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The intraday directional predictability of large Australian stocks: A cross-quantilogram analysis

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ABSTRACT

This study investigates the directional predictability of overnight periods for intraday returns of large Australian stocks. The intraday reactions to overnight developments are studied using cross-quantilograms, a new, flexible methodology that facilitates detailed insights into the quantile dependence between two time series. The results provide evidence for the existence of intraday reversals after overnight periods that carry very bad news, whereas the picture of the short-term reactions to very positive overnight returns is mixed. The observed rebounds concern extreme quantiles and occur with a short delay during the first part of the trading day. The study also shows that continuation and reversal effects are not mutually exclusive. The economic significance of the identified patterns is illustrated by analysing the performance of a simple contrarian strategy.

1. Introduction

Stock market securities' short-term reactions to large price movements are important to both academia and practitioners, as they concern financial markets' efficiency and securities prices' predictability, which could be exploited to earn abnormal returns. This issue has received considerable attention in literature, but the results are mixed. The current study uses the newly introduced cross-quantilogram of Han et al. (2016), a powerful and flexible approach, to investigate the directional predictability in the Australian equity market. In particular, we study intraday stock performance after overnight returns fall in extreme quantiles.

Reviewing more than sixty papers in the area of financial markets' short-term predictability, conditional on large price changes, Amini et al. (2013) demonstrate that the literature has investigated a wide range of markets, assets, time periods, and sampling frequencies.[1] Extant studies vary in terms of methodology and findings, and an important point is the definition of what makes a large price move large. Most of these studies use a pre-defined absolute number, with the 10% threshold very common (Corrado and Jordan, 1997; Yu and Leistikow, 2011; Larson and Madura, 2003; Choi and Jayaraman, 2009, among others). Fewer studies define a large price move in other terms, including as an asset-pricing model's residual (e.g., Lasfer et al., 2003), the range between the most extreme price observations during a certain period (e.g., Ma et al., 2005), the number of extreme observations on a rolling basis (e.g., Hirschey, 2003), or a move measured in terms of standard deviations (e.g., Zawadowski et al., 2006) that exceeds a certain level. Accordingly, while some studies identify reversals after both large price increases and large price declines (e.g., Fung et al., 2000; Hirschey, 2003), others observe reversals in one case but not both (e.g., Claes et al., 2010; Klössner et al., 2012). In contrast, some contributions document continuations after large price movements (e.g., Koutmos, 1998; Mazouz et al., 2009). In addition, most of the studies look at daily frequencies, while only a few use intraday data (e.g., Wang et al., 2009; Zawadowski et al., 2006; Ammann and Kessler, 2009), although gaining insights into the return predictability at high frequencies is essential for intraday traders.

The present study fills the void identified by Amini et al. (2013) regarding the intraday return dynamics and predictability, investigating in particular the intraday behaviour of ten major Australian stocks after extreme overnight returns.[2] This issue is particularly important for Australia as the Australian Stock Exchange (ASX) operates in a six-hour trading day from 10:00 Australian Eastern Standard Time (AEST) (00:00 GMT) to 16:00 AEST (06:00 GMT). Therefore, trading takes place only during the night in major US and European markets while the ASX is closed when the US and European markets are open (Fig. 1). Information

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[1] Some of the prominent papers in these area are Fung et al. (2000), Fung et al. (2008) and Grant et al. (2005).

[2] Many investors have large holdings of individual stocks (e.g., Campbell et al., 2001), justifying the need for investigating short-term reactions at more than a market index level.

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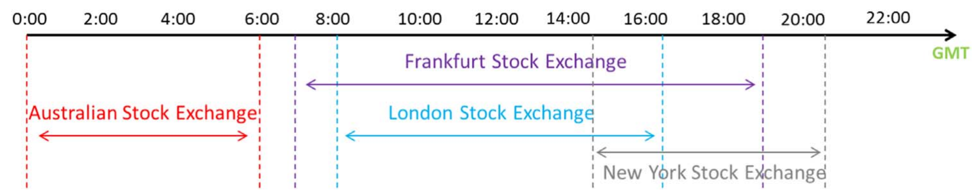

Fig. 1. Open hours of major exchanges, measured in Greenwich Mean Time (GMT). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that arrives overnight in Australia may reflect local market news accumulated during non-trading hours and news that originates from other markets.[3] The market efficiency paradigm postulates that the events that occur overnight (during non-trading hours) are typically reflected rapidly in asset prices when the new trading day begins, ideally in the prices at the market opening. However, motivated by existing research on short-term stock price reactions, we investigate whether extreme overnight returns can cause overreactions, resulting in subsequent price adjustments.

The past few years have witnessed vibrant theoretical developments in modelling the multivariate lead-lag cross-correlations beyond the conditional mean (e.g., Davis and Mikosch, 2009; Davis et al., 2012, 2013). The quantilogram of Linton and Whang (2007) was developed to measure and test the directional predictability of a stationary time series at various quantiles. Recently, Han et al. (2016) extended the univariate quantilogram to a multivariate version, the bivariate cross-quantilogram. The cross-quantilogram is an easy-to-interpret method that measures whether a time series can predict another time series in another part of the distribution. Since the method is based on quantile hits it does not require moment conditions. Consistent confidence intervals can be obtained with stationary bootstrapping. Other than Han et al. (2016), who look at the volatility-return relationship and dependence on systematic risks at daily or lower frequencies, the present study is the first to apply the cross-quantilogram to equity markets.[4]

