Smales, 2012). In addition, since news events are released at some particular point in (calendar) time (e.g. 14:30:00) at which there might not be any transaction being executed, prior research in the literature normally converts transaction time or tick-by-tick data into calendar time data by aggregating trades over some fixed time interval such as a day or 5 minutes to match the occurrence of the news announcements. However, such an aggregation procedure inevitably results in a loss of information and may potentially bias the analysis (Engle, 2000, Russell and Engle, 2005), because, as highlighted in the theoretical work by

Easley and O'Hara (1992) and Diamond and Verrecchia (1987), the existence or absence of each individual trade is informative about the price formation process.

Our analysis is conducted in transaction time. This circumvents the information loss coming from trade aggregation, but this makes it difficult to incorporate information that is released in calendar time at which there are usually no trades (Hamilton and Jordà, 2002, Nowak and Anderson, 2014). To address this issue, we adopt a simple approach that is along a similar line to Ederington and Lee (2001) and Nowak and Anderson (2014) to match calendar time with transaction time. This accounts for the effects of the RBA announcements in our *Endo-VAR* and *WCAD-VAR* specifications by including three announcement indicator variables that record the occurrence of the news events. These dummies, denoted by bef_t, aro_t and aft_t, respectively identify transactions executed five minutes *before* (i.e. 14:24:30-14:29:30), one minute *around* (14:29:30-14:30:30), and ten minutes *after* (14:30:30-14:40:30) the RBA announcements. The length of the event windows chosen in this chapter is suggested by Simonsen (2006) and Nowak and Anderson (2014). The modified models that incorporate the effects of RBA announcements are given by

$$
\begin{aligned}
r_t &= \alpha^r + \beta^r D_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r D_t \otimes x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^r \ln(T_{t-i}) + u_t^r, \\
x_t &= \alpha^x + \beta^x D_t + \sum_{i=1}^{p} a_i^x r_{t-i} + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \lambda^x D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^x \ln(T_{t-i}) + u_t^x, \\
\ln(T_t) &= \alpha^T + \beta^T D_{t-1} + \sum_{i=1}^{p} a_i^T r_{t-i} + \sum_{i=1}^{p} b_i^T |r_{t-i}| + \lambda^T D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} \left[\gamma_i^T + \delta_i^T \ln(T_{t-i})\right] x_{t-i} + \sum_{i=1}^{p} c_i^T \ln(T_{t-i}) + u_t^T,
\end{aligned}
\tag{8}
$$

and

$$
\begin{aligned}
r_t &= \alpha^r + \beta^r D_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r D_t \otimes x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^r \ln(T_{t-i}) + u_t^r, \\
x_t &= \alpha^x + \beta^x D_t + \sum_{i=1}^{p} a_i^x r_{t-i} + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \lambda^x D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})] x_{t-i} + \sum_{i=1}^{p} c_i^x \ln(T_{t-i}) + u_t^x, \\
\widetilde{T}_t &= T_t / \varphi(t) = [\phi_t \Gamma(1 + 1/\theta)] \epsilon_t, \\
\ln(\phi_t) &= \alpha^T + \sum_{i=1}^{p_1} a_i^T r_{t-i} + \sum_{i=1}^{p_1} b_i^T |r_{t-i}| + \sum_{i=1}^{p_1} \gamma_i^T x_{t-i} + \sum_{i=1}^{p_1} \rho_i \ln(\widetilde{T}_{t-i}) + \sum_{i=1}^{p_2} \zeta_i \ln(\phi_{t-i}) + \lambda^T D_{t-1},
\end{aligned}
\tag{9}
$$

where $D_t = (\text{open}_t, \text{bef}_t, \text{aro}_t, \text{aft}_t)'$, β's and λ's are conformable matrices of associated coefficients, and $\otimes$ denotes the Kronecker product.[6]

[6]Note that $D_t \otimes x_t = (\text{open}_t x_t^0, \text{bef}_t x_t^0, \text{aro}_t x_t^0, \text{aft}_t x_t^0, \text{open}_t v_t, \text{bef}_t v_t, \text{aro}_t v_t, \text{aft}_t v_t)'$. The quote revision equation in models (8) and (9) has the following full expression:

$$
r_t = \alpha^r + \beta_{op}^r \text{open}_t + \beta_{be}^r \text{bef}_t + \beta_{ar}^r \text{aro}_t + \beta_{af}^r \text{aft}_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda_{x^0,op}^r \text{open}_t x_t^0 + \lambda_{x^0,be}^r \text{bef}_t x_t^0 + \lambda_{x^0,ar}^r \text{aro}_t x_t^0
$$

3 Data

The current study focuses on all transactions for six major Australian banking stocks, namely ANZ Banking Group (ANZ), Commonwealth Bank of Australia (CBA), National Australia Bank (NAB), Westpac Banking Corporation (WBC), Macquarie Group (MQG) and Bendigo and Adelaide Bank (BEN), in eleven weeks that contain the eleven RBA interest rate announcement days in 2013, which were Feb 5, Mar 5, Apr 2, May 7, Jun 4, Jul 2, Aug 6, Sep 3, Oct 1, Nov 5 and Dec 3. Of these eleven announcements, two reported an interest rate fall of 25 basis points (May 7, from 3% to 2.75% and Aug 6, from 2.75% to 2.5%), and nine reported no changes in the cash rate. In total, there are 54 days in the sample.[7]

Most previous empirical microstructure work uses US data. In contrast, we work with Australian data provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). We choose the Australian market for several reasons. First, unlike the US stock market which has a high degree of market fragmentation with 11 equity exchanges and many alternative trading systems (O'Hara, 2015), the Australian stock market is much less fragmented, which enables a more complete investigation of the joint dynamics of returns, trade attributes and durations. Second, the information about trade direction (which is shown to be an important determinant of the price dynamics (Hasbrouck, 1991a, Dufour and Engle, 2000)) is directly available to traders in Australia but concealed in the US markets. This helps avoid the need to use an indirect procedure to classify buys and sells such as the widely used Lee and Ready's (1991) algorithm which has an accuracy rate of only about 85% (Odders-White, 2000, Lillo et al., 2003). Finally, since the Australian stock market is a limit order book market and so are most major financial markets around the globe (Næs and Skjeltorp, 2006, Goettler et al., 2009, Malinova and Park, 2013), our findings may provide implications for these similarly structured markets.

We collect two datasets from the SIRCA database. The first dataset records details on every order submitted to the central limit order book, including stock code, order type (order submission,

$$+\lambda^r_{x^0,af}\mathrm{aft}_t x^0_t+\sum_{i=0}^{p}\left[\gamma^r_{x^0,i}+\delta^r_{x^0,i}\ln(T_{t-i})\right]x^0_{t-i}+\lambda^r_{v,op}\mathrm{open}_t v_t+\lambda^r_{v,be}\mathrm{bef}_t v_t+\lambda^r_{v,ar}\mathrm{aro}_t v_t+\lambda^r_{v,af}\mathrm{aft}_t v_t$$
$$+\sum_{i=0}^{p}\left[\gamma^r_{v,i}+\delta^r_{v,i}\ln(T_{t-i})\right]v_{t-i}+\sum_{i=1}^{p}c^r_i\ln(T_{t-i})+u^r_t.$$

Full expressions for trade attribute and time duration equations are similarly obtained.

[7] Normally, there are five trading days in a typical week, so we might expect the sample to consist of 55 days. However, Apr 1, 2013, the day before the cash rate announcement in April, was Easter Monday on which the market was closed, which consequently leaves us with a sample of 54 trading days.

order revision, order cancellation and execution), date and time, order price, order volume (number of shares), order value (dollar value), and order direction (buy or sell order). We extract information for all transactions (order executions) in the continuous trading session (from 10:10:00 to 16:00:00) and discard all trades that are performed in the opening auction (10:00:00-10:10:00). We extract buyer-initiated and seller-initiated trades based on the directions of the (marketable) orders that initiate each trade.

The second dataset contains information on the intra-day bid and ask quotes, including stock code, date, time (precise to the millisecond), and the best bid-ask quotes and volumes in the limit order book. We remove all observations with negative bid or ask quote, with zero volume, and with a bid quote higher than ask quote. We merge the transaction data with the bid-ask quote data to work out the bid-ask midpoint and the prevailing depth before each transaction. Since one large buy (sell) order can be matched against several orders on the sell (buy) side and result in multiple transactions, we aggregate trades executed at the same time and initiated by the same order into one "large" trade by summing up the volumes of the simultaneous trades. This aggregation approach, which is standard in the literature (see, amongst others, Hasbrouck, 1991a, Dufour and Engle, 2000, Nowak and Anderson, 2014), leaves us with nearly 900,000 trades for all six stocks during the sample period. All continuous variables in this chapter are winsorized at the 0.5th and 99.5th quantiles to avoid the effects of outliers.

Table 1 provides the market capitalization, as at the beginning of 2013, and some summary statistics for the six banking stocks in 11 RBA announcement weeks (Panel A), on 11 RBA announcement days (Panel B) and on the remaining 43 non-RBA announcement days (Panel C). For the whole sample, the averages of absolute quote revisions, share volumes, volume to prevailing depth ratios and trade durations, together with the number of transactions, for each stock are reported. For smaller subsamples (Panels B and C), the summary is further categorized into five different time intervals, namely opening 30 minutes of the trading day (10:10:00-10:40:00), 5 minutes before the RBA announcement time (14:24:30-14:29:30), one minute around the announcements (14:29:30-14:30:30), 10 minutes after the announcements (14:30:30-14:40:30), and the remaining trading period (10:40:00-14:24:30 and 14:40:30-16:00:00). An asterisk (*) signifies that the average of a quantity of interest in a time interval is statistically significantly different from that of the “Remaining” period at a 5% significance level.[8]

<<INSERT TABLE 1 ABOUT HERE>>

The big four Australian banks, namely CBA, WBC, ANZ and NAB, are much larger and more heavily traded than the other two banks, with an average trade duration between 5.2 and 6.9 seconds. MQG, despite being relatively small, is traded quite intensively at every 8.3 seconds. Trades in the smallest stock, BEN, are much more dispersed and occur once in every 24.9 seconds on average. The majority of transactions in the six banking stocks are of smaller size than the prevailing quoted depths available right before these trades (which, in theory, should not move the best bid or ask levels), since the average volume to depth ratios for all stocks are significantly less than unity. This is consistent with an observation by Dufour and Engle (2000) and Pham et al. (2017) that the majority of trades in their samples do not result in any quote revisions. For all stocks, an average transaction has a volume of 78.8 to 244.8 shares and moves quotes by 0.65 to 2.63 basis points (bps) (see Panel A). In general, the summary statistics are in agreement with the conventional wisdom that trades in more liquid stocks are more frequent and have less impact on prices (e.g. Dufour and Engle, 2000, Lillo et al., 2003).

More interesting features are observed when the whole sample is partitioned into RBA and non-RBA announcement days, as shown in Panels B and C. In both subsamples, stocks are traded much more frequently at the market open than during the reference (“Remaining”) time period. Moreover, trades performed in the first 30 minutes of the day have significantly larger sizes and volume to depth ratios and result in bigger price adjustments. This observation is in conformance with Anand et al. (2005), Bloomfield et al. (2005), and Duong et al. (2009), who show that higher trading intensity observed at the market open is driven by an increased engagement of informed investors whose transactions, according to Easley and O’Hara’s (1992) theory, normally have a large volume and big impact on prices.

On the eleven days when the RBA announces its monetary policy stance, trades are performed with very short durations during the one minute around the announcement time (see Panel B). With the exception of stock BEN regarding time durations, such trades have remarkably smaller

[8]Strictly speaking, reference made to the release time of the monetary policy decisions, such as “before”, “around” and “after” the announcements, is only applicable to days on which such decisions are announced. However, to obtain an overall picture of how the cash rate announcements affect trades and prices, we also examine the same time windows on the non-RBA announcement days as those on the announcement days.

durations, larger volumes, larger volume to depth ratios and bigger price impact than those transacted in the reference period, and even than those executed at the market open in some cases. Similar features (although less noticeable) are also observed for transactions performed within 10 minutes after the news release in comparison to those in the base period, whereas trades that are executed during 5 minutes before the announcement often exhibit opposite characteristics. The summary statistics seem to suggest a relatively tranquil market before the announcement, while market participants are awaiting the RBA interest rate decision. Near the announcement time, the market becomes more active and is very active for one minute around the release of the decision, possibly due to the heightened activities of informed investors. The high trading intensity gradually attenuates as more time elapses after the announcement.

The above trading pattern, however, is not observed on non-RBA announcement days (see Panel C). In particular, transactions executed during the same time intervals (i.e. between 14:24:30 and 14:40:30) typically have larger durations, smaller volumes, smaller volume to depth ratios and less price impact than those performed outside these times, with statistical significance realized in many cases. Most noticeably, trades transacted within one minute around the RBA announcements typically lead to a price impact that is twice as large as that resulting from trades during the same time period on a non-RBA day, while their durations are often a half of the latter's (except for BEN). The contrasting results between RBA and non-RBA announcement samples suggest that the release of the RBA monetary policy decisions has significant effects on the dynamic behaviors of prices, trade attributes and trade arrival times. Such effects are formally investigated in the next section.

4 Empirical Results

In this section, we empirically investigate the joint dynamics of returns, trade attributes (signs and volumes), and trade durations for 6 major Australian banking stocks around interest rate announcements in 2013. We begin with a description of the estimated results for the two joint models, namely *Endo-VAR* and *WACD-VAR*, which are proposed in Section 2 of the current study (subsection 4.1). We then conduct an impulse response analysis to study how the prices of the banking stocks change when there are shocks to the joint system and how the reactions of prices to the shocks depend on the occurrence of an exogenous monetary policy announcement (subsection 4.2). We also provide detailed forecast error variance decomposition that compares the relative importance of trade durations and trade attributes to the explanation of price dynamics (subsection 4.3).

4.1 Estimation results

4.1.1 *Endo-VAR* models

We begin with the estimation of the *Endo-VAR* model (**??**) for a representative stock NAB and discuss this in detail before presenting results for the remaining five stocks. Since one of the main objectives of the current study is to relax the strict exogeneity assumption that is often imposed on durations in previous studies (e.g. Dufour and Engle, 2000, Engle, 2000, Xu et al., 2006), we draw attention to the duration equation of the estimated *Endo-VAR* model, reported in Table 2 using the whole sample period of eleven RBA announcement weeks. We compute Student's t (in parentheses) and Wald statistics using the Newey and West (1994) robust standard errors, and use bold format to signify statistical significance at a 5% level. As expected, trade durations are positively and persistently autocorrelated (see coefficients on $\ln(T_{t-i})$), which implies the clustering feature inherent in the duration process: long (short) durations tend to follow long (short) durations. This stylized fact is widely seen and documented in numerous empirical studies on durations (Engle and Russell, 1998, Engle, 2000, Russell and Engle, 2005).

<<INSERT TABLE 2 ABOUT HERE>>

The observation that trade durations are correlated with price adjustments and trade attributes is of particular interest here, given the focus on the possible endogeneity of the time between trades. We find that the magnitude of price changes or the variation in prices, rather than the direction of price moves, is informative about the durations of future trades since the coefficients of absolute returns, $|r_{t-i}|$, are highly significant, whereas those of raw returns, r_{t-i}, are not. A positive coefficient sum of past absolute returns implies that larger price adjustments increase future trade durations. This is in conformance with the predictions from the Admati and Pfleiderer's (1988) theoretical model and the empirical findings of Grammig and Wellner (2002) and Wei and Pelletier

(2015) that show a positive feedback effect of past volatility on future durations. However, it appears to be inconsistent with Manganelli (2005) and Russell and Engle (2005), who document an opposite result. If big variation in quote midpoints is interpreted by market participants as a result of informed trades, then the presence of informed agents in the market might discourage uninformed investors from trading and reduce the likelihood of trades (Admati and Pfleiderer, 1988, Grammig and Wellner, 2002). Consequently, trade durations might be longer following large price changes.

Past trading volumes are also an important predictor of the time between trades. Negative and strongly significant coefficients and coefficient sums of previous trade sizes imply that larger transactions shorten the duration of incoming trades. This lends support to Easley and O'Hara (1992), who hypothesize that large trades are more likely to be initiated by informed traders who always trade to capitalize on new information. Thus, large transactions are likely to lead to higher trading rates and, consequently, shorter durations. The negative relationship between durations and trading volumes is also found in previous empirical studies such as Bauwens and Giot (2000), Manganelli (2005), and Nowak and Anderson (2014).

The positive coefficient on trade sign, x^0_{t-1}, suggests that it takes longer time for a trade to occur when it is preceded by a purchase than by a sale. Moreover, the positive serial dependencies of time durations are stronger for buyer-initiated trades but weaker for seller-initiated ones, as implied by the significantly positive coefficient on $x^0_{t-1}\ln(T_{t-1})$. However, the asymmetry in the autocorrelation of trade durations between buys and sells appears short-lived, and so do the effects of trade signs on future trade durations, as suggested by the insignificance of the coefficient sums of $x^0_{t-i}\ln(T_{t-i})$ and x^0_{t-i}, respectively. While there is evidence that trading intensifies at the market open, no similar evidence is observed around the RBA announcements since the coefficients on the RBA announcement dummies and their interactions with trade characteristics are not significant, even though they are generally of expected signs and are economically meaningful in comparison with the corresponding coefficients on the open_t dummy. This result is surprising, given the clear pattern shown in Table 1 that durations between trades in stock NAB are significantly shorter during the one minute around the RBA interest rate releases. Perhaps, however, the unconditional pattern in trade durations around the RBA announcements simply reflects those in the marks (i.e. returns and trade attributes) and thus disappears when one conditions on the latter.

We now examine the dynamics of prices by looking at the equation for quote revisions. The results are reported in Panel A of Table 3 that uses the whole eleven RBA announcement week sample. Consistent with previous studies such as Hasbrouck (1991a,b) and Dufour and Engle (2000), price changes are negatively serially correlated, as indicated by a negative first lag coefficient. Meanwhile, a signed trade positively affects prices in the sense that a buy leads to an upward adjustment in prices while a sell drags prices down. The price impact of a trade in stock NAB is influenced by both the direction (x_t^0) and the volume (v_t) of the trade, which is consistent with the findings of Hasbrouck (1991a,b). Immediately following a buy with an average volume to depth ratio of 0.417 and an average duration of 6.906 seconds (i.e. an average buy, see Table 1), the price of stock NAB is lifted up by 0.984 bps, assuming that the buy is executed during the reference time period (i.e. not at the market open or during the 16-minute window around an RBA interest rate announcement).[9] Meanwhile, the coefficients on lagged trade signs and lagged volumes are generally negative but are much smaller in magnitude compared to the contemporaneous coefficients, implying that the cumulative price impact of a buy remains strongly positive.