Our study is related to Berkman et al. (2012). However, while these authors focus on positive overnight returns, we study the whole empirical return distribution. Moreover, Berkman et al. (2012) show that intraday reversals following positive overnight returns are more pronounced for stocks which are difficult to value and costly to arbitrage. In contrast, we rule out these effects by focusing on the most liquid shares in the Australian market. Our methodology is particularly suitable for investigating the dependence of intraday returns on the immediately preceding overnight development and providing detailed insights into the quantile dependence of stock returns. More specifically, it is possible simultaneously to uncover continuation and rebound effects, which cannot be done with commonly used methodologies in this area of research. By relating the magnitude of overnight returns to their own empirical distribution, the more or less arbitrary nature of defining "large" returns boils down to the choice of historical quantiles. Bertram (2004) studies the time-series properties of a large stock sample of the Australian market with intraday data and advocates treating the stock price as two separate processes: an intraday process and an overnight process. In a study on volatility modelling, Andersen et al. (2011) decompose the total daily return variability into the continuous sample path variance, the variation arising from discontinuous jumps that occur during the trading day, as well as the overnight return variance based on the notion for a very different price dynamics exhibited by overnight and intraday returns. These results provide an imperative for treating overnight and intraday returns as two individual time series. Thus, the current study aligns also with the strand of recent literature seeking to exploit the informational content inherent in time series other than the own intraday return history (e.g., Narayan et al., 2015; Narayan and Sharma, 2016; Phan et al., 2016, among others). For example, Narayan et al. (2015) show that order imbalances can be utilized to predict intraday Chinese stock returns. Narayan and Sharma (2016) investigate the potential of S & P500 futures returns to predict Chinese spot market returns. Phan et al. (2016) show that trading activity indicators such as bid-ask spreads and trading volume information can be employed to improve the performance of price volatility forecasts.

Based on intraday data from January 2010 to March 2016, we observe negative and significant cross-quantilograms for extreme quantiles to find that, after a non-trading period with very low returns, the likelihood of having a large positive intraday return increases. After particularly bad overnight developments, the intraday stock prices tend to rebound and exhibit values that are often assigned to the opposite extreme of the intraday return distribution; on the contrary, intraday price behaviour after nights of very positive return developments measured in terms of quantile dependence does not suggest consistent reversal effects. Extending the intraday horizon up to open-close (daily) returns shows that rebounds emerge at the beginning of the trading day, and their overall impact tends to fade during the next few hours. In addition, the cross-quantilograms show that continuation and reversal effects are not mutually exclusive, which is a cue to the varying results documented in the literature. Finally, based on a simple contrarian rule motivated by the documented cross-quantilogram results, we investigate the economic significance of the identified intraday reversals, taking bid-ask spreads into account.

The structure of the paper is as follows. Section 2 introduces the cross-quantilogram, followed by Section 3, which describes the data. Section 4 presents and discusses the findings, and Section 5 concludes.

2. The cross-quantilogram

This section describes the chosen approach for empirical analysis. We follow closely the notation of Han et al. (2016) and Jiang et al. (in press). Different than a quantile regression which allows considering quantiles of the dependent variable only, the methodology used in this study is constructed to reveal cross-quantile predictability of two time series.[5]

Define $\{x_{i,t},\ t \in \mathbb{Z}\}$, $i = 1, 2$ as two strictly stationary time series. In the context of this paper, $x_{1,t}$ and $x_{2,t}$ are the overnight stock returns and the consecutive intraday returns, respectively.[6] Let $F_i(\cdot)$ and $f_i(\cdot)$ be the distribution function and the density function of the series $x_{i,t}$. The

[3] Around 25% of the ASX 200 index volatility and up to half of individual Australian stocks' volatility emerges overnight (Todorova and Soucek, 2014). In comparison, only around 20% of the US stock market volatility emerges during inactive market periods (Hansen and Lunde, 2005). Bertram (2004), Heaton et al. (2011) and Moshirian et al. (2012) further confirm the relevance of overnight periods to the Australian stock market.

[4] So far, the cross-quantilogram has been used only to study cross-market dependencies for agricultural futures (Jiang et al., in press) and the directional predictability from stock market sector indices to the gold market (Baumöhl and Lyócsa, in press).

[5] To check whether the application of a cross-quantilogram methodology is justified, quantile regressions with intraday and the immediately preceding overnight returns as dependent and independent variables, respectively, were conducted for various intraday periods. In the majority of the cases, the quantile regression coefficient estimates for the impact of the overnight returns are not statistically significant. Since the cross-quantilograms allow to explicitly select the quantiles of both series under consideration, while the quantile regression approach allows looking at individual quantiles of the dependent variable only, the cross-quantilogram approach is likely to detect directional predictability in a more precise manner. Quantile regression results are available upon request.

[6] Without exception, all overnight and intraday return series considered are stationary. Table 1 presents the corresponding test statistics of the unit root tests conducted for the overnight returns. Those for the intraday returns are not reported to save space but are available upon request.

quantile of $x_{i,t}$ is $q_i(\alpha_i) = inf\{v: F_i(v) \geq \alpha_i\}$ for $\alpha_i \in (0, 1)$. For simplicity, q_α stands for the two dimensional series of quantiles $(q_1(\alpha_1), q_2(\alpha_2))^{tr}$ for $\alpha \equiv (\alpha_1, \alpha_2)^{tr}$.