<<INSERT TABLE 3 ABOUT HERE>>

We find a significant role for the time of trade arrivals in the process of price formation for stock NAB, lending support to Diamond and Verrecchia (1987), Easley and O'Hara (1992), Dufour and Engle (2000) and Xu et al. (2006). As implied by the significantly negative contemporaneous coefficients and coefficient sums of the interactions between trade attributes and durations, the price impact of a trade is negatively dependent on its duration, suggesting that prices adjust more following a trade that has a shorter duration. The explanation is that shorter time between trades or higher trading intensity is inferred by the market maker as a signal of more private news being released to the market and the increased presence of informed traders to exploit such information (Easley and O'Hara, 1992, Dufour and Engle, 2000). Since a higher probability of informed trading discourages liquidity providers, possibly via toxic order flows that adversely select the latter (Easley et al., 2011, 2012), trades result in larger price adjustments. In addition, there is some positive direct impact of durations on price changes which suggests that prices tend to adjust upward after

[9] $0.984 = \underbrace{-0.002}_{\text{const}} + \underbrace{1.227}_{x_t^0} - \underbrace{0.031 \times \ln 6.906}_{x_t^0 \ln(T_t)} + \underbrace{0.219 \times \ln 0.417}_{v_t} - \underbrace{0.006 \times \ln 0.417 \times \ln 6.906}_{v_t \ln(T_t)}$. Note that v_t is calculated as the signed logarithm of the volume to depth ratio of the t-th transaction.

a long time interval from a previous trade, as indicated by a positive sum of coefficients on $\ln(T_{t-i})$. However, this positive direct dependence is relatively weak and dominated by the negative indirect influence of durations on prices (which is a portion of the price impact of a trade captured by the interaction terms $x_t^0 \ln(T_t)$ and $v_t \ln(T_t)$), leading to an overall negative relation between price changes and trade durations, which supports Easley and O'Hara's (1992) theory.

The price impact of a trade also exhibits a diurnal pattern. Purchases (sales) that are performed within the first 30 minutes of a trading day raise (reduce) prices markedly more than do those executed during the reference period, as shown by the positive coefficients on $x_t^0\text{open}_t$ and $v_t\text{open}_t$. This can be explained by higher trading intensity induced by a larger proportion of informed traders who are trying to capitalize on relatively more information that has accumulated overnight being revealed to the market in the early morning (Anand et al., 2005, Bloomfield et al., 2005, Duong et al., 2009, Pham et al., 2017). Since prices move more with higher informed trading rates, the price impact of a trade is higher at the beginning of the trading day.

The RBA monetary policy announcements significantly affect the price impact of a trade, through both sign and size channels. While trades performed within five minutes before the release of monetary decisions result in a price impact that is statistically indistinguishable from that of those occurring during the reference time window, trades executed within one minute around the announcement and during the subsequent ten minutes affect prices significantly more. Practically, an average buy in stock NAB transacted one minute around (ten minute after) the announcements immediately raises the quote midpoint by about 1.206 bps (0.239 bps) higher than, or equivalently 2.23 times (1.24 times) as high as, does a similar purchase arriving during the reference time period.[10] Trades around the announcements are even more informative than those at the market open, suggesting a higher concentration of informed traders during the one minute around the interest rate releases than at the market open. It appears that informed investors await the interest rate decisions from the RBA and thus are relatively inactive five minutes before the announcement. As time draws closer to 14:30:00 - the scheduled release time, more information is revealed, inducing a higher likelihood of informed traders. The presence of informed market participants is highest during the one minute around the release, and gradually decreases in the next ten minutes when

[10] $1.206 = \underbrace{0.182}_{\text{aro}_t} + \underbrace{1.310}_{x_t^0\text{aro}_t} + \underbrace{0.327 \times \ln 0.417}_{v_t\text{aro}_t}$, and $0.239 = \underbrace{0.004}_{\text{aft}_t} + \underbrace{0.319}_{x_t^0\text{aft}_t} + \underbrace{0.096 \times \ln 0.417}_{v_t\text{aft}_t}$. Note that the immediate price impact of an average buy executed in the reference period is 0.984 bps (see Footnote 9).

more information is incorporated into prices. Consequently, trades occurring within one minute around the announcements have the greatest impact on prices.

To further highlight the impact of the monetary announcements on prices of stock NAB, we re-estimate the return equation of the *Endo-VAR* model using data on the non-RBA announcement days of our sample only. The results are reported in Panel B of Table 3. On non-RBA announcement days, the effects of trade characteristics and time durations on quote revisions for stock NAB remain qualitatively similar to those previously discussed. Differences, however, are found when looking at the 16-minute window that corresponds to the announcement time period on the announcement days. On days with no monetary policy releases, trades performed within the 16-minute period typically have a smaller impact on prices than those executed in the reference period, reflecting a typical diurnal pattern on a normal day (see Table 1). This result thus confirms the important information content of the interest rate announcements that significantly affect prices of stock NAB, which is in agreement with previous findings such as Kim and Nguyen (2008) and Smales (2012).

Regarding the estimation for trade attributes which is tabulated in Table 4, trades exhibit a strong positive serial correlation structure, both in terms of direction and volume. This pattern is typically observed in empirical applications (e.g. Hasbrouck, 1991a, Dufour and Engle, 2000, Manganelli, 2005), and it suggests a clustering feature inherent in a trade series. In particular, buyer-initiated (seller-initiated) trades tend to follow buyer-initiated (seller-initiated) trades, and large (small) transactions tend to induce large (small) transactions. Moreover, there is a significant bilateral Granger-causal relationship between trade directions and volumes, as well as strong Granger-causality running from quote revisions to trade characteristics, which is in conformance with the findings of Hasbrouck (1991a). Consistent with Dufour and Engle (2000), trade signs become more positively autocorrelated when time durations between trades get shorter, as reflected in Panel A of Table 4 by a significantly negative coefficient on $x^0_{t-1}\ln(T_{t-1})$ at the first lag, even though the coefficient sum is not significant. Similarly, not only does higher trading intensity or shorter trade duration induce larger future transactions (see the coefficients on $\ln(T_{t-i})$ in Panel B - which is in harmony with Easley and O'Hara's (1992) theory that predicts a negative association between trade durations and trading size), but it also strengthens the positive autocorrelation of trading volumes, as evidenced by the coefficients on $v_{t-i}\ln(T_{t-i})$ in Panel B.

<<INSERT TABLE 4 ABOUT HERE>>

From Tables 2-4, the Ljung-Box statistics suggest that the *Endo-VAR* model appears to capture most of the dynamics of the joint system by filtering out most of the serial correlation exhibited in the raw series. However, there is still significant autocorrelation in the residuals for trade direction, size and duration. For all four equations, the residuals are not normally distributed, as shown by large Jarque-Bera statistics. Nevertheless, significant Wald test statistics at a 5% level again confirm the role of time in explaining the price and trade formation processes.

We now investigate the results for the remaining stocks. Since our main interest is on the dynamics of prices and trade durations as well as on how the interest rate announcements affect these quantities, we only report the results for the quote revision and duration equations in Tables 5 and 6 respectively, using the whole sample of eleven RBA announcement weeks. The results for these stocks' trade attributes are qualitatively similar to those for stock NAB.

<<INSERT TABLES 5 & 6 ABOUT HERE>>

The dynamic behavior of prices and trade durations for the other Australian banking stocks is qualitatively similar to that for stock NAB. For example, Table 6 shows that the time between trades exhibits a persistent positive dependence structure and is positively related to past volatility while negatively linked to trading volumes (except for WBC). From Table 5, a trade has a significant impact on prices which is contributed by both trade direction and trading volume channels and negatively related to trade durations. Trades performed within one minute around the RBA announcement have higher price impact, although statistical significance is not obtained for WBC. However, there are some important differences with regard to the duration dynamics shown in Table 6. First, in contrast to other stocks it takes less (similar) time, instead of more time, for a trade in stock BEN (MQG) to occur when it is preceded by a purchase rather than a sale. Second, there is some evidence that time durations for stocks ANZ, WBC and MQG are significantly shorter within one minute around the RBA monetary policy releases (see the coefficients on aro_t), which is consistent with the duration pattern observed in Table 1 and implies a higher concentration of informed agents around the announcements that consequently increases the probability of trades in these stocks.

Overall, we find strong evidence of the endogeneity of trade durations, supporting the theories of Diamond and Verrecchia (1987) and Easley and O'Hara (1992). In particular, larger past trading volumes and smaller past volatility tend to shorten subsequent trade durations. Further, the price impact of a signed trade is positive, contributed by both trade direction and trading volumes, and negatively related to trade durations. Higher trading intensity or shorter trade duration not only increases the price impact of a trade but also strengthens the positive serial correlation of trade characteristics. Moreover, the release of the RBA monetary policy decisions significantly affects the joint system of trade arrival times and the associated marks of interest, with trades executed within one minute around the announcement time typically being more informative about prices (i.e. having a larger price impact) and having shorter durations.

4.1.2 *WACD-VAR* models

Although the VAR framework is able to capture the internal dynamics of the joint system of durations and the marks, it does not seem to find changes in the pattern of trade durations around the interest rate announcements, especially for NAB and CBA. We now examine if the WACD model, which is widely used in the duration modeling literature, finds evidence of such changes. The estimated WACD(2,1) models for six Australian banking stocks in eleven RBA announcement weeks in 2013 are reported in Table 7. Panel A shows the results when the strict exogeneity assumption of trade durations is imposed (as in Dufour and Engle (2000) and Xu et al. (2006)), while Panel B reports the results when this assumption is relaxed. From both panels, all autoregressive parameter estimates for durations and conditional durations are highly significant and sum up to between 0.938 and 0.994 for all stocks, suggesting that the duration process is strongly persistent, which is consistent with the results from the estimated *Endo-VAR* models. The estimate for the Weibull parameter, θ, ranges between 0.44 and 0.51 and is significantly less than one. This implies an overdispersed distribution for the time between trades - a stylized fact typically observed in empirical duration data (Engle and Russell, 1998, Bauwens and Veredas, 2004, Renault and Werker, 2011, Renault et al., 2014), and it suggests that the use of an exponential distribution with unit mean (i.e. $\theta = 1$), which implies equi-dispersion, to model trade durations is deficient.

<<INSERT TABLE 7 ABOUT HERE>>

From Panel B, most the parameter estimates for trade attributes and absolute returns (a proxy for volatility) are highly statistically significant, indicating that these variables are important predictors of trade durations, which in turn invalidates the strict exogeneity assumption of durations typically imposed in the literature. Consequently, the incorporation of these additional variables into the conditional duration model improves the log likelihood of the model markedly; and it is easy to verify that likelihood ratio (LR) tests strongly support the endogenous duration model. Consistent with the *Endo-VAR* model, it is the magnitude of price changes, rather than the direction of price adjustments, that is informative about the (conditional) durations of future trades. The lag-one coefficients of absolute returns are positive, implying that conditional trade durations increase with larger price adjustments. However, they are almost offset by the negative lag-two coefficients, suggesting that conditional trade durations will be higher the larger the change in quote revisions (i.e. the second order difference in prices). While conditional time durations tend to be larger if the last trade is a buy than a sell for four stocks ANZ, CBA, NAB and WBC, the reverse is observed for BEN, and there appears to be no relation between the conditional durations and trade signs for MQG. However, similar to the effect of quote revisions on durations, it appears that big changes in the direction of previous trades lengthen future durations. Conversely, larger trading volumes and bigger volume changes for all stocks (except WBC) induce higher future trading intensity, and thus reduce time durations, which is in agreement with previous studies such as Bauwens and Giot (2000), Manganelli (2005) and Nowak and Anderson (2014).

There is evidence that the RBA interest rate announcements have significant impact on trade durations. In particular, trades in stocks other than BEN that occur within one minute around the announcement lead to higher future trading intensity, and hence are followed by trades that have shorter durations. This is in line with the findings of Nowak and Anderson (2014) that airline stocks in the U.S. are more frequently traded around the release of macroeconomic news. Meanwhile, the insignificant coefficients of bef_{t-1} and aft_{t-1}, which respectively signify 5 minutes before and 10 minutes after the interest rate release, suggest that there appears to be no information leak prior to the announcement and the information content of the news release is quickly absorbed within one minute. There is also evidence that trades performed at the market open have shorter conditional durations than those executed at other times, even though trade durations have been diurnally adjusted using a cubic spline. Thus, it seems that intraday periodicities have not been totally removed by the spline. In addition, although most of the serial autocorrelation associated with adjusted trade durations is explained by the conditional duration equation, the residuals of the model are still strongly autocorrelated. A deeper lag structure may be required.

4.2 Impulse response analysis

We now examine how prices evolve if there are shocks to the trade, duration, and/or return equation(s) of the system at an event time t. Conditioning on all information up to the transaction time $t-1$, $\mathcal{I}_{t-1}$, the best guess of the value of the quote revision h periods after unexpected shocks to trade attributes, trade durations, and/or returns at time t is its conditional expectation $\mathbb{E}\left(r_{t+h}|\varepsilon_t = \varepsilon, \mathcal{I}_{t-1}\right)$ given the shock vector ε_t, which is $(u_t^r, u_t^{x\prime}, u_t^T)'$ if the joint system is *Endo-VAR* and $(u_t^r, u_t^{x\prime}, \epsilon_t)'$ if the joint system is *WACD-VAR*. However, if there is no shock at time t, the quote revision h periods later is expected to be $\mathbb{E}\left(r_{t+h}|\mathcal{I}_{t-1}\right)$. The impact of the unanticipated trade, duration, and/or return shocks at t on quote revisions after h periods is calculated as the difference between the two conditional expectations, denoted by $I_r(\cdot)$, when all other current and future shocks (for r_t, x_t and T_t) are integrated out. That is,

$$I_r(h, \varepsilon, \mathcal{I}_{t-1}) = \mathbb{E}\left(r_{t+h}|\varepsilon_t = \varepsilon, \mathcal{I}_{t-1}\right) - \mathbb{E}\left(r_{t+h}|\mathcal{I}_{t-1}\right), \tag{10}$$

defines a *generalized impulse response* function (GIRF) for quote revisions r_t which was initially proposed by Koop et al. (1996). GIRFs generated by a multivariate system typically depend on the past history $\mathcal{I}_{t-1}$ before the system is shocked and the size and sign of the shocks hitting the system at time t (Koop et al., 1996, Pesaran and Shin, 1998, Lanne and Nyberg, 2016). Since quote revisions and trade attributes are nonlinearly linked to time durations via either the *Endo-VAR* or the *WACD-VAR* system, the impulse response function specified in (10) is also nonlinear. To calculate $I_r(\cdot)$, we follow Koop et al. (1996) and Dufour and Engle (2000) to simulate all possible trajectories for $(r_{t+k}, x_{t+k}, T_{t+k}), k = 0, 1, ..., h$ that share the same initial information set, $\mathcal{I}_{t-1}$, with and without the shock(s) at t. The impulse response $I_r(\cdot)$ is computed by averaging the realizations obtained from all trajectories. Steps to compute $I_r(\cdot)$ are described in more details in Appendix A.

In the subsequent analysis, we will examine how prices of each stock evolve under the following two scenarios: (1) there is an unanticipated purchase (i.e. sign shock = +1, while other shocks including return, volume and duration shocks are integrated out); and (2) there is an unanticipated purchase with a one standard deviation duration shock. We consider both positive and negative duration shocks in the latter scenario.[11,12] In order to see how the release of RBA interest rate decisions affects prices, we shock the system on days with and without the monetary policy announcements. Since the GIRFs of a nonlinear system are dependent on the state of the system at time $t-1$ before being shocked (Koop et al., 1996, Pesaran and Shin, 1998, Lanne and Nyberg, 2016) and there are many RBA and non-RBA announcement days in the current sample, we shock the joint system of quote revisions, trade attributes and trade durations conditioning on a *hypothetical* average RBA announcement time (RBAAT) and non-RBAAT histories. A hypothetical average RBAAT (non-RBAAT) history for each stock is defined as an equally weighted average of all histories right before the interest rate release time, 14:30:00, on the eleven RBA (forty-three non-RBA) announcement days in the current sample for that stock. Conditioning on the history and shock vectors, the simulation is conducted for $h = 300$ steps into the future with $N = 10,000$ repetitions.

The cumulative quote changes for stock NAB following an unanticipated purchase with either (i) no duration shock, (ii) a positive one standard deviation duration shock, or (iii) a negative one standard deviation duration shock are plotted in Panels (a), (b), and (c) of Figure 1, respectively.[13] In addition to reporting the cumulative price impact produced by the *Endo-VAR* and *WACD-VAR* systems, we also chart those for the augmented Dufour and Engle (2000) exogenous-duration VAR model (i.e. with volume incorporated) for comparison.[14] These impulse responses are pictured in

[11] Since the *Endo-VAR* system assumes an additive error model for durations, while the *WACD-VAR* framework differs and specifies durations with a multiplicative error model, a one standard deviation positive (negative) duration shock is defined as $\widehat{\sigma}^T_{Endo-VAR}$ ($-\widehat{\sigma}^T_{Endo-VAR}$) for the former system, but as $\widehat{\sigma}^T_{WACD-VAR}$ ($1/\widehat{\sigma}^T_{WACD-VAR}$) for the latter.

[12] These two scenarios enable us to see how an unexpected buy affects prices if it arrives as quickly as expected, slower than expected, or more quickly than expected.

[13] We employ the estimated joint system using the whole sample of eleven RBA announcement weeks in all simulation experiments.

[14] The original Dufour and Engle (2000) VAR framework contains only two equations for quote revisions and trade signs and does not include RBA dummy variables. However, an augmented Dufour and Engle (2000) framework that incorporates another equation for trading volumes as well as the RBA dummy variables is employed. By allowing all three systems to have comparable trade attribute information (i.e. sign and size), the differences amongst the cumulative price impacts obtained from these systems can be attributed to the differences in their treatments of durations and/or to the effects of RBA announcements. The augmented Dufour and Engle (2000) model is given

both transaction time and calendar time starting from the conditioning trade that occurs immediately before 14:30:00 of the average RBAAT or non-RBAAT history. To convert the cumulative price impact from transaction time to calendar time, we follow Dufour and Engle (2000) to exploit the simulated trade duration series under the "shock" scenario (discussed in Points (A.2) and (A.3) in the Appendix A) to sample the cumulative quote changes every five seconds, and then we compute averages.

<<INSERT FIGURE 1 ABOUT HERE>>

Panel (a) of Figure 1 reveals that, for all models, after an unexpected purchase prices initially increase considerably and then taper off relatively quickly after about 10 transactions or 1 minute. As expected, prices respond more strongly to the unanticipated buy at around the announcement time on an average RBA announcement day than at the equivalent time on days when there is no interest rate release. In particular, while the unanticipated purchase performed around 14:30:00 in the average non-RBAAT history raises prices of stock NAB by about 1.5 bps in the long run, a twice-as-large permanent price increase (of about 2.7 bps) results from the same trade in the average RBAAT history, which suggests that trades at around the RBA announcement time are more informative about the price formation process. The result is consistent with the fact that there is higher trading intensity (i.e. shorter trade duration) around the release of the monetary policy news at 14:30:00 on the RBA days than around the corresponding time window on the non-RBA days (see Table 1). Since a higher trading rate or shorter duration implies a higher probability of informed traders in the market (Easley and O'Hara, 1992, Dufour and Engle, 2000), trades around RBA announcements have larger impact on prices. For each average history, there are negligible differences in the cumulative quote revisions produced by three models that augment the information of trade arrival times, namely the *Endo-VAR*, *WACD-VAR* and extended Dufour and Engle (2000) models. Given that there is no duration shock to the systems and the

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by

$$r_t = \alpha^r + \sum_{i=1}^{5} a_i^r r_{t-i} + \lambda^r S_t x_t + \sum_{i=0}^{5} \left[\gamma_i^r + \delta_i^r \ln(T_{t-i})\right] x_{t-i} + u_t^r,$$
$$x_t = \alpha^x + \sum_{i=1}^{5} a_i^x r_{t-i} + \lambda^x S_{t-1} x_{t-1} + \sum_{i=1}^{5} \left[\gamma_i^x + \delta_i^x \ln(T_{t-i})\right] x_{t-i} + u_t^x,$$
$$\widetilde{T}_t = T_t/\varphi(t) = \left[\phi_t \Gamma(1 + 1/\theta)\right] \epsilon_t,$$
$$\ln(\phi_t) = \alpha^T + \rho_1 \ln(\widetilde{T}_{t-1}) + \rho_2 \ln(\widetilde{T}_{t-2}) + \zeta_1 \ln(\phi_{t-1}) + \lambda^T D_{t-1}.$$

main differences amongst these three models lie in their treatment of durations, this result is not surprising.

The impact on prices when the aforementioned joint systems are disturbed with a duration shock from an unexpected purchase is depicted in Panels (b) and (c) of Figure 1. Overall, the comparison of the cumulative quote revisions for stock NAB conditioning on the average RBAAT and non-RBAAT histories remains qualitatively unchanged in the sense that an unexpected buy with a duration shock that occurs right before the monetary policy release conveys more information about prices and hence has higher price impact than does a comparable buy transacted on a no-news day. In addition, there are almost no changes to the shape and level of the cumulative GIRFs for quote revisions produced by the three time-augmented VAR systems based on the average non-RBAAT history, either with or without the duration shock. It appears that the informativeness of trade durations about prices is negligible for trades executed at around 14:30:00 on non-RBA days, during which the market is relatively tranquil (see Table 1). This lends support to the Easley and O'Hara (1992) theory which demonstrates that long trade durations neither imply the appearance of informed traders nor news, and hence they have little impact on prices.

Interestingly, conditioning on the average RBAAT history, the cumulative price impact functions of an unexpected purchase with a duration shock implied by the augmented Dufour and Engle (2000) model are almost the same as those under no duration shock. Although it highlights a significant difference in the response of prices to an unanticipated trade that comes from different trading histories (e.g. active versus inactive histories), the augmented Dufour and Engle (2000) model seems to suggest a minimal role for duration shocks in explaining prices, once the history before the shocks has been taken into account. This might be a consequence of the exogeneity assumption of trade durations imposed by the model.

When the exogeneity of durations is relaxed, we observe some differences in the shape and/or level of the cumulative quote revisions around the RBA announcements. In particular, when the duration shock is positive and an unexpected trade arrives slower than expected, the two endogenous-duration models (i.e. *Endo-VAR* and *WACD-VAR*) show an initial surge in the cumulative price impact, followed by a gradual decline to the equilibrium level (which is about 0.9 bps lower than the steady state when there is no duration shock) after about 60 transactions or about 11 minutes. When the duration shock is negative and an unanticipated trade occurs more quickly than expected, prices adjust more strongly according to the *Endo-VAR* model, with the accumulation of quote revisions of roughly 3.4 bps in the long run (approximately 0.7 bps higher than that under no duration shock). Surprisingly, such a large price increase is not observed for the *WACD-VAR* system. Generally, the result suggests an overall negative relationship between trade durations and quote revisions, even after controlling for the history: given the average RBAAT history, trades possess a richer (poorer) information content about prices when they arrive sooner (later) than expected, which is in conformance with Easley and O'Hara's (1992) theory. However, this result is obtained only when trade durations are endogenously determined.

The cumulative impulse response functions of quote revisions to different shock scenarios for the remaining banking stocks are plotted in Figure 2. Consistent with the conventional wisdom, Figure 2 shows that the more liquid a stock, the smaller the price impact of a trade (compare the scales on the vertical axis of the plots). In general, the long-run price impact functions for other banking stocks exhibit qualitatively similar features to those for stock NAB. Specifically, the cumulative quote changes of an unanticipated purchase executed around the RBA announcements is generally higher than that of a comparable trade occurring at a similar time on a no-news day (except for stock WBC). Moreover, when there is no duration shock, the differences in the long-run price impact of an unanticipated purchase produced by the time-augmented VAR models (i.e. the *Endo-VAR*, *WACD-VAR* and extended Dufour and Engle (2000) models) conditioning on the same history are negligible, except for stock BEN (see the left plots). However, when an unexpected buy is accompanied by a one standard deviation duration shock, prices typically respond less (more) strongly (i.e. the long run price impact is lower (higher)) when the shock to durations is positive (negative) than do they without the duration shock, except for stock MQG (see the middle (right) plots). This observation is only obtained when one conditions on an average history for an RBA announcement day and utilizes a joint specification that allows for the endogeneity of trade durations such as the *Endo-VAR* or *WACD-VAR* model.[15]

<<INSERT FIGURE 2 ABOUT HERE>>

Overall, the impulse response analysis for quote revisions confirms the previous findings in the literature that the time of trade arrivals conveys important information about prices (Diamond and

[15] Note, however, that a negative duration shock leading to higher long-run price impact is only obtained using the *Endo-VAR* model.

Verrecchia, 1987, Easley and O'Hara, 1992) and that trades have a larger price impact when the time durations between trades are shorter (Easley and O'Hara, 1992, Dufour and Engle, 2000). In addition, we find that trades transacted around the release of monetary policy news possess more important information about prices and have larger price impacts than do comparable trades on non-RBA days. If there is no duration shock to the system, the cumulative price impact of an unanticipated trade is almost the same, regardless of whether or not trade durations are endogenously modeled. However, when the unexpected trade is accompanied by a duration shock, the long-run price impact of the trade whose duration is treated as exogenous is quite different, in terms of shape and/or level, to that when its duration is endogenously determined. In particular, after controlling for the trading history prior to the interest rate announcements, the permanent price impact of a trade is higher (lower) when there is a negative (positive) duration shock if trade durations are endogenous, and yet it will be almost the same if durations are assumed to be exogenous.

4.3 Forecast error variance decomposition analysis

The previous impulse response analysis demonstrates that both trade durations and trade attributes convey important information about prices to the market. However, the impulse response methodology does not directly estimate the relative importance of each trade attribute in the overall price formation process. We now quantify their relative importance, which helps answer the question of whether a trade duration contributes more to the process of price formation than other trade attributes by decomposing the forecast error variance of quote revisions into portions that are accounted for by innovations in each trade characteristic, including its duration.

Forecast error variance decomposition (FEVD) of a weakly stationary linear VAR model is often computed from an infinite-order vector moving average (VMA) representation of the model with orthogonal shocks, assuming that suitable identification restrictions to recover the structural shocks from the reduced-form errors are available. However, since our *Endo-VAR* and *WACD-VAR* models, as well as the original and volume-augmented Dufour and Engle (2000) models, are nonlinear multivariate systems for which a VMA equivalent does not exist, the traditional orthogonalized FEVD cannot be applied. Instead, we employ the generalized FEVD (GFEVD) method proposed by Lanne and Nyberg (2016) that mimics the traditional orthogonalized FEVD by replacing the orthogonal impulse response functions with the GIRFs that are calculated based on the notion that only one equation of the multivariate system is shocked at a time. By construction and similar to the traditional orthogonalized FEVD, Lanne and Nyberg's (2016) GFEVD features a nice property that the proportions of the forecast error variance of the h-period forecast of a variable that are accounted for by innovations in all variables in the system always sum to unity, facilitating the economic interpretation.[16] Conditioning on a history $\mathcal{I}_{t-1}$, Lanne and Nyberg (2016) define the contribution of shocks to variable i to the forecast error variance of the h-period forecast of variable j, denoted by $\lambda_{i\to j,\mathcal{I}_{t-1}}(h)$, in a K-dimensional multivariate system of the form $y_t = G(y_{t-1}, y_{t-2}, \cdots, y_{t-p}; \mu) + \eta_t$, where $G(\cdot)$ is some linear or nonlinear function characterized by the parameter vector μ, as

$$\lambda_{i\to j,\mathcal{I}_{t-1}}(h) = \frac{\sum_{k=0}^{h} I_j(k, \eta_{i,t} = \delta_i, \mathcal{I}_{t-1})^2}{\sum_{i=1}^{K}\sum_{k=0}^{h} I_j(k, \eta_{i,t} = \delta_i, \mathcal{I}_{t-1})^2}, \qquad i, j = 1, 2, \cdots, K, \tag{11}$$

and $I_j(k, \eta_{i,t} = \delta_i, \mathcal{I}_{t-1}) = \mathbb{E}\left(y_{j,t+k}|\eta_{i,t} = \delta_i, \mathcal{I}_{t-1}\right) - \mathbb{E}\left(y_{j,t+k}|\mathcal{I}_{t-1}\right), k = 0, 1, 2, \cdots, h$, is the GIRF of the j-th variable k periods after a shock at time t of size δ_i to the i-th variable, given the past history $\mathcal{I}_{t-1}$, where all other contemporaneous and future shocks are integrated out; and K is the number of variables in the system. The GFEVD is often calculated by averaging $\lambda_{i\to j,\mathcal{I}_{t-1}}(h)$ over shocks δ_i that are bootstrapped from the residuals, over all histories $\mathcal{I}_{t-1}$. However, if interest is drawn to a particular subset of shocks and/or histories, the conditional GFEVD can also be computed.

We note that Lanne and Nyberg's (2016) GFEVD is different from the efficient price variance decomposition (Hasbrouck, 1991b) and the information share methodology (Hasbrouck, 1995), which are widely used in the microstructure literature to compare the information contributions of different trader groups or different markets to price discovery (e.g. Barclay et al., 2003, Hendershott and Riordan, 2011, Benos and Sagade, 2016, Brogaard et al., 2018). In both Hasbrouck's methods, the observed price or midpoint is written as the sum of an unobserved random walk (which is equated with the permanent efficient price) and an unobserved stationary component (considered

[16] Lanne and Nyberg (2016) modify the original GFEVD proposed by Pesaran and Shin (1998) (which was developed for a linear Gaussian VAR model) to address a shortcoming of the latter that is that the forecast error variance proportions generally do not add up to 1, as a consequence of the potential contemporaneous correlatedness amongst the reduced-formed innovations. Moreover, Lanne and Nyberg's (2016) GFEVD can be applied to any linear or nonlinear, Gaussian or non-Gaussian model for which GIRFs can be computed.

as transient noise). The total price discovery is defined as the variance of the efficient price innovations, whereas the transient disturbance, which might be correlated with the efficient price, is effectively ignored. Hasbrouck's methodologies rely on a critical assumption that there exists a ***linear*** stationary VAR that links price changes or returns with other trade-related information (Hasbrouck, 1991b) or a ***linear*** vector error correction model (VCEM) that connects different price series closely related to a single security (Hasbrouck, 1995). Consequently, Hasbrouck's price discovery decomposition can be straightforwardly calculated from a VMA equivalent of the linear VAR or VECM. However, if the VAR or VECM is nonlinear such that its VMA representation cannot be obtained, it is not clear how Hasbrouck's price discovery decomposition can be computed.

In contrast, GFEVD decomposes the forecast error variance (FEV) of a variable, such as returns, into portions that are accounted for by innovations in each variable of the system. Since returns are defined as changes in prices, the FEV of returns effectively captures the FEV of both the efficient price and transient noise, and is consequently different from the variance of the efficient price innovations. As Lanne and Nyberg's (2016) GFEVD can be computed for nonlinear VARs while Hasbrouck's measures are inapplicable in our context, we employ the former in the subsequent analysis. However, in order to prevent any confusion with the price discovery literature we interpret a GFEVD result as the relative informativeness or importance of a variable (e.g. durations) to another (e.g. returns), as in the traditional FEVD literature, and deliberately avoid saying "the contribution to the price discovery process".

Steps to compute the GFEVD, conditioning on the average RBAAT and non-RBAAT histories, for various multivariate systems discussed in the current study are detailed in Appendix B. The GFEVD results of quote revisions, conditioning on the average RBAAT history (up to $h = 50$ future transactions) and the average non-RBAAT history (up to $h = 20$), for six Australian banking stocks for the *Endo-VAR* and *WACD-VAR* models are reported in Tables 8 and 9, respectively. Each entry in these tables, reported in %, is computed according to equation (11) by averaging over $M = 1,000$ vectors of shocks bootstrapped from the estimated residuals; for each shock vector, the GIRF $I_j(\cdot)$ in equation (11) is calculated from $N = 1,000$ simulated repetitions. We also compute the corresponding results for the augmented Dufour-Engle (i.e. with volume) and original Dufour-Engle (without volume) models for comparison.[17]

[17]The specification of the augmented Dufour-Engle model is shown in Footnote 14. Meanwhile, the original

<<INSERT TABLES 8 & 9 ABOUT HERE>>

From both tables a big proportion of the FEV of returns is accounted for by trade-related innovations (i.e. shocks to trade attributes and durations) which are often considered private information in the market microstructure literature. Amongst these sources of private information, trade direction is found to be the most important factor to explain the price dynamics. Its innovations account for between 22% and 33% of the FEV of returns based on the original Dufour and Engle (2000) model that does not incorporate the information from trade sizes, and for more than 35% (even above 50% in some cases) of the returns' FEV according to other models that have also included trading volumes. This result lends support to Hasbrouck (1991a), Dufour and Engle (2000), Barclay et al. (2003), and Hendershott and Riordan (2011), who show that trade sign is an important determinant of the price formation process. Likewise, consistent with the findings of Easley and O'Hara (1987), Hasbrouck (1988, 1991a), and O'Hara et al. (2014) that there is a significant price-quantity relationship, shocks to trading volume possess remarkable explanatory power for the FEV of returns, which ranges between 12% and 31%. Moreover, the inclusion of trade sizes into a joint system significantly increases the informativeness of trade direction about the dynamic behavior of prices, possibly due to the correlatedness between trade signs and sizes.

Meanwhile, shocks to durations contribute much less to the FEV of returns than do other trade attributes' shocks. The contribution of duration innovations is less than 9% for all stocks and is typically below 1% in cases where durations are treated as exogenous and/or one conditions on an average history prior to 14:30:00 on non-RBA days during which the market is relatively tranquil (see Table 1). On the other hand, the contribution of other trade attributes' shocks is normally above 50%. These results suggest that the time between trades is significantly less important in explaining price dynamics than trade characteristics. Despite this, the informativeness of trade durations about the price formation process is much higher when durations are endogenously

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Dufour-Engle model, which does not include trading volumes and RBA dummy variables, is given by

$$r_t = \alpha^r + \sum_{i=1}^{5} a_i^r r_{t-i} + \lambda^r \text{open}_t x_t^0 + \sum_{i=0}^{5} \left[\gamma_i^r + \delta_i^r \ln(T_{t-i})\right] x_{t-i}^0 + u_t^r,$$

$$x_t^0 = \alpha^x + \sum_{i=1}^{5} a_i^x r_{t-i} + \lambda^x \text{open}_{t-1} x_{t-1}^0 + \sum_{i=1}^{5} \left[\gamma_i^x + \delta_i^x \ln(T_{t-i})\right] x_{t-i}^0 + u_t^x,$$

$$\widetilde{T}_t = T_t/\varphi(t) = \left[\phi_t \Gamma(1 + 1/\theta)\right] \epsilon_t,$$

$$\ln(\phi_t) = \alpha^T + \rho_1 \ln(\widetilde{T}_{t-1}) + \rho_2 \ln(\widetilde{T}_{t-2}) + \zeta_1 \ln(\phi_{t-1}) + \lambda^T \text{open}_{t-1}.$$

We employ a logarithmic WACD model, rather than a WACD model as in Dufour and Engle (2000), to ensure the positivity of the conditional durations.

modeled than when they are treated as exogenous (which is consistent with the results in subsection 4.2), since the proportion of the FEV of quote revisions explained by duration shocks under the former scenario is many times as high as that under the latter case, especially when one conditions on the average RBAAT history. This finding is in agreement with theory in Easley and O'Hara (1992) which demonstrates that the informativeness of trade arrival time about security prices is related to its correlatedness and joint determination with trading volumes and prices. Duration shocks have a significantly larger relative contribution to the returns' FEV in the *Endo-VAR* model than in the *WACD-VAR* model, especially on the RBA announcement days. The reasons for this might be that durations exhibit a significant nonlinear dynamic behavior (Zhang et al., 2001, Fernandes and Grammig, 2006), and the *Endo-VAR* model, which allows for a higher degree of nonlinearity in the duration dynamics (which includes not only a deeper lag serial dependence of durations but also interactions between durations and trade attributes) than does the *WACD-VAR* model, might better capture this nonlinearity.