The cross-quantilogram for α-quantile with k lags is defined as

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t} - q_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\psi_{\alpha_1}^2(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\psi_{\alpha_2}^2(x_{2,t} - q_2(\alpha_2))]}}, \tag{1}$$

for $k = 0, \pm1, \pm2, \ldots$. $\psi_a(u) \equiv 1[u < 0] - a$, $1[\cdot]$ is the indicator function, and $1[x_{i,t} \leq q_i(\alpha_i)]$ is the quantile-hit (or quantile-exceedance) process. The cross-quantilogram in Eq. (1) captures the serial dependence between two series at different quantile levels. With $\alpha = (\alpha_1, \alpha_2) = (\alpha_{IN}, \alpha_{ON})$ as an example, $\rho_\alpha(1)$ measures the cross-correlation between the intraday returns that are above or below quantile $q_{IN}(\alpha_{IN})$ on day t and the overnight return on the same stock between days $t-1$ and t being above or below quantile $q_{ON}(\alpha_{ON})$. Therefore, $\rho_\alpha(1) = 0$ suggests that the overnight stock return's being above or below quantile $q_{ON}(\alpha_{ON})$ in the night between days $t-1$ and t does not usually help to predict whether the subsequent intraday return will be above or below quantile $q_{IN}(\alpha_{IN})$ on the next trading day. In contrast, if $\rho_\alpha(1) \neq 0$, there is one-day directional predictability from the overnight to the intraday stock return at $\alpha = (\alpha_{IN}, \alpha_{ON})$.

The sample counterpart of the cross-quantilogram can be estimated as

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T}\psi_{\alpha_1}(x_{1,t} - \hat{q}_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - \hat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T}\psi_{\alpha_1}^2(x_{1,t} - \hat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T}\psi_{\alpha_2}^2(x_{2,t-k} - \hat{q}_2(\alpha_2))}} \tag{2}$$

for $k = 0, \pm1, \pm2, \ldots$. In Eq. (2), $\hat{q}_i(\alpha_i)$ is the unconditional sample quantile of $x_{i,t}$ defined as in Han et al. (2016). Han et al. (2016) also propose a quantile version of the Ljung-Box-Pierce type of statistic with H_0: $\rho_\alpha(k) = 0$ for all $k \in \{1, \ldots, p\}$ against the alternative H_1: $\rho_\alpha(k) \neq 0$ for some $k \in 1, \ldots, p$:

$$\hat{Q}_\alpha^{(p)} \equiv \frac{T(T+2)\sum_{k=1}^{p}\hat{\rho}_\alpha^2(k)}{T-p}. \tag{3}$$

The portmanteau test $\hat{Q}_\alpha^{(p)}$ can be used to test the directional predictability of returns from one time series to another for events up to p lags at a pair of quantiles.

Since the asymptotic distribution of the cross-quantilogram is not free of nuisance parameters under the null hypothesis of no directional predictability, Han et al. (2016) suggest using the stationary bootstrap from Politis and Romano (1994) to approximate the null distribution and conduct inference. This block bootstrap procedure takes into account the serial dependence inherent in the data and, unlike usual block bootstraps, allows for random block lengths. Let $B_{K_i,L_i} = \{(x_{1,t}, x_{2,t-k})\}_{t=K_i}^{L_i-1}$ be the i-th block with block length L_i starting from K_i. Here, L_i is an *iid* variable with distribution $Pr(L_i = s) = \gamma(1-\gamma)^{s-1}$, $s = 1, 2\ldots$ for some $\gamma \in (0, 1)$, and K_i is an *iid* sequence drawn from a uniform distribution on $\{1, 2, \ldots, T\}$. Because the upper limit of B_{K_i,L_i} may exceed the sample size T, when $t > T$, $(x_{1,j}, x_{2,j-k})$ with $j = k + (t \bmod (T-k))$ replaces the pair $(x_{1,t}, x_{2,t-k})$. The pseudo resample is constructed based on a sequence of blocks. The cross-quantilogram and associated portmanteau test statistic can be applied to the resampled data set to obtain bootstrapped confidence intervals.

3. Data

To investigate the directional predictability of the Australian stock market, we focus on the ten largest stocks listed at the ASX as of mid-March 2016. The sample covers a large number of sectors: the Commonwealth Bank of Australia (CBA), Westpac Banking Corporation (WBC), Australia and New Zealand Banking Group Limited (NAB), and National Australia Bank Limited (NAB) represent the financial sector; Wesfarmers (WES) and Woolworths (WOW) the consumer staples sector; Telstra Corporation Limited (TLS) the telecommunications sector; BHP Billiton Limited (BHP) the materials sector; CSL Limited (CSL), a biotechnology company, the health care sector; and Woodside Petroleum Limited (WPL) the energy sector. Scentre Group Stapled and Macquarie Group Limited, albeit larger than WPL in terms of market capitalisation, were excluded in order to avoid too much concentration in the financial sector.

The data set consists of intraday transaction prices and quotes sampled at five-minute intervals, for each of which the opening and closing transaction price and corresponding bid and ask quotes are given. The data were obtained from the Thomson Reuters Tick History database through the portal of the Securities Industry Research Centre of Australia (SIRCA). The data sets span the period from 2 January 2010 to 4 March 2016 with the number of the observations varying between 1550 and 1560 trading days for the individual equities.[7]

At 10:00 AEST, the ASX opens for normal trading on a staggered basis. Opening lasts about ten minutes, during which ASX calculates opening prices. Securities open in five groups based on the starting letter of their ASX codes, and trading for all shares is open by 10:10 AEST. The closing auction takes place between 16:10 and 16:12 AEST. The opening and closing prices are established with an algorithm that has four steps such that, if a result is not achieved when the first decision rule is applied, the model progresses to the next decision rule and so on. The first rule maximizes the executed trading volume, the second rule selects the price at which the surplus is minimized otherwise, the third rule selects the highest (lowest) price if the market pressure is on the buy (sell) side, and the fourth rule sets the opening price based on a reference price.[8]