We find that the RBA announcements significantly affect the relative importance of durations and trade attributes to the process of price adjustments for Australian banking stocks. In particular, shocks to both trade characteristics and durations account for larger proportions of the FEV of returns on the RBA announcement days than on days without RBA announcements, implying that trades executed around the interest rate announcements convey more important information, through both durations and other trade attributes, about prices than trades transacted during a similar calendar time window on a non-RBA day. Consistent with the findings in previous subsections, this result suggests that trades around the RBA announcements are likely to be initiated by informed traders and thus are more informative about the price dynamics.

5 Conclusions

This paper relaxes the strict exogeneity assumption of time between trades that is often imposed in prior studies by proposing a nonlinear VAR model for trade durations, trade characteristics (signs and volumes) and returns that allows for the feedback effects amongst these variables. Building upon the general econometric methodology developed by Engle (2000), our proposed model extends the VAR model in Hasbrouck (1991a) and Dufour and Engle (2000) to study the joint dynamics of trades and returns. We apply this model to examine the effects of trade arrival times and other trade attributes on the price dynamics of Australian banking stocks around the RBA interest rate announcements. Consistent with Dufour and Engle (2000) and Manganelli (2005), we find strong evidence to reject the exogeneity of trade durations. The time between trades is positively dependent on past absolute price changes but negatively related to previous trading volumes. We also observe that as trading intensifies or trade durations get shorter, trades become more positively autocorrelated and have a bigger impact on prices, which is in line with the findings of Dufour and Engle (2000).

Our results show the significant effects of the RBA announcements on the role that durations and trade characteristics play in explaining the price dynamics. Trades executed within one minute around the releases of the monetary policy news typically have shorter durations and larger price impacts. Conditioning on an average before-announcement history, when an unanticipated trade arrives faster (slower) than on average, its cumulative impact on prices is higher (lower) only if durations are endogenously modeled. No similar results are found if durations are treated as exogenous. This result confirms the importance of allowing for the endogeneity of trade durations that underlies the theoretical model of Easley and O'Hara (1992).

Using Lanne and Nyberg's (2016) GFEVD methodology, we find that duration shocks account for a significantly smaller proportion of the forecast error variance of returns than do other trade attribute shocks. The relative importance of duration innovations to returns is, however, remarkably higher when durations are endogenously modeled. Moreover, conditioning on RBA announcements, the contributions of both duration and other trade attribute shocks to the forecast error variance of returns increase. The results indicate that the time between trades is an important determinant of banking stock prices, especially around the interest rate announcements, even though it explains the dynamics of prices significantly less than do other trade characteristics.

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Table 1: Descriptive statistics for Australian banking stocks

	ANZ	CBA	NAB	WBC	MQG	BEN
Market cap ($AUD bn)	68.727	100.059	58.555	80.821	12.037	3.420
Panel A: Whole sample						
Absolute Quote Revision (bps)	1.033	0.658	1.298	1.127	1.342	2.634
Volume (shares)	207.92	105.90	233.43	244.84	78.86	150.95
Volume/depth	0.370	0.525	0.417	0.460	0.496	0.256
Duration (seconds)	6.139	5.205	6.906	6.756	8.266	24.924
Observations	178,545	211,088	159,316	162,725	132,867	43,958
Panel B: RBA announcement days						
Absolute Quote Revision (bps)						
Open (10:10:00-10:40:00)	1.615*	1.118*	1.888*	1.527*	2.035*	3.135*
Before (14:24:30-14:29:30)	0.928	0.523	1.037*	0.955	0.975	1.795*
Around (14:29:30-14:30:30)	1.657*	0.898*	2.522*	1.838*	2.000*	4.809*
After(14:30:30-14:40:30)	1.245*	0.742*	1.598*	1.270*	1.482*	2.820
Remaining	0.946	0.576	1.354	1.011	1.143	2.516
Volume (shares)						
Open (10:10:00-10:40:00)	258.06*	129.99*	307.76*	279.15*	101.19*	168.77
Before (14:24:30-14:29:30)	202.43	85.18*	231.10	148.10*	51.78*	130.54
Around (14:29:30-14:30:30)	199.43	126.07	273.02	334.26*	83.58	228.24
After(14:30:30-14:40:30)	222.40*	139.25*	248.32	273.02*	91.15*	138.72
Remaining	173.96	106.62	218.21	220.35	66.94	143.74
Volume/depth						
Open (10:10:00-10:40:00)	0.480*	0.526*	0.502*	0.429*	0.603*	0.274*
Before (14:24:30-14:29:30)	0.327	0.529	0.354*	0.371	0.386	0.241
Around (14:29:30-14:30:30)	0.496*	0.509	0.531*	0.503*	0.524	0.276
After(14:30:30-14:40:30)	0.400*	0.520	0.460	0.446*	0.470	0.275*
Remaining	0.334	0.491	0.422	0.367	0.441	0.216
Duration (seconds)						
Open (10:10:00-10:40:00)	4.710*	4.422*	5.267*	4.836*	5.507*	19.826*
Before (14:24:30-14:29:30)	7.800*	5.826	8.033	8.043	10.607	23.966
Around (14:29:30-14:30:30)	2.856*	3.984*	5.197*	3.660*	3.931*	25.136
After(14:30:30-14:40:30)	5.025*	4.855*	6.339*	5.918*	7.327	23.282
Remaining	6.111	5.594	7.593	7.202	8.157	23.720
Observations						
Open (10:10:00-10:40:00)	4,153	4,400	3,728	4,065	3,518	966
Before (14:24:30-14:29:30)	412	549	401	410	320	130
Around (14:29:30-14:30:30)	198	184	132	188	173	37
After(14:30:30-14:40:30)	1,305	1,326	1,000	1,104	882	278
Remaining	31,940	35,204	25,892	27,358	24,186	8,358
Panel C: Non RBA announcement days						
Absolute Quote Revision (bps)						
Open (10:10:00-10:40:00)	1.579*	1.132*	1.653*	1.652*	2.157*	3.845*
(14:24:30-14:29:30)	0.846*	0.523*	0.994*	0.844*	1.055*	1.897*
(14:29:30-14:30:30)	0.850	0.580	1.106	0.936	1.541	2.210
(14:30:30-14:40:30)	0.869*	0.491*	1.030*	0.906*	1.178	2.231
Remaining	0.960	0.607	1.218	1.067	1.263	2.550
Volume (shares)						
Open (10:10:00-10:40:00)	257.29*	136.14*	303.15*	304.85*	103.69*	218.12*
(14:24:30-14:29:30)	169.27*	76.75*	209.86	183.09*	75.99	149.94
(14:29:30-14:30:30)	172.16	86.03	168.93*	267.36	73.40	108.36
(14:30:30-14:40:30)	208.13	102.22	210.87	245.03	77.16	115.95*
Remaining	208.56	101.20	224.65	241.02	77.90	146.72
Volume/depth						
Open (10:10:00-10:40:00)	0.461*	0.554*	0.475*	0.469	0.616*	0.350*
(14:24:30-14:29:30)	0.324*	0.489	0.390	0.516	0.473	0.239
(14:29:30-14:30:30)	0.367	0.450*	0.432	0.331*	0.479	0.281
(14:30:30-14:40:30)	0.344	0.501	0.371*	0.626	0.449*	0.273
Remaining	0.364	0.531	0.406	0.479	0.492	0.257
Duration (seconds)						
Open (10:10:00-10:40:00)	4.418*	3.943*	4.581*	4.500*	6.241*	23.047*
(14:24:30-14:29:30)	7.965*	6.508*	7.530	8.135*	9.617	23.657
(14:29:30-14:30:30)	7.985*	6.989*	7.466	9.504*	9.727	26.785
(14:30:30-14:40:30)	7.157*	5.983*	7.449	8.303*	10.600*	25.254
Remaining	6.405	5.262	7.137	7.011	8.607	25.654
Observations						
Open (10:10:00-10:40:00)	17,350	19,320	16,725	16,985	12,073	3,110
(14:24:30-14:29:30)	1,536	1,868	1,644	1,493	1,292	521
(14:29:30-14:30:30)	322	385	346	283	261	113
(14:30:30-14:40:30)	3,387	4,121	3,317	2,979	2,342	928
Remaining	117,942	143,731	106,131	107,860	87,820	29,517

Continued on next page

This table reports summary statistics for six Australian banks. The sample consists of trades occurring between 10:10:00 and 16:00:00 in eleven weeks that contain eleven RBA interest rate announcement days in 2013. Market capitalization for each stock is at the beginning of 2013. Panels A, B and C respectively provide the summary for the whole sample (eleven weeks), the eleven RBA announcement days and the remaining non-RBA announcement days. For the latter two subsamples (Panels B and C), descriptive statistics over different time intervals for absolute quote revision, volume, volume divided by prevailing depth, duration and number of transactions are reported. These time intervals include "Open" which covers the first 30 minutes of the trading day (10:10:00-10:40:00), "Before" which covers 5 minutes before the RBA announcement time (14:24:30-14:29:30), "Around" which covers one minute during the RBA announcement time (14:29:30-14:30:30), "After" which covers 10 minutes after the RBA announcement time (14:30:30-14:40:30), and "Remaining" which covers the remaining time of a trading day. Except for "Observations" and "Market capitalization", all other numbers are averages. Asterisks (*) denote statistically significant difference from the averages for the "Remaining" period at a 5% level.

Table 2: Estimated trade duration equation of the *Endo-VAR* model for stock NAB in eleven RBA announcement weeks in 2013

	Coef.	t-stat		Coef.	t-stat
const	**-0.083**	**(-7.88)**	v_{t-1}	**-0.014**	**(-4.62)**
open_{t-1}	**-0.163**	**(-8.61)**	v_{t-2}	**-0.010**	**(-3.21)**
bef_{t-1}	0.082	(0.73)	$\sum_{i=1}^{5} v_{t-i}$	**-0.023**	**(-4.85)**
aro_{t-1}	-0.410	(-1.81)	$v_{t-1}\text{open}_{t-1}$	**-0.027**	**(-3.21)**
aft_{t-1}	-0.120	(-1.55)	$v_{t-1}\text{bef}_{t-1}$	0.057	(1.02)
r_{t-1}	-0.004	(-1.53)	$v_{t-1}\text{aro}_{t-1}$	-0.047	(-0.36)
r_{t-2}	0.006	(1.50)	$v_{t-1}\text{aft}_{t-1}$	-0.016	(-0.39)
$\sum_{i=1}^{5} r_{t-i}$	-0.002	(-0.28)	$v_{t-1}\ln(T_{t-1})$	0.002	(1.77)
$\|r_{t-1}\|$	**0.281**	**(80.85)**	$v_{t-2}\ln(T_{t-2})$	**-0.002**	**(-2.23)**
$\|r_{t-2}\|$	**-0.204**	**(-53.39)**	$\sum_{i=1}^{5} v_{t-i}\ln(T_{t-i})$	0.004	(1.79)
$\sum_{i=1}^{5} \|r_{t-i}\|$	**0.029**	**(4.62)**	$\ln(T_{t-1})$	**0.174**	**(64.72)**
x_{t-1}^0	**0.030**	**(2.50)**	$\ln(T_{t-2})$	**0.067**	**(25.01)**
x_{t-2}^0	**-0.026**	**(-2.20)**	$\sum_{i=1}^{5} \ln(T_{t-i})$	**0.342**	**(70.94)**
$\sum_{i=1}^{5} x_{t-i}^0$	0.007	(0.39)	Adj. R^2	0.092	-
$x_{t-1}^0\text{open}_{t-1}$	-0.025	(-0.97)	$\text{Wald}_{\text{diur}}$	**89.8**	-
$x_{t-1}^0\text{bef}_{t-1}$	0.014	(0.07)	$\text{Wald}_{\text{time}}$	**7124.0**	-
$x_{t-1}^0\text{aro}_{t-1}$	0.056	(0.17)	$Q_{15,\text{raw}}$	**11897.6**	-
$x_{t-1}^0\text{aft}_{t-1}$	-0.150	(-1.26)	$Q_{15,\text{resid}}$	**670.5**	-
$x_{t-1}^0\ln(T_{t-1})$	**0.007**	**(2.06)**	JB_{resid}	**10373.8**	-
$x_{t-2}^0\ln(T_{t-2})$	0.000	(0.10)			
$\sum_{i=1}^{5} x_{t-i}^0\ln(T_{t-i})$	0.010	(1.36)			

This table reports the coefficient estimates and Newey and West (1994) heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) for the trade duration equation of the *Endo-VAR* model specified in (8) for stock NAB.

$$\ln(T_t) = \alpha^T + \beta^T D_{t-1} + \sum_{i=1}^{p} a_i^T r_{t-i} + \sum_{i=1}^{p} b_i^T |r_{t-i}| + \lambda^T D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} \left[\gamma_i^T + \delta_i^T \ln(T_{t-i})\right] x_{t-i} + \sum_{i=1}^{p} c_i^T \ln(T_{t-i}) + u_t^T.$$

r_t is the logarithmic change in midquotes following the t-th trade. x_t is a column vector of trade signs (x_t^0, which equals 1 for buys and -1 for sells) and volumes (v_t, defined as the signed logarithm of the ratio of the share volume to the prevailing quoted depth) of the t-th trade. T_t is the time duration between the $(t-1)$-th and t-th trades. $D_t = (\text{open}_t, \text{bef}_t, \text{aro}_t, \text{aft}_t)'$ is a vector of four diurnal dummy variables including open_t that marks the first 30 minutes of a trading day (i.e. 10:10:00-10:40:00), and bef_t, aro_t and aft_t that respectively identify trades executed 5 minutes *before* (14:24:30-14:29:30), one minute *around* (14:29:30-14:30:30), and 10 minutes *after* (14:30:30-14:40:30) the RBA announcements. $\otimes$ denotes the Kronecker product.

The lag length p is set to $p = 5$. We only report the individual coefficients of the first two lags. $\text{Wald}_{\text{diur}}$ is the Wald test statistic associated with the null hypothesis that the coefficients on all diurnal dummies (i.e. open_t, bef_t, aro_t and aft_t) are jointly zero. $\text{Wald}_{\text{time}}$ is the Wald test statistic associated with the null hypothesis that the coefficients on all diurnal dummies and durations are jointly zero. $Q_{15,\text{raw}}$ ($Q_{15,\text{resid}}$) is the Ljung-Box statistic associated with the null hypothesis of no autocorrelation up to order 15 in the raw (residual) series. JB_{resid} is the Jarque-Bera statistic associated with the null that the residuals are normally distributed. Bold format denotes statistical significance at a 5% level.

Table 3: Estimated return equation of the *Endo-VAR* model for stock NAB

Panel A: Eleven RBA announcement weeks

	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat
const	-0.002	(-0.30)	x_t^0	**1.227**	**(126.26)**	v_t	**0.219**	**(92.44)**	$\ln(T_{t-1})$	0.000	(-0.06)
open_t	-0.016	(-0.89)	x_{t-1}^0	-0.012	(-1.21)	v_{t-1}	-0.004	(-1.69)	$\ln(T_{t-2})$	0.000	(0.21)
bef_t	-0.039	(-0.42)	x_{t-2}^0	**-0.045**	**(-4.48)**	v_{t-2}	**-0.014**	**(-5.91)**	$\sum_{i=1}^5 \ln(T_{t-i})$	**0.010**	**(2.80)**
aro_t	0.182	(0.58)	$\sum_{i=0}^5 x_{t-i}^0$	**1.099**	**(70.42)**	$\sum_{i=0}^5 v_{t-i}$	**0.185**	**(47.37)**	Adj. R^2	0.178	-
aft_t	0.004	(0.05)	$x_t^0\text{open}_t$	**0.300**	**(11.30)**	$v_t\text{open}_t$	**0.097**	**(11.27)**	$\text{Wald}_{\text{diur}}$	**169.8**	-
r_{t-1}	**-0.027**	**(-7.56)**	$x_t^0\text{bef}_t$	-0.058	(-0.35)	$v_t\text{bef}_t$	-0.034	(-0.91)	$\text{Wald}_{\text{time}}$	**316.8**	-
r_{t-2}	**0.010**	**(2.98)**	$x_t^0\text{aro}_t$	**1.310**	**(3.18)**	$v_t\text{aro}_t$	**0.327**	**(2.14)**	$Q_{15,\text{raw}}$	**4397.2**	-
$\sum_{i=1}^5 r_{t-i}$	0.006	(0.73)	$x_t^0\text{aft}_t$	**0.319**	**(2.84)**	$v_t\text{aft}_t$	**0.096**	**(2.77)**	$Q_{15,\text{resid}}$	19.9	-
$\|r_{t-1}\|$	**-0.009**	**(-2.76)**	$x_t^0\ln(T_t)$	**-0.031**	**(-11.16)**	$v_t\ln(T_t)$	**-0.006**	**(-8.03)**	JB_{resid}	**37992.9**	-
$\|r_{t-2}\|$	-0.001	(-0.18)	$x_{t-1}^0\ln(T_{t-1})$	0.000	(-0.13)	$v_{t-1}\ln(T_{t-1})$	-0.001	(-1.46)			
$\sum_{i=1}^5 \|r_{t-i}\|$	-0.009	(-1.58)	$x_{t-2}^0\ln(T_{t-2})$	0.004	(1.46)	$v_{t-2}\ln(T_{t-2})$	0.000	(0.62)			
			$\sum_{i=0}^5 x_{t-i}^0\ln(T_{t-i})$	**-0.020**	**(-3.18)**	$\sum_{i=0}^5 v_{t-i}\ln(T_{t-i})$	**-0.004**	**(-2.35)**			