Table 1 shows summary statistics for the overnight returns of the selected stocks. In addition to the average returns, average absolute returns are reported in order to show the magnitude of overnight developments. BHP exhibits the highest absolute returns, with an average 1.25% overnight price move, followed by WPL, with 1%. TLS has the lowest overnight return variation, with an average price movement of 0.6% per non-trading period. The conducted unit root test confirm conclusively that all returns are stationary.[9]

4. Results

All returns are in log form. The overnight stock returns are calculated as

$$r_t^{ON} = \ln(P_{O,t}) - \ln(P_{C,t-1}), \tag{4}$$

where $P_{O,t}$ is the opening price on date t, and $P_{C,t-1}$ is the closing price of trading day $t-1$.

The starting point for calculating intraday returns is the first observation recorded ϵ seconds after 10:10 ($\epsilon \geq 0$),

$$r_t^{IN} = \ln(P_{10:10+\epsilon+\tau,t}) - \ln(P_{10:10+\epsilon,t}). \tag{5}$$

That the opening auction for all ASX stocks is complete by 10:10 ensures the practicability of potential trading strategies, as the market participant is aware of the opening auction's stock price and can react

[7] Earlier sample periods are omitted to avoid the potential for impracticable trading simulations that may arise from bans of short sales in previous years. Even though the paper presents results from trading strategies based only on long positions, earlier versions of the paper contain additional simulations that require short positions. Overnight returns from 2008 and 2009 are used for trading simulations based on a rolling-window approach. The cross-quantilogram results presented in Figs. 2 and 3 are based on the empirical distributions observed since January 2010.

[8] The data set does not show which step has been used for the given open prices, so it is not possible to investigate the results in light of the microstructure of the opening auction. For further reference and examples regarding open and close price calculations, see Frino et al. (2012).

[9] The descriptive statistics of intraday returns from time slots with various lengths as used in the study are not presented for brevity but are available upon request. All return series, without exception, are stationary.

Table 1
Summary statistics of overnight returns.

	Mean	Mean abs	StDev	Min	Max	ADF
ANZ	0.00014	0.0091	0.0137	−0.0901	0.0958	−33.9200*
BHP	0.00001	0.0125	0.0177	−0.0990	0.1196	−31.2766*
CBA	0.00007	0.0083	0.0126	−0.1182	0.0771	−33.4506*
CSL	0.00090	0.0085	0.0123	−0.0926	0.0867	−31.9910*
NAB	0.00012	0.0097	0.0148	−0.1277	0.1012	−32.6065*
TLS	0.00085	0.0059	0.0089	−0.0734	0.0630	−31.4747*
WBC	0.00029	0.0092	0.0130	−0.0888	0.0818	−32.7354*
WES	0.00036	0.0083	0.0120	−0.0961	0.0773	−29.4104*
WOW	−0.00005	0.0066	0.0098	−0.0883	0.0703	−31.9257*
WPL	0.00068	0.0103	0.0150	−0.0906	0.1166	−33.1874*

Note: The sample period is from 1 January 2008 to 4 March 2016. The overnight returns are calculated as the log differences of the first price on a day and the previous day's last price. The column labelled “Mean abs” denotes the average absolute overnight return. The column labelled “ADF” shows the test statistics of the Augmented Dickey Fuller test with null hypothesis that the corresponding time series has an unit root.
* denotes a rejection at the 1% level.

by putting in a trading order at or after 10:10. We calculate intraday returns for various values of τ:. over the first five minutes (using the last transaction price before or at 10:15), and then in steps of 10 minutes (market opening to 10:20, 10:30, etc.) in order to investigate longer-term effects. The return over the longest intraday interval is the open-to-close return.

For the quantiles of the intraday stock return $q_{IN}(\alpha_{IN})$, we consider α_{IN}=0.05, 0.5, and 0.95. For the quantiles of the overnight stock return $q_{ON}(\alpha_{ON})$, we consider α_{ON}=0.05 and 0.95. Figs. 1 and 2 show the directional predictability results for the ten stocks considered when the stocks' overnight returns are in the lowest and highest 5%, respectively. The tables report cross-quantilogram values with their bootstrapped confidence intervals (in red) for no predictability.[10] The bootstrapped confidence intervals are obtained with 1000 replicates. As the focus of the study is on the short-term reactions of extreme overnight developments, we report results at the first lag only. Cross-quantilograms at other lags are consistently insignificant.

4.1. Intraday returns after very low overnight returns

The cross-quantilograms for $q_{ON}(\alpha_{ON}) = 0.05$ (Fig. 2) - that is, the case of very bad overnight development - reveal a clear pattern. For $q_{IN}(\alpha_{IN}) = 0.05$, the cross-quantilograms exhibit mostly insignificant values often close to zero and no consistency in the signs. In contrast, the cross-quantilograms for $q_{IN}(\alpha_{IN}) = 0.5$ and 0.95 are consistently negative and are often statistically significant, especially for the higher quantiles. For example the value for the intraday return ending at 10:40 for ANZ and $\alpha_{IN} = 0.95$ is -0.1227 which implies that when the overnight return of ANZ is very low, there is an increased likelihood of having a very large positive gain within the first half an hour of the next trading day. The negative values go as low as −0.161 (WOW) but are higher for higher quantiles of the intraday return, suggesting a strong bounce-back effect. The pattern, which is similar across the ten stocks under consideration, shows that intraday reversals tend to follow overnight periods that are characterized by particularly bad news.