Panel B: Non RBA announcement days

	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat
const	0.003	(0.33)	x_t^0	**1.212**	**(110.53)**	v_t	**0.216**	**(81.97)**	$\ln(T_{t-1})$	0.002	(0.97)
open_t	-0.002	(-0.08)	x_{t-1}^0	-0.003	(-0.29)	v_{t-1}	-0.002	(-0.58)	$\ln(T_{t-2})$	0.000	(0.18)
bef_t	-0.059	(-1.41)	x_{t-2}^0	**-0.048**	**(-4.36)**	v_{t-2}	**-0.016**	**(-6.22)**	$\sum_{i=1}^5 \ln(T_{t-i})$	**0.009**	**(2.39)**
aro_t	0.105	(1.05)	$\sum_{i=0}^5 x_{t-i}^0$	**1.093**	**(63.18)**	$\sum_{i=0}^5 v_{t-i}$	**0.183**	**(42.57)**	Adj. R^2	0.178	-
aft_t	**0.081**	**(2.69)**	$x_t^0\text{open}_t$	**0.269**	**(9.29)**	$v_t\text{open}_t$	**0.088**	**(9.46)**	$\text{Wald}_{\text{diur}}$	**155.6**	-
r_{t-1}	**-0.031**	**(-7.81)**	$x_t^0\text{bef}_t$	**-0.203**	**(-3.13)**	$v_t\text{bef}_t$	**-0.038**	**(-2.46)**	$\text{Wald}_{\text{time}}$	**272.4**	-
r_{t-2}	**0.008**	**(2.14)**	$x_t^0\text{aro}_t$	-0.257	(-1.83)	$v_t\text{aro}_t$	-0.063	(-1.82)	$Q_{15,\text{raw}}$	**3683.3**	-
$\sum_{i=1}^5 r_{t-i}$	-0.005	(-0.57)	$x_t^0\text{aft}_t$	**-0.159**	**(-3.38)**	$v_t\text{aft}_t$	**-0.042**	**(-3.41)**	$Q_{15,\text{resid}}$	21.1	-
$\|r_{t-1}\|$	**-0.007**	**(-1.97)**	$x_t^0\ln(T_t)$	**-0.030**	**(-9.83)**	$v_t\ln(T_t)$	**-0.006**	**(-7.00)**	JB_{resid}	**32183.3**	-
$\|r_{t-2}\|$	-0.003	(-0.68)	$x_{t-1}^0\ln(T_{t-1})$	-0.002	(-0.57)	$v_{t-1}\ln(T_{t-1})$	-0.001	(-1.65)			
$\sum_{i=1}^5 \|r_{t-i}\|$	-0.011	(-1.79)	$x_{t-2}^0\ln(T_{t-2})$	0.002	(0.79)	$v_{t-2}\ln(T_{t-2})$	0.000	(0.36)			
			$\sum_{i=0}^5 x_{t-i}^0\ln(T_{t-i})$	**-0.028**	**(-3.92)**	$\sum_{i=0}^5 v_{t-i}\ln(T_{t-i})$	**-0.005**	**(-2.26)**			

This table reports the coefficient estimates and Newey and West (1994) heteroskedasticity and autocorrelation consistent t-statistics (in parentheses) for the return equation of the *Endo-VAR* model specified in (8) for stock NAB in eleven RBA announcement weeks (Panel A) and on non-RBA announcement days (Panel B) in 2013.

$$r_t = \alpha^r + \beta^r D_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r D_t \otimes x_t + \sum_{i=0}^{p} [\gamma_i^r + \delta_i^r \ln(T_{t-i})]\, x_{t-i} + \sum_{i=1}^{p} c_i^r \ln(T_{t-i}) + u_t^r.$$

See Table 2 notes for definitions of the variables. In Panel B, bef_t, aro_t and aft_t are respectively indicator variables identifying trades performed within 14:24:30-14:29:30, 14:29:30-14:30:30 and 14:30:30-14:40:30 time periods (i.e. corresponding time intervals to those on the RBA announcement days).

Table 4: Estimated trade sign and volume equations of the *Endo-VAR* model for stock NAB in eleven RBA announcement weeks in 2013

Panel A: Trade sign equation

	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat
const	**0.039**	**(10.46)**	x^0_{t-1}	**0.395**	**(97.69)**	v_{t-1}	**0.017**	**(14.87)**	$\ln(T_{t-1})$	0.000	(0.05)
open_t	**0.029**	**(4.10)**	x^0_{t-2}	**0.076**	**(18.78)**	v_{t-2}	-0.001	(-0.81)	$\ln(T_{t-2})$	0.001	(0.83)
bef_t	-0.015	(-0.38)	$\sum_{i=1}^5 x^0_{t-i}$	**0.502**	**(83.68)**	$\sum_{i=1}^5 v_{t-i}$	**-0.004**	**(-2.36)**	$\sum_{i=1}^5 \ln(T_{t-i})$	-0.001	(-0.50)
aro_t	0.057	(0.69)	$x^0_{t-1}\text{open}_{t-1}$	**0.030**	**(3.28)**	$v_{t-1}\text{open}_{t-1}$	**0.014**	**(4.22)**	Adj. R^2	0.246	-
aft_t	-0.017	(-0.61)	$x^0_{t-1}\text{bef}_{t-1}$	0.079	(1.33)	$v_{t-1}\text{bef}_{t-1}$	0.016	(0.85)	$\text{Wald}_{\text{diur}}$	**41.3**	-
r_{t-1}	**-0.199**	**(-139.13)**	$x^0_{t-1}\text{aro}_{t-1}$	0.172	(1.73)	$v_{t-1}\text{aro}_{t-1}$	0.056	(1.30)	$\text{Wald}_{\text{time}}$	**239.4**	-
r_{t-2}	**-0.028**	**(-21.41)**	$x^0_{t-1}\text{aft}_{t-1}$	0.028	(0.74)	$v_{t-1}\text{aft}_{t-1}$	0.024	(1.64)	$Q_{15,\text{raw}}$	**19196.9**	-
$\sum_{i=1}^5 r_{t-i}$	**-0.217**	**(-70.17)**	$x^0_{t-1}\ln(T_{t-1})$	**-0.005**	**(-4.59)**	$v_{t-1}\ln(T_{t-1})$	**0.002**	**(5.96)**	$Q_{15,\text{resid}}$	**393.8**	-
$\lvert r_{t-1}\rvert$	**-0.008**	**(-6.29)**	$x^0_{t-2}\ln(T_{t-2})$	0.001	(1.26)	$v_{t-2}\ln(T_{t-2})$	**0.002**	**(4.11)**	JB_{resid}	**4649.9**	-
$\lvert r_{t-2}\rvert$	0.000	(0.15)	$\sum_{i=1}^5 x^0_{t-i}\ln(T_{t-i})$	-0.002	(-0.99)	$\sum_{i=1}^5 v_{t-i}\ln(T_{t-i})$	**0.004**	**(5.61)**			
$\sum_{i=1}^5 \lvert r_{t-i}\rvert$	**-0.008**	**(-3.72)**									

Panel B: Trade volume equation

	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat
const	**-0.232**	**(-15.81)**	x^0_{t-1}	**-0.239**	**(-18.79)**	v_{t-1}	**0.183**	**(38.92)**	$\ln(T_{t-1})$	**-0.010**	**(-3.41)**
open_t	**-0.087**	**(-4.45)**	x^0_{t-2}	-0.022	(-1.70)	v_{t-2}	**0.080**	**(18.73)**	$\ln(T_{t-2})$	-0.003	(-0.87)
bef_t	-0.090	(-0.55)	$\sum_{i=1}^5 x^0_{t-i}$	**-0.151**	**(-7.80)**	$\sum_{i=1}^5 v_{t-i}$	**0.442**	**(58.38)**	$\sum_{i=1}^5 \ln(T_{t-i})$	**-0.013**	**(-2.54)**
aro_t	-0.103	(-0.56)	$x^0_{t-1}\text{open}_{t-1}$	**-0.067**	**(-2.78)**	$v_{t-1}\text{open}_{t-1}$	**-0.054**	**(-4.57)**	Adj. R^2	0.114	-
aft_t	**0.189**	**(2.39)**	$x^0_{t-1}\text{bef}_{t-1}$	-0.332	(-1.64)	$v_{t-1}\text{bef}_{t-1}$	-0.102	(-1.24)	$\text{Wald}_{\text{diur}}$	**64.4**	-
r_{t-1}	**0.223**	**(66.27)**	$x^0_{t-1}\text{aro}_{t-1}$	**-0.452**	**(-2.35)**	$v_{t-1}\text{aro}_{t-1}$	-0.045	(-0.34)	$\text{Wald}_{\text{time}}$	**136.4**	-
r_{t-2}	**0.029**	**(7.74)**	$x^0_{t-1}\text{aft}_{t-1}$	-0.160	(-1.46)	$v_{t-1}\text{aft}_{t-1}$	**-0.122**	**(-2.94)**	$Q_{15,\text{raw}}$	**36259.6**	-
$\sum_{i=1}^5 r_{t-i}$	**0.189**	**(23.44)**	$x^0_{t-1}\ln(T_{t-1})$	**0.014**	**(4.30)**	$v_{t-1}\ln(T_{t-1})$	0.000	(0.12)	$Q_{15,\text{resid}}$	**1180.6**	-
$\lvert r_{t-1}\rvert$	**0.018**	**(4.62)**	$x^0_{t-2}\ln(T_{t-2})$	-0.004	(-1.23)	$v_{t-2}\ln(T_{t-2})$	**-0.006**	**(-3.98)**	JB_{resid}	**5230.6**	-
$\lvert r_{t-2}\rvert$	**0.011**	**(2.86)**	$\sum_{i=1}^5 x^0_{t-i}\ln(T_{t-i})$	0.002	(0.29)	$\sum_{i=1}^5 v_{t-i}\ln(T_{t-i})$	**-0.011**	**(-3.41)**			
$\sum_{i=1}^5 \lvert r_{t-i}\rvert$	**0.051**	**(6.92)**									

This table reports the coefficient estimates and Newey and West (1994) heteroskedasticity and autocorrelation consistent t-statistics (in parentheses) for the trade sign and volume equations of the *Endo-VAR* model specified in (8) for stock NAB.

$$x_t = \alpha^x + \beta^x D_t + \sum_{i=1}^{p} a_i^x r_{t-i} + \sum_{i=1}^{p} b_i^x |r_{t-i}| + \lambda^x D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} [\gamma_i^x + \delta_i^x \ln(T_{t-i})]\, x_{t-i} + \sum_{i=1}^{p} c_i^x \ln(T_{t-i}) + u_t^x.$$

See Table 2 notes for definitions of the variables.

Table 5: Estimated return equation of the *Endo-VAR* model for banking stocks in eleven RBA announcement weeks in 2013

		ANZ		CBA		WBC		MQG		BEN	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
const		**-0.030**	**(-5.81)**	0.005	(1.52)	-0.012	(-1.92)	0.014	(1.64)	**-0.181**	**(-4.93)**
open_t	Lag 0	0.004	(0.26)	**0.026**	**(2.39)**	**-0.041**	**(-2.31)**	0.029	(1.19)	0.172	(1.59)
bef_t	Lag 0	0.103	(1.06)	0.083	(1.81)	0.148	(1.80)	0.046	(0.53)	-0.396	(-0.98)
aro_t	Lag 0	0.158	(1.10)	0.092	(0.70)	0.134	(0.75)	-0.262	(-1.15)	1.422	(1.22)
aft_t	Lag 0	0.027	(0.44)	0.051	(1.42)	0.058	(0.87)	0.030	(0.40)	0.035	(0.11)
r_t	Lag 1	**-0.055**	**(-15.38)**	**-0.027**	**(-7.87)**	**-0.050**	**(-14.42)**	0.000	(-0.04)	**-0.056**	**(-7.26)**
	Lag 2	0.005	(1.38)	**0.033**	**(10.05)**	0.003	(0.84)	**0.027**	**(7.15)**	-0.002	(-0.34)
	$\Sigma_{1:p}$	**-0.033**	**(-3.86)**	**0.072**	**(10.08)**	**-0.030**	**(-3.73)**	**0.076**	**(9.27)**	**-0.100**	**(-5.68)**
$\|r_t\|$	Lag 1	0.002	(0.54)	-0.006	(-1.58)	-0.004	(-1.27)	**-0.012**	**(-2.77)**	-0.003	(-0.52)
	Lag 2	0.001	(0.24)	0.000	(0.02)	0.000	(-0.01)	-0.002	(-0.47)	-0.007	(-1.13)
	$\Sigma_{1:p}$	**0.016**	**(3.36)**	-0.002	(-0.49)	-0.005	(-1.03)	-0.011	(-1.75)	-0.014	(-1.46)
x_t^0	Lag 0	**1.040**	**(111.11)**	**0.595**	**(119.95)**	**1.085**	**(106.89)**	**1.205**	**(115.19)**	**3.633**	**(59.12)**
	Lag 1	**0.048**	**(5.51)**	0.009	(1.95)	0.008	(0.88)	**-0.038**	**(-3.73)**	0.091	(1.43)
	$\Sigma_{0:p}$	**0.991**	**(67.57)**	**0.490**	**(65.33)**	**0.958**	**(61.28)**	**0.952**	**(53.76)**	**3.011**	**(36.66)**
$x_t^0\text{open}_t$	Lag 0	**0.395**	**(16.11)**	**0.427**	**(26.10)**	**0.334**	**(12.75)**	**0.716**	**(20.34)**	**0.499**	**(2.91)**
$x_t^0\text{bef}_t$	Lag 0	0.152	(1.00)	-0.071	(-1.03)	-0.042	(-0.22)	-0.127	(-0.86)	-0.452	(-0.78)
$x_t^0\text{aro}_t$	Lag 0	**0.562**	**(2.87)**	**0.410**	**(3.09)**	0.120	(0.39)	**0.761**	**(2.15)**	**2.993**	**(2.13)**
$x_t^0\text{aft}_t$	Lag 0	**0.262**	**(2.59)**	0.098	(1.52)	0.158	(1.58)	**0.269**	**(2.14)**	-0.018	(-0.04)
$x_t^0 \ln(T_t)$	Lag 0	**-0.044**	**(-16.69)**	**-0.021**	**(-14.60)**	**-0.034**	**(-12.11)**	**-0.011**	**(-3.62)**	**-0.092**	**(-6.26)**
	Lag 1	**-0.007**	**(-2.72)**	0.002	(1.55)	0.005	(1.93)	0.006	(1.90)	-0.005	(-0.33)
	$\Sigma_{0:p}$	**-0.056**	**(-9.62)**	**-0.008**	**(-2.65)**	**-0.015**	**(-2.37)**	0.008	(1.22)	**-0.104**	**(-3.43)**
v_t	Lag 0	**0.197**	**(90.17)**	**0.129**	**(93.66)**	**0.192**	**(82.66)**	**0.265**	**(80.38)**	**0.566**	**(50.73)**
	Lag 1	0.001	(0.28)	-0.001	(-0.72)	-0.004	(-1.81)	**-0.007**	**(-2.24)**	0.012	(1.05)
	$\Sigma_{0:p}$	**0.161**	**(47.40)**	**0.091**	**(44.20)**	**0.152**	**(41.93)**	**0.196**	**(35.39)**	**0.462**	**(27.97)**
$v_t\text{open}_t$	Lag 0	**0.085**	**(11.12)**	**0.098**	**(17.69)**	**0.092**	**(11.84)**	**0.179**	**(12.78)**	**0.121**	**(3.22)**
$v_t\text{bef}_t$	Lag 0	0.010	(0.27)	-0.020	(-1.16)	0.005	(0.09)	-0.029	(-0.66)	-0.003	(-0.02)
$v_t\text{aro}_t$	Lag 0	**0.175**	**(2.57)**	**0.111**	**(2.67)**	0.101	(0.92)	0.132	(1.00)	0.519	(1.41)
$v_t\text{aft}_t$	Lag 0	**0.075**	**(2.80)**	0.017	(0.94)	**0.079**	**(2.75)**	**0.143**	**(2.75)**	0.010	(0.10)
$v_t \ln(T_t)$	Lag 0	**-0.011**	**(-16.24)**	**-0.007**	**(-16.21)**	**-0.007**	**(-9.96)**	**-0.009**	**(-8.13)**	**-0.015**	**(-5.11)**
	Lag 1	**-0.002**	**(-2.62)**	**0.001**	**(2.02)**	0.000	(0.47)	**0.002**	**(2.14)**	0.001	(0.49)
	$\Sigma_{0:p}$	**-0.015**	**(-9.76)**	**-0.004**	**(-3.84)**	-0.002	(-1.25)	0.000	(-0.03)	-0.011	(-1.79)
$\ln(T_t)$	Lag 1	0.001	(0.61)	**0.003**	**(2.69)**	-0.002	(-1.18)	**0.005**	**(2.20)**	0.015	(1.66)
	Lag 2	0.001	(0.65)	0.000	(0.18)	-0.001	(-0.75)	0.000	(-0.15)	0.005	(0.53)
	$\Sigma_{1:p}$	0.003	(0.91)	**0.004**	**(2.50)**	-0.003	(-0.95)	0.002	(0.58)	**0.045**	**(3.07)**
Adj. R^2		0.171		0.161		0.155		0.175		0.192	
$\text{Wald}_{\text{diur}}$		**278.7**		**702.9**		**197.5**		**429.1**		**27.7**	
$\text{Wald}_{\text{time}}$		**622.0**		**1038.0**		**370.6**		**542.5**		**88.5**	
$Q_{15,\text{raw}}$		**6221.7**		**2721.7**		**4282.3**		**922.2**		**1993.8**	
$Q_{15,\text{resid}}$		23.6		**105.2**		**36.2**		**34.6**		**31.0**	
JB_{resid}		**64575.3**		**208084.3**		**60180.5**		**101836.4**		**19233.0**	

This table reports the coefficient estimates and Newey and West (1994) heteroskedasticity and autocorrelation consistent t-statistics (in parentheses) for the return equation of the *Endo-VAR* model specified in (8) for stocks ANZ, CBA, WBC, MQG and BEN.

$$r_t = \alpha^r + \beta^r D_t + \sum_{i=1}^{p} a_i^r r_{t-i} + \sum_{i=1}^{p} b_i^r |r_{t-i}| + \lambda^r D_t \otimes x_t + \sum_{i=0}^{p} \left[\gamma_i^r + \delta_i^r \ln(T_{t-i})\right] x_{t-i} + \sum_{i=1}^{p} c_i^r \ln(T_{t-i}) + u_t^r.$$

See Table 2 notes for definitions of the variables.