Across all stocks, significant values are seldom observed for the first five minutes of the trading day suggesting that intraday reversals take longer than five minutes to occur. The directional predictability seem to be strongest for the first part of the trading day, although how it is pronounced across the individual stocks differs. For example, the directional predictability is weaker for BHP and strong for WES, for which there are significant cross-quantilograms up until the end of the trading day. Some cross-quantilograms remain significant but with gradually declining magnitude. In order to drill down to the main source of intraday reversals, the analysis was repeated with intraday returns for time slots starting after 10:20. The results (not tabulated) show that excluding the first half hour almost completely eliminates any directional predictability. Therefore, the first hour of the trading day is a main avenue of predictable short-term price reactions after very low overnight returns.

Albeit pronounced, this phenomenon is not pervasive. For example, in the case of WPL, where only a relatively weak reversal effect is observed, the cross-quantilogram methodology detects additional positive and significant values for $\alpha_{IN} = 0.05$. This result suggests that, when WPL's overnight returns are very low (in their lowest historical 5%), the likelihood of a very large negative return in the first hours of the next day as well increases. This observation provides further evidence for the directional predictability of stock markets but suggests possible continuation effects rather than reversals.

4.2. Intraday returns after very high overnight returns

Fig. 3 shows the cross-quantilograms of intraday periods following overnight periods that are characterised by returns in the highest 5% of the distribution, $q_{ON}(\alpha_{ON}) = 0.95$. The reported values uncover a mixed picture. Some stocks show no significant directional predictability at all following extremely positive overnight returns (ANZ, CSL, WOW). For others (WES, TLS), continuation effects are observed at the beginning of the trading day. For example, the cross-quantilogram for BHP for the first five minutes of the trading day at $q_{IN}(\alpha_{IN}) = 0.95$ is 0.062 and significant, which suggests that, after a very high overnight return, the likelihood of an intraday return within the highest 5% across the sample period increases. Intraday reversals are documented as well. The cross-quantilograms for CBA and WPL are negative and often significant for the quantiles investigated that are at or below the median throughout the trading day. The significant values at $q_{IN}(\alpha_{IN}) = 0.05$ suggest that, after a very positive development, stocks' prices are likely to bounce back to their lowest values across the distribution over the whole sample period. This effect is observed for other stocks (CSL, NAB, WBC) as well but is less intense and less often significant, and the reversals occur at various times.

Continuation and reversal effects are not mutually exclusive. While NAB appears to reverse at the beginning of the trading day, it indicates some continuation later on, as the cross-quantilogram has positive and significant values for $q_{IN}(\alpha_{IN}) = 0.95$ around 11:00. Surprisingly, it is exactly the reverse for BHP: the continuation during the first five minutes (significant at $q_{IN}(\alpha_{IN}) = 0.95$) is followed by a reversal observed until 13:00.

Reversals observed for the one extreme, $q_{ON}(\alpha_{ON}) = 0.05$, are not related to strong reversals at the other extreme, $q_{ON}(\alpha_{ON}) = 0.95$. While WBC has consistently significant rebound effects for $q_{ON}(\alpha_{ON}) = 0.05$ (Fig. 2), WBC suggests reversals for $q_{ON}(\alpha_{ON}) = 0.95$ at around 11:00. On the other hand, WPL, the actions of which were more ambiguous after very low overnight returns, with both continuation and reversal effects observable for $q_{ON}(\alpha_{ON}) = 0.05$, exhibits strong reversals spanning intraday periods until early afternoon.

4.3. Robustness of the results

To assess the robustness of the results, the analysis was repeated with intraday returns starting at or after 10:15. The results show similar patterns, providing evidence that the intraday reversals take place soon after the market opening (mostly within an hour), but not immediately.

In addition, to alleviate the potential noisiness of the stocks' overnight returns, the analysis was repeated using overnight returns based on the transaction prices of the futures on the ASX 200 (ASX SPI 200 index futures) recorded at the market opening and closing of the ASX rather than their own overnight returns, as specified in Eq.

[10] The corresponding portmanteau tests $\widehat{Q}_{\alpha}^{(p)}$ provide results consistent with those of the cross-quantilogram. Results are not reported here for brevity.

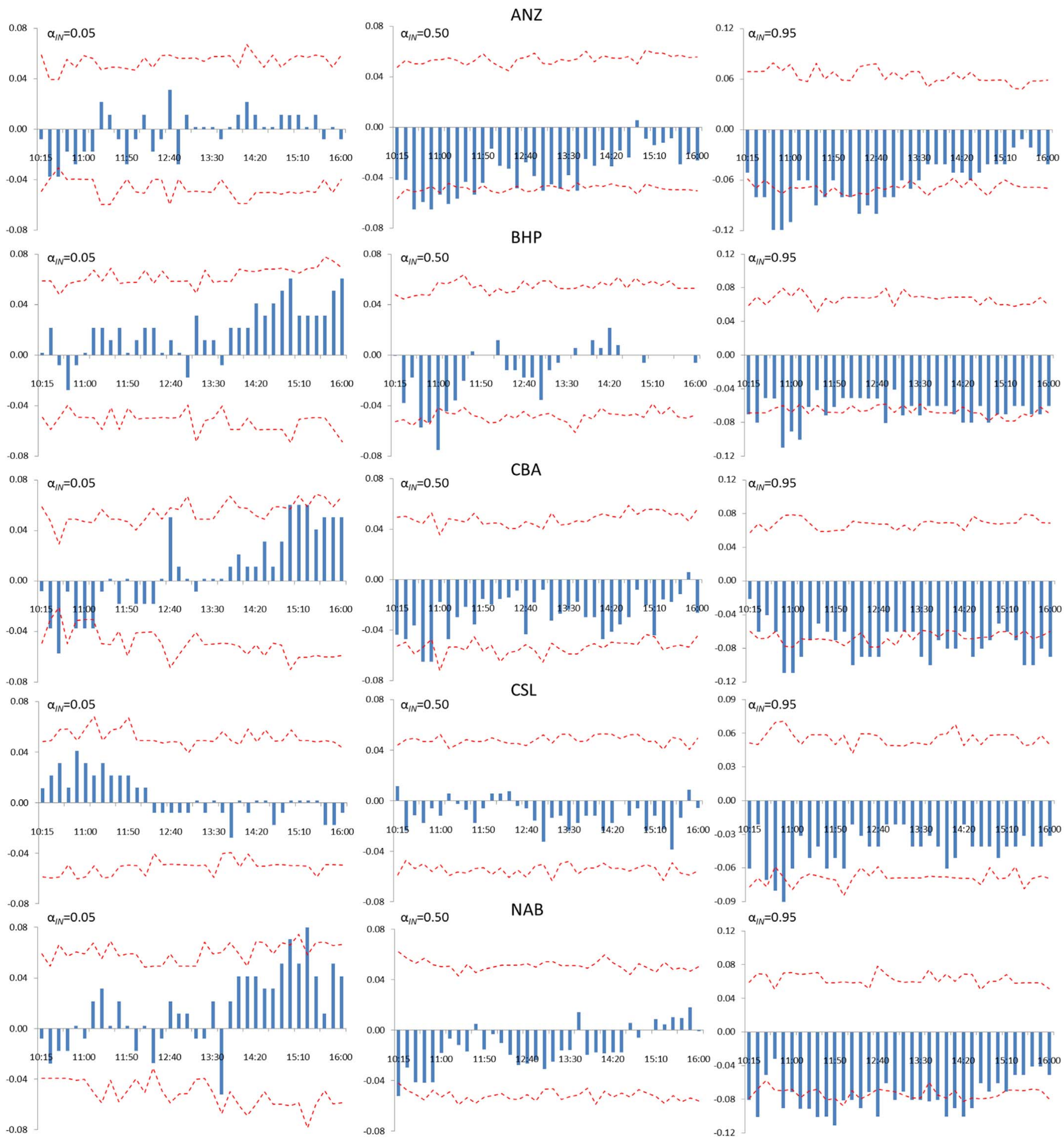

Fig. 2. Cross-quantilogramms for $q_{ON}(\alpha_{ON}) = 0.05$. The table reports the cross-quantilograms from overnight stock returns to the intraday stock returns on the following day from 10:10 to the time given on the horizontal axis. The dashed curves are bootstrapped 95% confidence intervals obtained with 1000 replicates for no predictability. The left, mid and right panels show results for $q_{IN}(\alpha_{IN}) = 0.05$, 0.5 and 0.95, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(5).[11] Using the SPI futures not only smooths potential microstructure issues but also provides an intriguing complement to the analysis by asking whether short-term price behaviour is responsive to the overall stock market development.

The results obtained are similar but not as strong (i.e., in terms of lower absolute values of the cross-quantilograms) as when the individual overnight performance is used.[12] Similar results are obtained particularly for the larger stocks in terms of market capitalisation. This result is expected since the largest stocks in the sample (CBA, WBC, ANZ, and NAB) have weights of 5–9% of the ASX 200 stocks'[13] overall

[11] A continuous futures series is created by rolling over the nearest month contract to the next most liquid month when the daily volume of the current contract is exceeded.

[12] The results are available upon request.

[13] As of 21 March 2016.