Table 6: Estimated trade duration equation of the *Endo-VAR* model for banking stocks in eleven RBA announcement weeks in 2013

		ANZ		**CBA**		**WBC**		**MQG**		**BEN**	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
const		**-0.166**	**(-18.90)**	**-0.324**	**(-41.01)**	**-0.054**	**(-5.84)**	**-0.247**	**(-21.83)**	**0.764**	**(32.47)**
open_t	Lag 1	**-0.077**	**(-4.21)**	**-0.123**	**(-6.95)**	**-0.171**	**(-9.20)**	-0.248	(-10.81)	**-0.171**	**(-3.49)**
bef_t	Lag 1	0.170	(1.30)	0.126	(1.21)	0.082	(0.60)	0.020	(0.12)	0.083	(0.29)
aro_t	Lag 1	**-0.465**	**(-2.72)**	-0.228	(-1.43)	**-0.691**	**(-4.09)**	**-0.627**	**(-2.89)**	0.504	(1.35)
aft_t	Lag 1	**-0.163**	**(-2.29)**	-0.045	(-0.67)	-0.105	(-1.36)	0.035	(0.42)	0.037	(0.24)
r_t	Lag 1	-0.004	(-1.23)	0.004	(0.80)	**-0.016**	**(-5.41)**	0.003	(0.86)	0.001	(0.53)
	Lag 2	-0.002	(-0.41)	0.000	(-0.08)	**-0.013**	**(-3.33)**	**0.011**	**(2.84)**	0.005	(1.52)
	$\Sigma_{1:p}$	-0.005	(-0.53)	-0.007	(-0.58)	**-0.038**	**(-4.41)**	**0.023**	**(2.92)**	0.004	(0.50)
$\|r_t\|$	Lag 1	**0.234**	**(62.62)**	**0.523**	**(95.31)**	**0.273**	**(77.12)**	**0.337**	**(84.90)**	**0.067**	**(21.71)**
	Lag 2	**-0.204**	**(-51.01)**	**-0.328**	**(-54.82)**	**-0.199**	**(-51.10)**	**-0.171**	**(-39.93)**	**-0.063**	**(-19.27)**
	$\Sigma_{1:p}$	**-0.014**	**(-2.33)**	**0.033**	**(3.85)**	-0.001	(-0.22)	**0.107**	**(16.07)**	0.004	(0.78)
x_t^0	Lag 1	**0.038**	**(3.12)**	**0.023**	**(2.41)**	**0.059**	**(4.72)**	-0.018	(-1.42)	**-0.142**	**(-4.49)**
	Lag 2	-0.017	(-1.49)	-0.009	(-0.89)	**0.036**	**(3.02)**	-0.001	(-0.11)	**-0.119**	**(-3.84)**
	$\Sigma_{1:p}$	0.020	(1.07)	0.027	(1.86)	**0.126**	**(6.80)**	-0.003	(-0.15)	**-0.349**	**(-7.99)**
$x_t^0\text{open}_t$	Lag 1	-0.031	(-1.18)	-0.027	(-1.13)	**-0.069**	**(-2.60)**	-0.022	(-0.76)	0.032	(0.42)
$x_t^0\text{bef}_t$	Lag 1	0.413	(1.86)	0.056	(0.30)	-0.113	(-0.47)	-0.301	(-1.53)	-0.137	(-0.30)
$x_t^0\text{aro}_t$	Lag 1	**-0.509**	**(-2.14)**	0.040	(0.16)	-0.109	(-0.42)	-0.408	(-1.88)	-0.563	(-0.88)
$x_t^0\text{aft}_t$	Lag 1	0.157	(1.32)	-0.123	(-1.22)	-0.062	(-0.54)	0.070	(0.59)	**-0.608**	**(-2.09)**
$x_t^0 \ln(T_t)$	Lag 1	**0.020**	**(5.71)**	**0.006**	**(2.22)**	**0.009**	**(2.46)**	-0.001	(-0.41)	**0.017**	**(2.10)**
	Lag 2	-0.002	(-0.50)	0.003	(1.01)	-0.004	(-1.00)	0.004	(1.25)	0.005	(0.64)
	$\Sigma_{1:p}$	**0.034**	**(4.64)**	**0.022**	**(3.65)**	0.007	(0.83)	0.006	(0.75)	0.022	(1.33)
v_t	Lag 1	**-0.015**	**(-4.89)**	**-0.009**	**(-2.83)**	-0.001	(-0.38)	**-0.040**	**(-9.05)**	**-0.039**	**(-6.02)**
	Lag 2	**-0.006**	**(-1.97)**	-0.005	(-1.58)	0.003	(1.05)	0.004	(0.92)	**-0.013**	**(-2.02)**
	$\Sigma_{1:p}$	**-0.024**	**(-4.98)**	**-0.021**	**(-4.47)**	**0.013**	**(2.70)**	-0.012	(-1.82)	**-0.043**	**(-4.57)**
$v_t\text{open}_t$	Lag 1	-0.015	(-1.80)	**-0.019**	**(-2.10)**	**-0.025**	**(-3.14)**	0.000	(-0.03)	-0.023	(-1.26)
$v_t\text{bef}_t$	Lag 1	0.102	(1.82)	0.047	(0.86)	-0.023	(-0.36)	**-0.155**	**(-2.09)**	-0.011	(-0.11)
$v_t\text{aro}_t$	Lag 1	-0.015	(-0.22)	0.130	(1.38)	0.026	(0.24)	-0.092	(-1.16)	-0.199	(-1.17)
$v_t\text{aft}_t$	Lag 1	0.064	(1.73)	0.027	(0.78)	0.011	(0.24)	-0.003	(-0.06)	-0.070	(-1.01)
$v_t \ln(T_t)$	Lag 1	0.002	(1.43)	**0.003**	**(2.69)**	-0.001	(-1.10)	**-0.005**	**(-3.29)**	0.003	(1.30)
	Lag 2	0.000	(0.01)	**0.004**	**(3.32)**	-0.001	(-0.94)	**0.004**	**(2.55)**	**-0.005**	**(-2.81)**
	$\Sigma_{1:p}$	**0.008**	**(3.71)**	**0.014**	**(6.29)**	-0.001	(-0.46)	0.001	(0.23)	**-0.007**	**(-2.03)**
$\ln(T_t)$	Lag 1	**0.180**	**(70.84)**	**0.186**	**(82.23)**	**0.173**	**(65.00)**	**0.173**	**(60.50)**	**0.195**	**(35.99)**
	Lag 2	**0.068**	**(26.92)**	**0.073**	**(31.23)**	**0.076**	**(28.66)**	**0.071**	**(24.38)**	**0.099**	**(18.25)**
	$\Sigma_{1:p}$	**0.338**	**(73.39)**	**0.387**	**(97.29)**	**0.362**	**(75.05)**	**0.374**	**(73.73)**	**0.422**	**(45.54)**
Adj. R^2		0.078		0.100		0.090		0.104		0.099	
$\text{Wald}_{\text{diur}}$		**45.1**		**64.8**		**108.8**		**134.8**		**22.8**	
$\text{Wald}_{\text{time}}$		**8029.3**		**12739.5**		**7862.9**		**7442.6**		**3327.9**	
$Q_{15,\text{raw}}$		**14708.3**		**24311.0**		**15032.9**		**14738.9**		**8677.8**	
$Q_{15,\text{resid}}$		**803.3**		**1354.4**		**795.7**		**1017.0**		**335.2**	
JB_{resid}		**10445.4**		**9150.2**		**12026.2**		**5882.9**		**7632.7**	

This table reports the coefficient estimates and Newey and West (1994) heteroskedasticity and autocorrelation consistent t-statistics (in parentheses) for the trade duration equation of the *Endo-VAR* model specified in (8) for stocks ANZ, CBA, WBC, MQG and BEN.

$$\ln(T_t) = \alpha^T + \beta^T D_{t-1} + \sum_{i=1}^{p} a_i^T r_{t-i} + \sum_{i=1}^{p} b_i^T |r_{t-i}| + \lambda^T D_{t-1} \otimes x_{t-1} + \sum_{i=1}^{p} \left[\gamma_i^T + \delta_i^T \ln(T_{t-i})\right] x_{t-i} + \sum_{i=1}^{p} c_i^T \ln(T_{t-i}) + u_t^T.$$

See Table 2 notes for definitions of the variables.

Table 7: Estimated W-ACD(2,1) models for banking stocks in eleven RBA announcement weeks in 2013

Panel A: Exogenous-duration W-ACD(2,1) model

Stock	θ	α^T	a_1^T	a_2^T	b_1^T	b_2^T	$\gamma_{x^0,1}^T$	$\gamma_{x^0,2}^T$	$\gamma_{v,1}^T$	$\gamma_{v,2}^T$	ρ_1	ρ_2	ζ	λ_{op}^T	λ_{be}^T	λ_{ar}^T	λ_{af}^T	Log Lik.	$Q_{15,\text{raw}}$	$Q_{15,\text{resid}}$
ANZ	**0.467**	**0.013**	-	-	-	-	-	-	-	-	**0.122**	**-0.108**	**0.979**	**-0.002**	-0.007	**-0.034**	0.003	-47118.4	**13705.3**	**2158.5**
	(0.001)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.002)**	**(0.002)**	**(0.001)**	**(0.000)**	(0.004)	**(0.007)**	(0.002)	-	-	-
CBA	**0.457**	**0.017**	-	-	-	-	-	-	-	-	**0.129**	**-0.107**	**0.967**	**-0.001**	-0.001	**-0.034**	0.003	-42621.6	**14516.2**	**1560.0**
	(0.001)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.002)**	**(0.003)**	**(0.003)**	**(0.001)**	(0.004)	**(0.010)**	(0.002)	-	-	-
NAB	**0.477**	**0.011**	-	-	-	-	-	-	-	-	**0.107**	**-0.093**	**0.977**	**-0.002**	0.000	**-0.024**	0.003	-52905.1	**10221.7**	**1452.8**
	(0.001)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.002)**	**(0.002)**	**(0.002)**	**(0.000)**	(0.004)	**(0.010)**	(0.002)	-	-	-
WBC	**0.475**	**0.014**	-	-	-	-	-	-	-	-	**0.109**	**-0.082**	**0.949**	**-0.002**	-0.002	**-0.066**	-0.001	-53651.8	**11006.7**	**1340.3**
	(0.001)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.002)**	**(0.003)**	**(0.005)**	**(0.001)**	(0.007)	**(0.011)**	(0.003)	-	-	-
MQG	**0.438**	**0.017**	-	-	-	-	-	-	-	-	**0.115**	**-0.094**	**0.968**	**-0.002**	-0.007	**-0.038**	0.003	-13480.4	**9964.4**	**1116.1**
	(0.001)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.002)**	**(0.003)**	**(0.002)**	**(0.001)**	(0.007)	**(0.010)**	(0.003)	-	-	-
BEN	**0.498**	**0.012**	-	-	-	-	-	-	-	-	**0.103**	**-0.082**	**0.958**	-0.001	-0.019	-0.017	0.004	-18768.8	**4328.6**	**683.3**
	(0.002)	**(0.001)**	-	-	-	-	-	-	-	-	**(0.004)**	**(0.004)**	**(0.005)**	(0.002)	(0.014)	(0.043)	(0.008)	-	-	-

Panel B: Endogenous-duration W-ACD(2,1) model

Stock	θ	α^T	a_1^T	a_2^T	b_1^T	b_2^T	$\gamma_{x^0,1}^T$	$\gamma_{x^0,2}^T$	$\gamma_{v,1}^T$	$\gamma_{v,2}^T$	ρ_1	ρ_2	ζ	λ_{op}^T	λ_{be}^T	λ_{ar}^T	λ_{af}^T	Log Lik.	$Q_{15,\text{raw}}$	$Q_{15,\text{resid}}$
ANZ	**0.471**	**0.012**	0.002	0.000	**0.176**	**-0.175**	**0.019**	**-0.020**	**-0.011**	**0.010**	**0.125**	**-0.110**	**0.977**	**-0.004**	-0.006	**-0.041**	0.002	-45312.1	**13705.3**	**1759.4**
	(0.001)	**(0.001)**	(0.002)	(0.002)	**(0.003)**	**(0.003)**	**(0.008)**	**(0.008)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.000)**	(0.004)	**(0.008)**	(0.002)	-	-	-
CBA	**0.465**	**0.019**	**0.007**	**-0.007**	**0.411**	**-0.408**	**0.022**	**-0.020**	**-0.008**	**0.005**	**0.133**	**-0.101**	**0.949**	**-0.004**	0.001	**-0.051**	0.001	-38684.3	**14516.2**	**935.7**
	(0.001)	**(0.001)**	**(0.003)**	**(0.003)**	**(0.005)**	**(0.005)**	**(0.007)**	**(0.007)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.003)**	**(0.005)**	**(0.001)**	(0.006)	**(0.012)**	(0.003)	-	-	-
NAB	**0.484**	**0.010**	0.000	0.002	**0.208**	**-0.205**	**0.024**	**-0.026**	**-0.010**	**0.010**	**0.113**	**-0.095**	**0.971**	**-0.004**	0.000	**-0.044**	0.003	-50127.6	**10221.7**	**1171.8**
	(0.001)	**(0.001)**	(0.002)	(0.002)	**(0.003)**	**(0.003)**	**(0.008)**	**(0.008)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.003)**	**(0.003)**	**(0.001)**	(0.005)	**(0.011)**	(0.002)	-	-	-
WBC	**0.482**	**0.016**	-0.004	**0.006**	**0.209**	**-0.210**	**0.040**	**-0.035**	-0.001	0.001	**0.114**	**-0.078**	**0.929**	**-0.003**	0.000	**-0.091**	-0.001	-51071.8	**11006.7**	**928.7**
	(0.001)	**(0.001)**	(0.002)	**(0.002)**	**(0.003)**	**(0.003)**	**(0.008)**	**(0.008)**	(0.002)	(0.002)	**(0.002)**	**(0.004)**	**(0.011)**	**(0.001)**	(0.009)	**(0.017)**	(0.005)	-	-	-
MQG	**0.448**	**0.011**	**0.007**	-0.003	**0.255**	**-0.250**	-0.015	0.012	**-0.030**	**0.030**	**0.118**	**-0.092**	**0.958**	**-0.009**	-0.007	**-0.050**	0.001	-10325.2	**9964.4**	**682.5**
	(0.001)	**(0.001)**	**(0.002)**	(0.002)	**(0.003)**	**(0.003)**	(0.009)	(0.009)	**(0.003)**	**(0.003)**	**(0.002)**	**(0.003)**	**(0.004)**	**(0.001)**	(0.008)	**(0.013)**	(0.004)	-	-	-
BEN	**0.506**	**0.003**	0.001	-0.001	**0.054**	**-0.050**	**-0.080**	**0.067**	**-0.027**	**0.026**	**0.109**	**-0.085**	**0.953**	**-0.008**	-0.005	-0.077	0.008	-18276.0	**4328.6**	**425.9**
	(0.002)	**(0.001)**	(0.002)	(0.002)	**(0.002)**	**(0.002)**	**(0.018)**	**(0.018)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.005)**	**(0.006)**	**(0.002)**	(0.014)	(0.043)	(0.009)	-	-	-

This table reports the estimates and robust standard errors (in parentheses) from the W-ACD(2,1) models in eleven RBA announcement weeks in 2013. Panel A shows the results for the Dufour and Engle (2000) exogenous-duration model with the following W-ACD specification

$$\widetilde{T}_t = [\phi_t \Gamma(1 + 1/\theta)]\epsilon_t,$$

$$\ln(\phi_t) = \alpha^T + \sum_{i=1}^{2} \rho_i \ln(\widetilde{T}_{t-i}) + \zeta \ln(\phi_{t-1}) + \lambda_{op}^T \text{open}_{t-1} + \lambda_{be}^T \text{bef}_{t-1} + \lambda_{ar}^T \text{aro}_{t-1} + \lambda_{af}^T \text{aft}_{t-1}.$$

Panel B shows the results for the WACD-VAR model (9) with the following W-ACD specification

$$\widetilde{T}_t = [\phi_t \Gamma(1 + 1/\theta)]\epsilon_t,$$

$$\ln(\phi_t) = \alpha^T + \sum_{i=1}^{2} a_i^T r_{t-i} + \sum_{i=1}^{2} b_i^T |r_{t-i}| + \sum_{i=1}^{2} \gamma_i^T x_{t-i} + \sum_{i=1}^{2} \rho_i \ln(\widetilde{T}_{t-i}) + \zeta \ln(\phi_{t-1}) + \lambda_{op}^T \text{open}_{t-1} + \lambda_{be}^T \text{bef}_{t-1} + \lambda_{ar}^T \text{aro}_{t-1} + \lambda_{af}^T \text{aft}_{t-1}.$$

$\widetilde{T}_t$ is the cubic-spline diurnally adjusted duration of the t-th trade. $\epsilon_t \overset{iid}{\sim}$ Weibull $\left(scale = \frac{1}{\Gamma(1+1/\theta)}, shape = \theta\right)$. $\phi_t \Gamma(1 + 1/\theta)]$ is the conditional duration mean of the t-th trade. open_t is a dummy variable for the first 30 minutes of the trading day. r_t and $|r_t|$ are quote revisions and *absolute* quote revisions, respectively; x_t is a column vector of trade signs (x_t^0, which equals 1 for buys and -1 for sells) and volumes (v_t, defined as the signed logarithm of the ratio of the share volume to the prevailing quoted depth) of the t-th trade. bef_t, aro_t and aft_t are indicator variables identifying trades that are executed 5 minutes *before* (14:24:30-14:29:30), one minute *around* (14:29:30-14:30:30), and 10 minutes *after* (14:30:30-14:40:30) the RBA announcements. $Q_{15,\text{raw}}$ ($Q_{15,\text{resid}}$) is the Ljung-Box statistic associated with the null hypothesis of no autocorrelation up to order 15 in the raw (residual) diurnally adjusted duration series. Bold format denotes statistical significance at a 5% level.