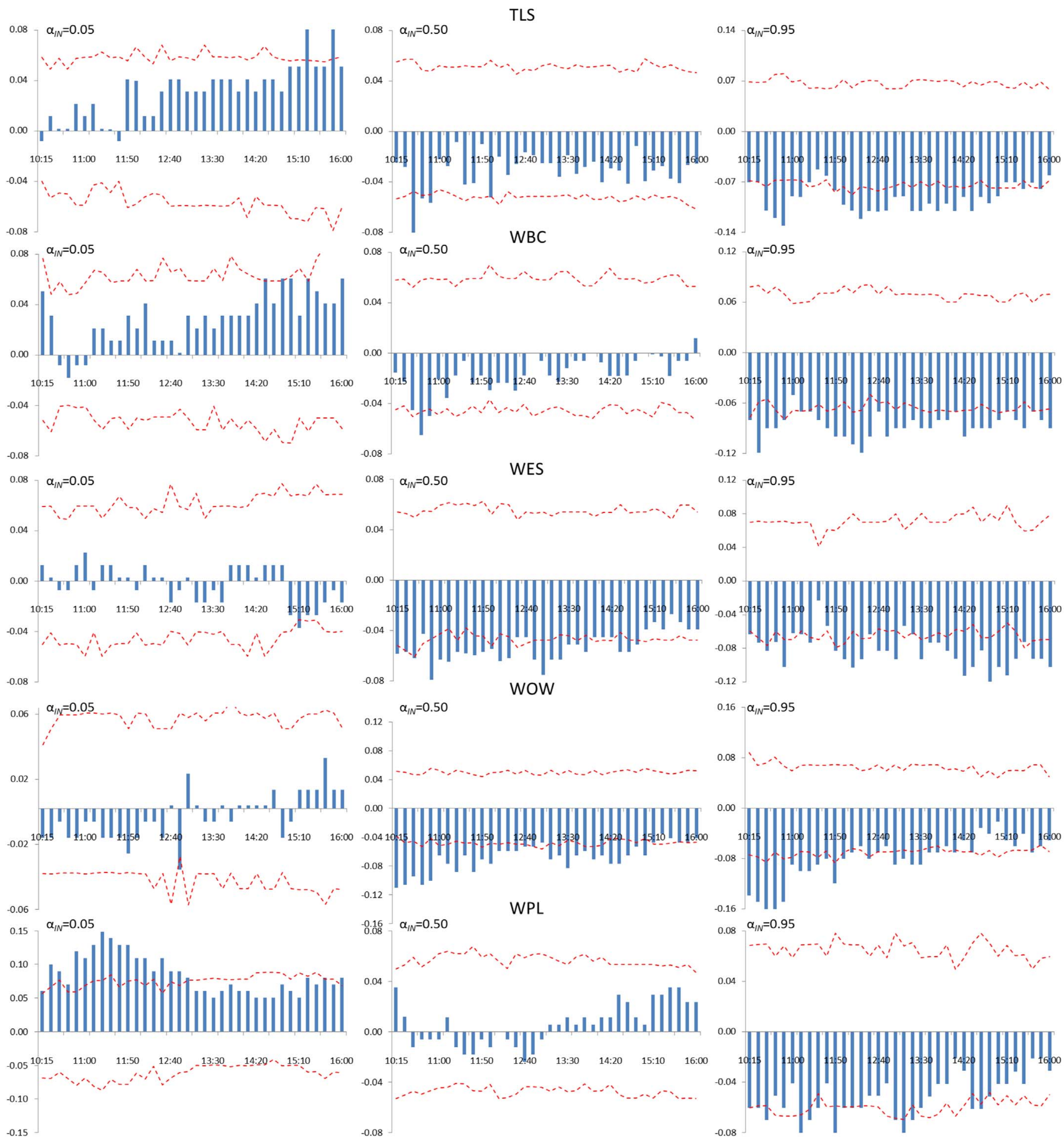

Fig. 2. (*continued*)

market cap and, correspondingly, the performance of the individual stocks is likely to have a notable impact on the market index and on its futures. At the same time, patterns similar to those of the stocks' own overnight returns rule out microstructure issues as the reason for potential reversals.

4.4. Daily performance after extreme overnight returns

The previous sections provide evidence for the directional predictability of the returns in intraday periods after the market opening. That this predictability for some stocks for all most of the considered intraday periods raises the question concerning whether the quantile dependence extends to the whole trading day. The final points of each panel in the Figs. 2 and 3 show the cross-quantilograms for the close-to-open returns following very high (α_{ON} = 0.95) and very low (α_{ON} = 0.05) overnight returns.

In summary, there is no consistent pattern across the ten stocks considered after either very low or very high overnight returns. Therefore, it seems that intraday reversals observed at the beginning of the trading day do not dominate the overall daily stock performance.

Fig. 3. Cross-quantilogramms for $q_{ON}(\alpha_{ON}) = 0.95$. The table reports the cross-quantilograms from overnight stock returns to the intraday stock returns on the following day from 10:10 to the time given on the horizontal axis. The dashed curves are bootstrapped 95% confidence intervals obtained with 1000 replicates for no predictability. The left, mid and right panels show results for $q_{IN}(\alpha_{IN}) = 0.05$, 0.5 and 0.95, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Next, we investigate whether intraday traders can exploit the intraday reversals economically.

4.5. Trading simulation

The cross-quantilograms presented in the previous sections confirm the reversal effects that occur particularly after overnight performance in the lowest 5% quantile, but the short-term reaction after very good news is much more ambiguous. These results are in line with studies that find strong evidence for intraday rebounds after bad news (e.g., Klössner et al., 2012; Sturm, 2003). To determine whether this pattern is economically exploitable, we run a trading simulation following a simple rule.

A rolling window comprised of the immediately preceding 100, 250, and 500 days identifies whether the last overnight return belongs to the lowest 5% of historical values. If it does, a contrarian trading rule is adopted: In anticipation of a price reversal, the stock is bought, held for a certain intraday period, and then sold. The trades are executed at the

Fig. 3. (*continued*)

first quotes available after 10:10 to allow for an execution lag. Transaction costs are taken into account by buying the stock at an ask price and selling at a bid price. The holding periods are from 10:00 until 10:15, 10:20, 10:40, 11:00, 12:00 and 13:00.[14]

Table 2 reports the cumulative returns and the corresponding annualized Sharpe ratios of this contrarian strategy. To put these metrics into perspective, the table also reports the cumulative returns and Sharpe ratios for a simple buy-and-hold strategy. Overall, there is compelling evidence against the relative profitability of such a contrarian intraday trading strategy. In most cases, the cumulative returns are negative, with no discernible patterns that show, for example, improved performance for extended intraday holding periods. For very badly performing stocks in terms of buy-and-hold strategy, such as BHP and WPL, the trading rule succeeds in reducing the high negative cumulative returns but still yields negative values. The strategy performs well only for NAB, especially for longer lookback and holding periods.

[14] The choice of intraday intervals follows Fung et al. (2008). Trading simulations including intraday intervals with various other lengths didn't result in deviating results. Results are available upon request.

Table 2
Trading simulation results.