Table 8: Generalized Forecast Error Variance Decomposition for **Returns** conditioning on the average **RBAAT** history

Stock	**ANZ**				**CBA**				**NAB**				**WBC**				**MQG**				**BEN**			
Response	**returns**				**returns**				**returns**				**returns**				**returns**				**returns**			
Impulse	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur
Horizon																								
A: Endo-VAR model																								
0	33.18	43.08	23.65	0.10	30.89	49.51	19.11	0.48	27.16	46.71	25.75	0.38	40.99	35.85	22.52	0.64	31.20	52.49	15.24	1.07	30.20	40.14	25.01	4.66
1	33.93	41.49	24.48	0.11	31.07	48.46	19.90	0.57	28.82	45.05	25.58	0.55	40.69	34.34	23.84	1.14	31.14	51.57	15.48	1.82	31.01	38.25	25.70	5.04
2	33.96	41.46	24.48	0.11	31.02	48.47	19.85	0.66	28.82	44.97	25.55	0.67	40.53	34.10	23.76	1.61	30.94	51.33	15.33	2.40	30.89	38.20	25.53	5.38
3	33.96	41.46	24.47	0.11	30.99	48.47	19.82	0.73	28.79	44.93	25.52	0.77	40.38	33.92	23.68	2.01	30.80	51.02	15.22	2.96	30.86	38.11	25.49	5.54
10	33.94	41.43	24.46	0.18	30.89	48.25	19.74	1.13	28.64	44.61	25.35	1.40	39.58	32.88	23.18	4.35	30.13	49.52	14.76	5.60	30.81	38.06	25.43	5.70
20	33.93	41.41	24.45	0.21	30.84	48.12	19.70	1.34	28.55	44.44	25.26	1.75	38.91	32.01	22.73	6.35	29.67	48.51	14.44	7.38	30.80	38.05	25.43	5.71
40	33.93	41.41	24.45	0.22	30.82	48.10	19.69	1.39	28.53	44.40	25.25	1.82	38.58	31.57	22.49	7.36	29.50	48.14	14.32	8.04	30.80	38.05	25.43	5.72
45	33.93	41.41	24.45	0.22	30.82	48.10	19.69	1.39	28.53	44.40	25.25	1.82	38.58	31.55	22.48	7.39	29.50	48.13	14.32	8.05	30.80	38.05	25.43	5.72
50	33.93	41.41	24.45	0.22	30.82	48.10	19.69	1.39	28.53	44.40	25.25	1.82	38.57	31.55	22.48	7.40	29.50	48.13	14.32	8.05	30.80	38.05	25.43	5.72
B: WACD-VAR model																								
0	33.25	42.19	24.55	0.01	30.36	49.02	20.59	0.04	28.09	47.78	24.08	0.05	41.07	36.32	22.54	0.07	31.49	54.35	13.97	0.20	27.84	44.25	25.94	1.96
1	33.97	40.66	25.36	0.01	30.57	47.95	21.43	0.05	29.77	46.24	23.90	0.09	40.96	34.99	23.94	0.11	31.57	53.82	14.26	0.35	28.86	41.53	27.36	2.25
2	34.01	40.63	25.35	0.01	30.55	47.99	21.40	0.06	29.79	46.19	23.90	0.11	40.96	34.95	23.95	0.14	31.49	53.86	14.19	0.47	28.76	41.57	27.18	2.49
3	34.01	40.63	25.35	0.01	30.53	48.02	21.38	0.07	29.78	46.19	23.89	0.14	40.94	34.94	23.95	0.17	31.45	53.80	14.17	0.59	28.74	41.48	27.15	2.63
10	34.00	40.62	25.35	0.03	30.50	48.01	21.36	0.13	29.73	46.09	23.85	0.33	40.82	34.81	23.89	0.48	31.32	53.52	14.08	1.09	28.69	41.42	27.09	2.81
20	34.00	40.62	25.35	0.04	30.49	47.98	21.35	0.19	29.70	46.04	23.83	0.42	40.69	34.63	23.82	0.86	31.28	53.42	14.05	1.25	28.69	41.41	27.08	2.82
40	34.00	40.61	25.35	0.04	30.48	47.96	21.34	0.21	29.70	46.03	23.83	0.44	40.60	34.48	23.76	1.16	31.27	53.41	14.05	1.28	28.69	41.41	27.08	2.82
45	34.00	40.61	25.35	0.04	30.48	47.96	21.34	0.22	29.70	46.03	23.83	0.44	40.59	34.47	23.75	1.19	31.27	53.40	14.05	1.28	28.69	41.41	27.08	2.83
50	34.00	40.61	25.34	0.04	30.48	47.96	21.34	0.22	29.70	46.03	23.83	0.44	40.58	34.46	23.75	1.21	31.27	53.40	14.05	1.28	28.69	41.41	27.08	2.83
C: Augmented Dufour-Engle model																								
0	33.98	40.61	25.41	0.00	29.99	48.97	21.03	0.02	29.62	46.88	23.51	0.00	42.21	34.70	23.09	0.01	32.49	51.31	16.20	0.00	26.32	44.25	29.39	0.04
1	34.68	39.10	26.21	0.00	30.16	47.87	21.95	0.02	31.37	45.24	23.39	0.00	42.04	33.37	24.57	0.01	32.61	50.87	16.51	0.00	27.57	41.61	30.76	0.06
2	34.72	39.07	26.21	0.00	30.14	47.92	21.92	0.02	31.39	45.20	23.40	0.00	42.04	33.35	24.60	0.01	32.55	50.98	16.46	0.01	27.55	41.69	30.68	0.08
3	34.71	39.07	26.21	0.00	30.12	47.96	21.91	0.02	31.39	45.21	23.39	0.00	42.04	33.35	24.60	0.01	32.54	51.00	16.45	0.01	27.55	41.67	30.69	0.09
10	34.71	39.07	26.21	0.01	30.11	47.97	21.89	0.03	31.39	45.21	23.39	0.01	42.04	33.35	24.59	0.01	32.53	51.01	16.44	0.02	27.54	41.67	30.66	0.13
20	34.71	39.07	26.21	0.01	30.11	47.97	21.89	0.04	31.39	45.20	23.39	0.02	42.04	33.35	24.59	0.02	32.53	51.00	16.44	0.03	27.54	41.67	30.66	0.13
40	34.71	39.07	26.21	0.01	30.11	47.96	21.89	0.04	31.38	45.20	23.39	0.03	42.04	33.35	24.59	0.02	32.53	51.00	16.44	0.03	27.54	41.67	30.66	0.13
45	34.71	39.07	26.21	0.01	30.11	47.96	21.89	0.05	31.38	45.20	23.39	0.03	42.04	33.35	24.59	0.02	32.53	51.00	16.44	0.03	27.54	41.67	30.66	0.13
50	34.71	39.07	26.21	0.01	30.10	47.96	21.89	0.05	31.38	45.20	23.39	0.03	42.04	33.35	24.59	0.02	32.53	51.00	16.44	0.03	27.54	41.67	30.66	0.13
D: Original Dufour-Engle model																								
0	75.75	24.23	-	0.02	71.22	28.77	-	0.01	76.84	23.15	-	0.01	73.28	26.68	-	0.04	68.27	31.73	-	0.00	74.64	25.36	-	0.00
1	75.89	24.09	-	0.02	70.78	29.21	-	0.01	76.98	23.00	-	0.01	73.31	26.65	-	0.04	67.92	32.08	-	0.00	75.09	24.91	-	0.00
2	75.83	24.15	-	0.02	70.64	29.35	-	0.01	76.92	23.07	-	0.01	73.23	26.74	-	0.04	67.82	32.18	-	0.00	75.02	24.97	-	0.00
3	75.79	24.19	-	0.02	70.58	29.41	-	0.01	76.89	23.10	-	0.01	73.21	26.75	-	0.04	67.82	32.18	-	0.00	75.02	24.98	-	0.00
10	75.78	24.20	-	0.02	70.56	29.43	-	0.01	76.88	23.11	-	0.01	73.19	26.77	-	0.04	67.81	32.19	-	0.00	74.98	25.01	-	0.00
20	75.78	24.20	-	0.02	70.56	29.43	-	0.01	76.88	23.11	-	0.01	73.19	26.77	-	0.04	67.81	32.19	-	0.00	74.98	25.02	-	0.01
40	75.78	24.20	-	0.02	70.56	29.43	-	0.01	76.88	23.11	-	0.01	73.19	26.77	-	0.04	67.81	32.19	-	0.00	74.98	25.02	-	0.01
45	75.78	24.20	-	0.02	70.56	29.43	-	0.01	76.88	23.11	-	0.01	73.19	26.77	-	0.04	67.81	32.19	-	0.00	74.98	25.02	-	0.01
50	75.78	24.20	-	0.02	70.56	29.43	-	0.01	76.88	23.11	-	0.01	73.19	26.77	-	0.04	67.81	32.19	-	0.00	74.98	25.02	-	0.01

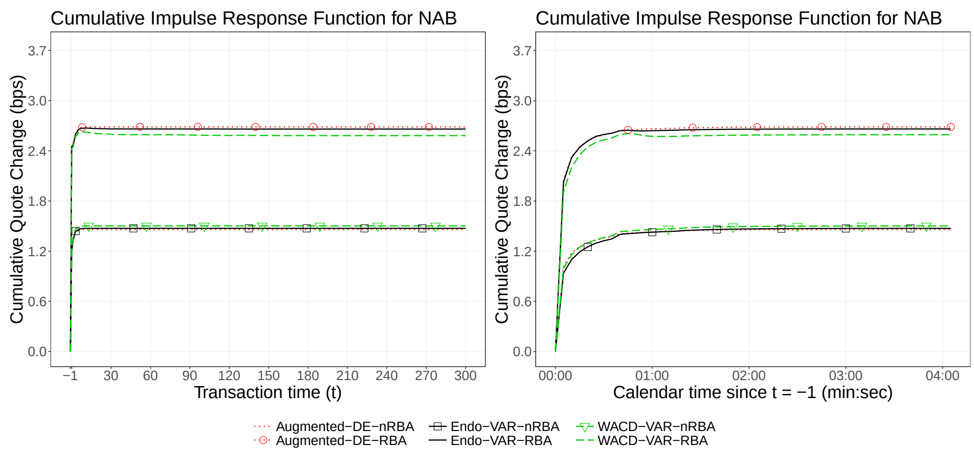
This table reports the generalized forecast error variance decomposition (GFEVD) for **returns**, conditioning on the average **RBAAT** history, for six Australian banking stocks in 2013 for 4 models, namely the *Endo-VAR*, *WACD-VAR*, Augmented Dufour-Engle (i.e. with volume), and Original Dufour-Engle (without volume) models. Following the step-by-step procedure described in Appendix B, each entry in the table, reported in %, is calculated according to Equation (11), by averaging over $M = 1,000$ vectors of shocks bootstrapped from the residuals of the corresponding estimated models. For each vector of shocks, the GIRF $I_j(\cdot)$ in Equation (11) is based on $N = 1,000$ simulated realizations. The average RBAAT history is defined as the average of all trading histories right before 14:30:00 on each of eleven RBA days in 2013.

Table 9: Generalized Forecast Error Variance Decomposition for **Returns** conditioning on the average **non-RBAAT** history

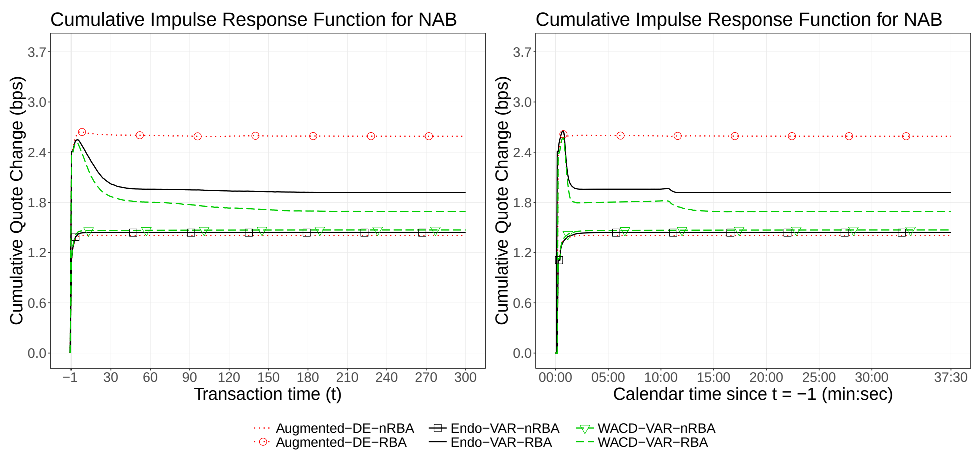
Stock	**ANZ**				**CBA**				**NAB**				**WBC**				**MQG**				**BEN**			
Response	**returns**				**returns**				**returns**				**returns**				**returns**				**returns**			
Impulse	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur	ret	sign	vol	dur
Horizon																								
A: Endo-VAR model																								
0	46.94	37.64	15.42	0.00	45.89	40.39	13.71	0.01	51.09	34.87	14.04	0.00	49.68	36.28	14.03	0.00	46.16	40.66	13.18	0.00	42.68	36.56	20.76	0.00
1	47.33	37.00	15.67	0.01	45.77	40.59	13.62	0.02	51.42	34.38	14.19	0.01	49.94	35.89	14.15	0.01	46.06	40.82	13.11	0.02	43.22	35.59	21.17	0.02
2	47.34	36.98	15.67	0.01	45.70	40.69	13.59	0.02	51.43	34.37	14.18	0.01	49.93	35.92	14.14	0.01	46.00	40.91	13.08	0.02	43.22	35.61	21.16	0.02
3	47.34	36.99	15.67	0.01	45.66	40.75	13.57	0.02	51.41	34.40	14.17	0.02	49.92	35.93	14.14	0.01	46.00	40.91	13.08	0.02	43.22	35.59	21.17	0.02
10	47.33	36.97	15.66	0.04	45.65	40.76	13.57	0.02	51.40	34.40	14.17	0.03	49.91	35.93	14.13	0.03	45.99	40.90	13.08	0.03	43.19	35.60	21.15	0.06
15	47.33	36.97	15.66	0.04	45.65	40.76	13.57	0.02	51.40	34.40	14.17	0.03	49.91	35.93	14.13	0.03	45.99	40.90	13.08	0.03	43.19	35.60	21.15	0.06
20	47.33	36.97	15.66	0.04	45.65	40.76	13.57	0.02	51.40	34.40	14.17	0.03	49.91	35.93	14.13	0.03	45.99	40.90	13.08	0.03	43.19	35.60	21.15	0.06
B: WACD-VAR model																								
0	46.83	37.09	16.08	0.00	43.84	40.92	15.24	0.01	51.43	34.67	13.90	0.00	50.09	35.40	14.50	0.00	46.55	41.14	12.31	0.00	41.16	36.63	22.21	0.00
1	47.23	36.44	16.33	0.00	43.72	41.12	15.15	0.01	51.76	34.20	14.05	0.00	50.37	34.99	14.63	0.01	46.45	41.31	12.24	0.01	41.71	35.62	22.66	0.01
2	47.25	36.42	16.34	0.00	43.66	41.21	15.11	0.01	51.76	34.19	14.05	0.00	50.36	35.01	14.63	0.01	46.39	41.39	12.21	0.01	41.71	35.64	22.65	0.01
3	47.24	36.42	16.33	0.00	43.63	41.27	15.10	0.01	51.74	34.21	14.04	0.01	50.35	35.02	14.62	0.01	46.39	41.39	12.21	0.01	41.71	35.62	22.66	0.01
10	47.24	36.42	16.33	0.02	43.62	41.28	15.09	0.01	51.74	34.22	14.03	0.01	50.34	35.03	14.62	0.02	46.39	41.39	12.21	0.01	41.69	35.64	22.64	0.03
15	47.24	36.42	16.33	0.02	43.62	41.28	15.09	0.01	51.74	34.22	14.03	0.01	50.34	35.03	14.62	0.02	46.39	41.39	12.21	0.01	41.69	35.64	22.64	0.03
20	47.24	36.42	16.33	0.02	43.62	41.28	15.09	0.01	51.74	34.22	14.03	0.01	50.34	35.03	14.62	0.02	46.39	41.39	12.21	0.01	41.69	35.64	22.64	0.03
C: Augmented Dufour-Engle model																								
0	47.44	37.29	15.27	0.00	46.04	39.92	14.05	0.01	51.01	35.31	13.68	0.00	47.27	37.57	15.16	0.00	44.38	42.64	12.98	0.00	42.60	36.83	20.57	0.00
1	47.83	36.65	15.52	0.00	45.93	40.08	13.99	0.01	51.36	34.80	13.84	0.00	47.54	37.15	15.31	0.00	44.29	42.78	12.93	0.00	43.15	35.84	21.01	0.00
2	47.85	36.63	15.53	0.00	45.88	40.16	13.96	0.01	51.37	34.79	13.84	0.00	47.52	37.17	15.30	0.00	44.24	42.86	12.90	0.00	43.15	35.85	21.00	0.00
3	47.84	36.63	15.52	0.00	45.85	40.21	13.94	0.01	51.35	34.82	13.83	0.00	47.52	37.18	15.30	0.00	44.24	42.86	12.90	0.00	43.15	35.84	21.01	0.00
10	47.84	36.63	15.52	0.00	45.84	40.22	13.94	0.01	51.35	34.82	13.83	0.00	47.51	37.19	15.30	0.00	44.23	42.86	12.90	0.00	43.14	35.87	21.00	0.00
15	47.84	36.63	15.52	0.00	45.84	40.22	13.94	0.01	51.35	34.82	13.83	0.00	47.51	37.19	15.30	0.00	44.23	42.86	12.90	0.00	43.14	35.87	21.00	0.00
20	47.84	36.63	15.52	0.00	45.84	40.22	13.94	0.01	51.35	34.82	13.83	0.00	47.51	37.19	15.30	0.00	44.23	42.86	12.90	0.00	43.14	35.87	21.00	0.00
D: Original Dufour-Engle model																								
0	77.19	22.81	-	0.00	70.03	29.96	-	0.01	75.12	24.88	-	0.00	75.50	24.50	-	0.01	68.76	31.24	-	0.00	74.45	25.53	-	0.03
1	77.32	22.68	-	0.00	69.59	30.40	-	0.01	75.27	24.73	-	0.00	75.53	24.47	-	0.00	68.42	31.58	-	0.00	74.89	25.08	-	0.02
2	77.26	22.74	-	0.00	69.44	30.55	-	0.01	75.20	24.80	-	0.00	75.44	24.55	-	0.00	68.32	31.68	-	0.00	74.83	25.15	-	0.02
3	77.22	22.77	-	0.00	69.38	30.61	-	0.01	75.17	24.83	-	0.00	75.43	24.57	-	0.00	68.31	31.69	-	0.00	74.82	25.15	-	0.02
10	77.22	22.78	-	0.00	69.36	30.63	-	0.01	75.16	24.84	-	0.00	75.41	24.59	-	0.00	68.31	31.69	-	0.00	74.79	25.19	-	0.03
15	77.22	22.78	-	0.00	69.36	30.63	-	0.01	75.16	24.84	-	0.00	75.41	24.59	-	0.00	68.31	31.69	-	0.00	74.78	25.19	-	0.03
20	77.22	22.78	-	0.00	69.36	30.63	-	0.01	75.16	24.84	-	0.00	75.41	24.59	-	0.00	68.31	31.69	-	0.00	74.78	25.19	-	0.03

This table reports the generalized forecast error variance decomposition (GFEVD) for **returns**, conditioning on the average **non-RBAAT** history, for six Australian banking stocks in 2013 for 4 models, namely the *Endo-VAR*, *WACD-VAR*, Augmented Dufour-Engle (i.e. with volume), and Original Dufour-Engle (without volume) models. Following the step-by-step procedure described in Appendix B, each entry in the table, reported in %, is calculated according to Equation (11), by averaging over $M = 1,000$ vectors of shocks bootstrapped from the residuals of the corresponding estimated models. For each vector of shocks, the GIRF $I_j(\cdot)$ in Equation (11) is based on $N = 1,000$ simulated realizations. The average non-RBAAT history is defined as the average of all trading histories right before 14:30:00 on each of forty-three non-RBA days in the current sample.

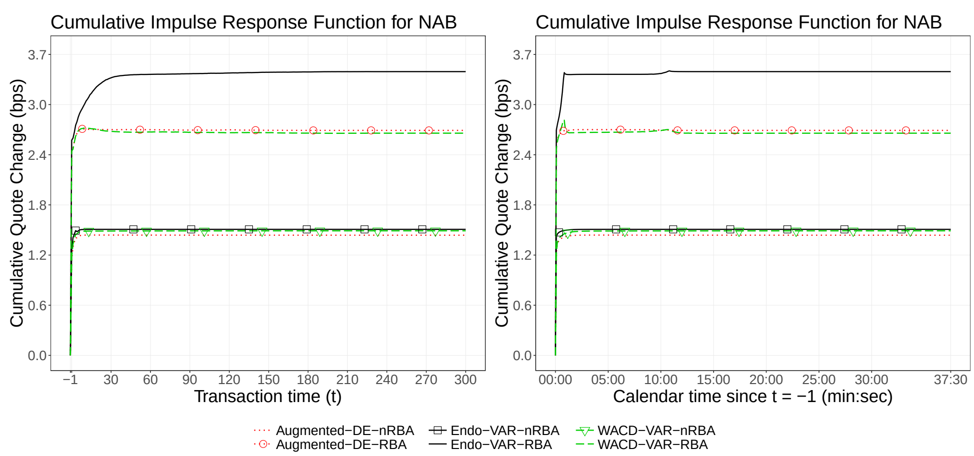
Figure 1: Impulse response functions for quote revisions of stock NAB



(a) No duration shock



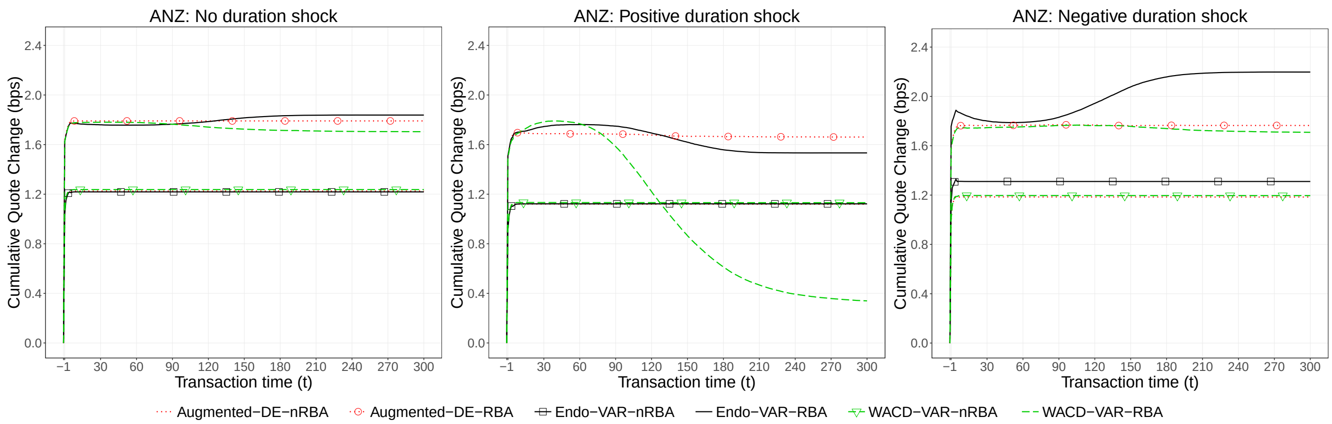
(b) A positive one standard deviation duration shock



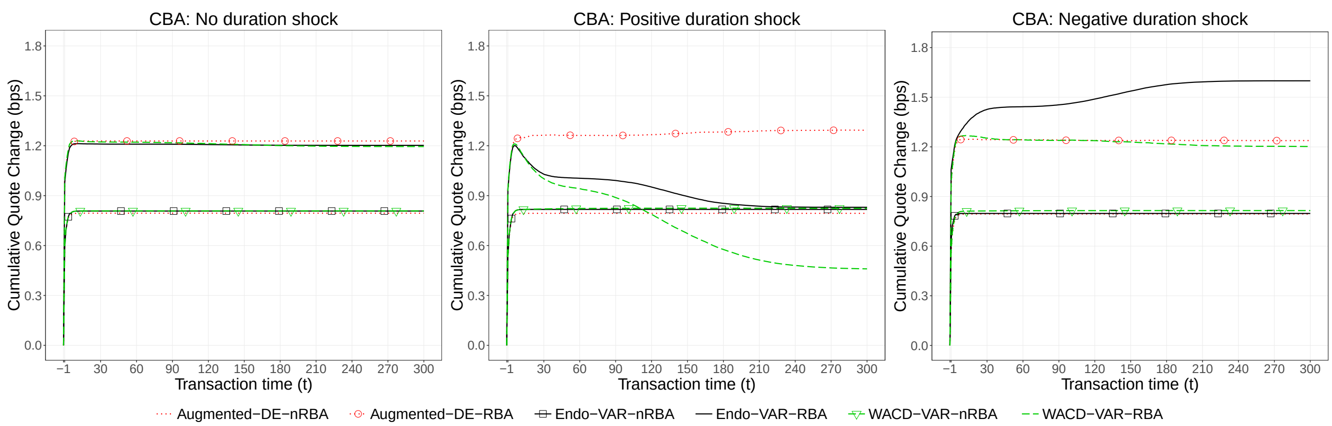
(c) A negative one standard deviation duration shock

Note: This figure plots the cumulative impulse response of quote revisions after an unexpected buy with either (i) no duration shock (Panel (a)), (ii) a positive one standard deviation duration shock (Panel (b)), or (iii) a negative one standard deviation duration shock (Panel (c)). Conditioning on a trade that occurred right before 14:30:00 of an **average** day on which the RBA made or did not make announcements (i.e. conditioning on the average RBAAT or non-RBAAT history), we simulate and compute 10,000 impulse response functions for 300 transactions into the future. Averages of cumulative quote changes at each step are calculated and plotted in both transaction time (left graphs) and calendar time (right graphs, for the first 4 minutes in Panel (a)) since the conditioning transaction (i.e. $t = -1$). Cumulative price impacts obtained from the *Endo-VAR* model (8) and *WACD-VAR* model (9) are pictured. We also chart the cumulative quote changes for the augmented Dufour and Engle (2000) (DE) exogenous-duration VAR model (i.e. with volume incorporated) for comparison.

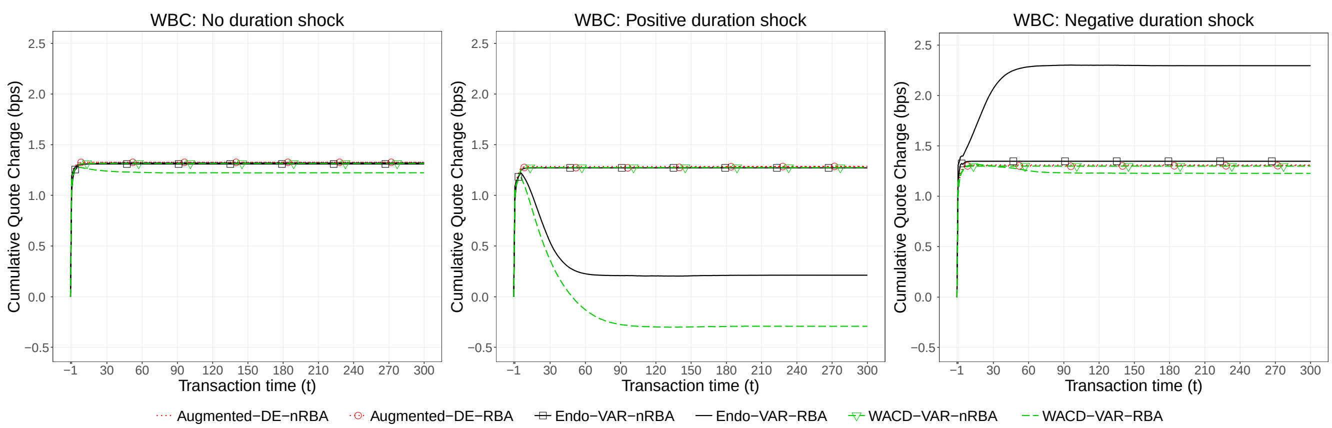
Figure 2: Impulse response functions for quote revisions of banking stocks



(a) ANZ



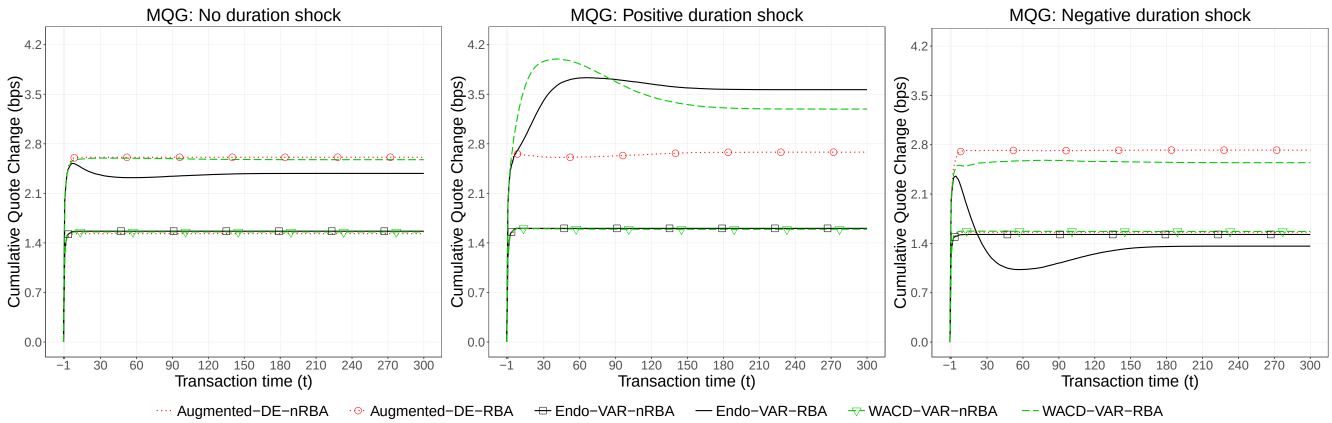
(b) CBA



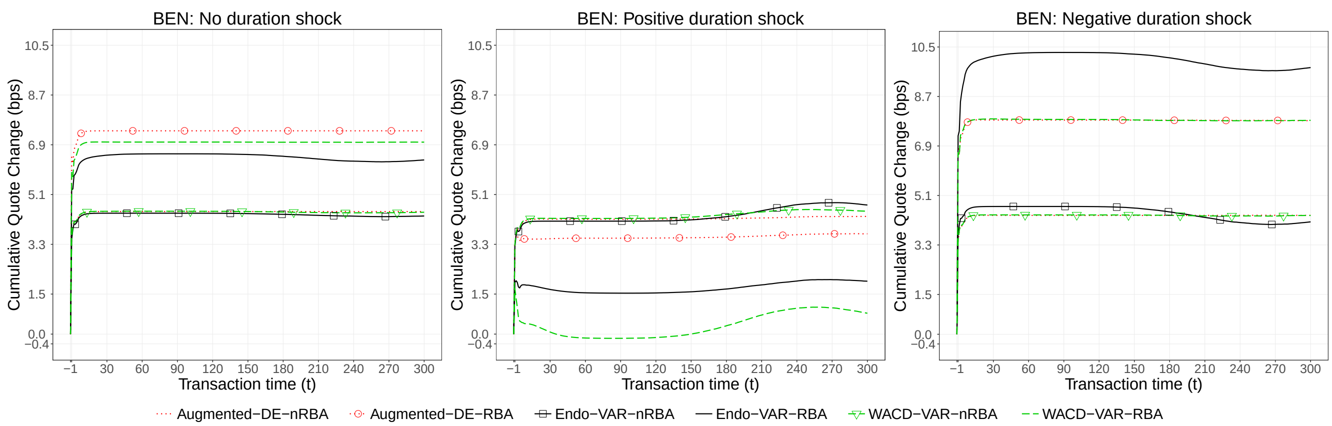
(c) WBC

(Figure continued on next page)

Figure 2 – *continued*



(d) MQG



(e) BEN

Note: This figure plots the cumulative impulse response of quote revisions after an unexpected buy with either (i) no duration shock (left plots), (ii) a positive one standard deviation duration shock (middle plots), or (iii) a negative one standard deviation duration shock (right plots) for 5 Australian banking stocks, namely ANZ, CBA, WBC, MQG and BEN. Conditioning on a trade that occurred right before 14:30:00 of an **average** day on which the RBA made or did not make announcements (i.e. conditioning on the average RBAAT or non-RBAAT history), we simulate and compute 10,000 impulse response functions for 300 transactions into the future. Averages of cumulative quote changes at each step are calculated and plotted in transaction time since the conditioning transaction (i.e. $t = -1$). Cumulative price impacts obtained from the *Endo-VAR* model (8) and *WACD-VAR* model (9) are pictured. We also chart the cumulative quote changes for the augmented Dufour and Engle (2000) (DE) exogenous-duration VAR model (i.e. with volume incorporated) for comparison.

Appendices

A Simulation procedure to compute GIRFs

The simulation experiment explained in subsection 4.2 to produce the GIRFs for quote revision r_t is carried out via the following steps.

A.1 Pick a history $\mathcal{I}_{t-1}$.

A.2 For a given horizon h, generate a $4\times(1+h)$ matrix of random noise for quote revisions, trade attributes and time durations. For the *Endo-VAR* system, the noise series are bootstrapped from their respective residuals $\widehat{\varepsilon}_t$ since the usual normal assumption is too restrictive, as implied by the large Jarque-Bera statistics discussed earlier. The bootstrapping avoids the imposition of unrealistic distributional assumptions on the error terms. The error terms (of sign and volume equations in particular) are contemporaneously correlated, so we first transform the correlated $\widehat{\varepsilon}_t$ to contemporaneously uncorrelated residuals, $\widehat{\zeta}_t = P^{-1}\widehat{\varepsilon}_t$, where P is the lower Cholesky decomposition of the estimated covariance matrix of ε_t (i.e. $\widehat{Var}(\varepsilon_t) = PP'$) (see Koop et al., 1996, Pesaran and Shin, 1996). We retain the serial correlation inherent in the observed $\widehat{\varepsilon}_t$ (which is also imported to $\widehat{\zeta}_t$) by applying the stationary bootstrap procedure proposed by Politis and Romano (1994) with an average block bootstrap length set to 10 to each element of $\widehat{\zeta}_t$. We recover $\widehat{\varepsilon}_t = P\widehat{\zeta}_t$ from the draws of $\widehat{\zeta}_t$. For the *WACD-VAR* system, duration innovations are randomly drawn from the estimated Weibull distribution, while the innovations for quote changes and trade characteristics are drawn using the above bootstrap method.

A.3 Given $\mathcal{I}_{t-1}$, compute T_t, x_t, and then r_t according to their joint system, using the disturbances produced in step A.2. Simulated values for (T, x, r) at each period are augmented into the past information set to compute the next period values until the h-th future period is reached. This gives a trajectory of $(r_{t+k}, x_{t+k}, T_{t+k})$ for $k = 0, 1, \cdots, h$ under the "no shock" scenario. Since the WACD model is applied to diurnally adjusted duration $\widetilde{T}_t$, after $\widetilde{T}_{t+k}, k = 0, 1, \cdots, h$ is calculated, these $\widetilde{T}_{t+k}$ are transformed back to T_{t+k}, for use in the other equations.

A.4 Shock the joint system at transaction time t with trade, duration, and/or return shocks and repeat step A.3 using the same set of noise series generated in step A.2.[18] At each horizon k, calculate a realization of $I_r(k, \cdot)$ as $r_{t+k,\text{ shock}} - r_{t+k,\text{ no shock}}$. The simulated path of $I_r(k, \cdot)$ indexed in transaction time can be used directly, and/or converted into calendar time.

A.5 Repeat steps A.3 to A.4 N times, where N is a sufficiently large number. This gives N realizations of the impulse response $I_r^{(l)}(k, \cdot)$ for $l = 1, 2, \cdots, N$. Averaging these realizations provides an estimate of $I_r(k, \cdot)$ for $k = 0, 1, \cdots, h$.

[18] That is, the first vector of the noise series in step A.2 (i.e. at time t), or a part of it, is replaced by the relevant shocks.

B Simulation procedure to compute GFEVD

The GFEVD for a multivariate system of quote revisions, trade attributes and trade durations is calculated via the following steps.

B.1 Pick a history $\mathcal{I}_{t-1}$ (i.e. either the average RBAAT or average non-RBAAT history in our case).

B.2 Draw a shock vector ε_t from the residuals of the estimated model. This can be done similarly to step A.2 in subsection 4.2, but without the embedded stationary bootstrap procedure since only one shock vector is drawn.

B.3 Compute the GIRF $I_j(\cdot)$ in equation (11) associated with each element of the shock vector drawn in step B.2 for all variables in the multivariate system. This consists of performing steps A.2 to A.5 in subsection 4.2 but now for all variables. Note that in step A.4 we now only shock one equation of the system at a time using the relevant element of the shock vector, and the GIRF $I_j(\cdot)$ corresponding to each shock element is computed for h future transactions based on N repetitions.

B.4 Use the GIRFs obtained in step B.3 to compute $\lambda_{i \to j, \mathcal{I}_{t-1}}(h), h = 0, 1, 2, \cdots$ as in equation (11) for the particular history and shock.

B.5 Repeat steps B.2 to B.4 M times. Compute the mean of $\lambda_{i \to j, \mathcal{I}_{t-1}}(h), h = 0, 1, 2, \cdots$ to average out the effects of different shock sizes.