	Buy & Hold		10:15 am		10:20 am		10:40 am		11:00		12:00 pm		1:00 pm	
	Return	Sharpe	Return	Sharpe	Return	Sharpe	Return	Sharpe	Return	Sharpe	Return	Sharpe	Return	Sharpe
			Lookback period: 100 days											
ANZ	0.089	0.069	−0.049	−0.539	0.026	0.123	0.016	0.069	0.041	0.166	0.014	0.056	0.062	0.219
BHP	−0.892	−0.559	0.015	0.134	0.014	0.115	−0.006	−0.037	−0.038	−0.241	0.042	0.209	0.034	0.126
CBA	0.323	0.284	−0.105	−1.441	−0.096	−1.015	−0.126	−0.923	−0.161	−0.970	−0.171	−0.920	−0.148	−0.693
CSL	1.150	0.914	−0.120	−1.320	−0.109	−1.055	−0.097	−0.714	−0.061	−0.363	−0.057	−0.272	−0.088	−0.360
NAB	−0.029	−0.022	−0.105	−1.239	−0.077	−0.783	−0.085	−0.650	0.066	0.166	0.036	0.087	0.043	0.106
TLS	0.391	0.359	−0.211	−2.415	−0.201	−2.136	−0.261	−2.004	−0.277	−1.800	−0.299	−1.867	−0.337	−1.879
WBC	0.226	0.166	−0.145	−1.143	−0.119	−1.030	−0.164	−1.150	−0.189	−1.138	−0.228	−1.222	−0.222	−1.078
WES	0.255	0.226	0.000	−0.002	−0.055	−0.297	−0.114	−0.778	−0.092	−0.549	−0.138	−0.765	−0.121	−0.586
WOW	−0.207	−0.183	−0.086	−0.794	−0.058	−0.414	−0.034	−0.183	−0.074	−0.376	−0.068	−0.321	−0.012	−0.043
WPL	−0.693	−0.163	−0.118	−0.641	−0.130	−0.641	−0.079	−0.393	−0.054	−0.235	−0.072	−0.278	−0.108	−0.401
			Lookback period: 250 days											
ANZ			−0.051	−0.529	0.013	0.061	0.002	0.010	0.021	0.084	−0.013	−0.049	0.031	0.109
BHP			0.013	0.110	0.008	0.067	−0.012	−0.077	−0.055	−0.348	0.013	0.061	0.016	0.056
CBA			−0.100	−1.241	−0.082	−0.796	−0.068	−0.454	−0.113	−0.632	−0.132	−0.688	−0.119	−0.539
CSL			−0.135	−1.433	−0.103	−0.878	−0.111	−0.771	−0.099	−0.549	−0.123	−0.539	−0.174	−0.663
NAB			0.139	0.299	0.173	0.369	0.174	0.356	0.341	0.539	0.285	0.445	0.292	0.458
TLS			−0.209	−2.360	−0.206	−2.086	−0.285	−2.060	−0.267	−1.716	−0.294	−1.776	−0.311	−1.689
WBC			−0.131	−0.951	−0.096	−0.722	−0.116	−0.692	−0.117	−0.561	−0.193	−0.861	−0.214	−0.800
WES			0.058	0.278	−0.047	−0.252	−0.076	−0.515	−0.062	−0.361	−0.065	−0.349	−0.078	−0.387
WOW			−0.045	−0.367	−0.048	−0.393	−0.011	−0.072	−0.046	−0.270	−0.030	−0.155	0.018	0.068
WPL			−0.154	−0.850	−0.202	−1.006	−0.196	−0.941	−0.169	−0.731	−0.185	−0.705	−0.256	−0.934
			Lookback period: 500 days											
ANZ			−0.046	−0.547	0.018	0.082	0.020	0.087	0.008	0.031	0.030	0.105	0.019	0.062
BHP			0.001	0.013	−0.001	−0.006	−0.004	−0.024	−0.014	−0.088	−0.038	−0.198	−0.045	−0.213
CBA			−0.062	−0.825	−0.032	−0.330	−0.009	−0.064	−0.051	−0.286	−0.023	−0.116	−0.043	−0.209
CSL			−0.117	−1.373	−0.034	−0.207	−0.031	−0.169	−0.011	−0.046	−0.075	−0.271	−0.095	−0.348
NAB			0.111	0.240	0.135	0.291	0.119	0.247	0.097	0.189	0.110	0.214	0.063	0.117
TLS			−0.219	−2.373	−0.212	−2.006	−0.290	−1.963	−0.301	−1.718	−0.318	−1.628	−0.378	−1.727
WBC			−0.098	−0.644	−0.081	−0.704	−0.091	−0.647	−0.127	−0.632	−0.110	−0.453	−0.108	−0.430
WES			0.079	0.385	−0.018	−0.101	−0.025	−0.195	0.019	0.119	−0.001	−0.008	0.042	0.211
WOW			−0.027	−0.210	−0.026	−0.203	0.005	0.030	−0.005	−0.026	0.036	0.136	−0.014	−0.058
WPL			−0.116	−0.603	−0.160	−0.734	−0.152	−0.703	−0.145	−0.511	−0.200	−0.677	−0.242	−0.794

Note: The table shows cumulative returns and annualised Sharpe ratios for a contrarian strategy within which the stock is purchased when the immediately preceding overnight return is within the lowest 5% of the lookback period and sold at the end of the corresponding intraday period. The results cover trading from 2 Jan 2010 to 4 March 2016. The upper left panel shows results for a buy-and-hold strategy.

Finally, the trading strategy considers no transaction costs other than the bid-ask spread and no opportunity cost of the capital needed to purchase the stocks. Both of these factors would reduce any potential profitability further. In addition, dividend payments that would increase the cumulative buy-and-hold returns are disregarded. In contrast to a number of studies documenting significant profitability based on price rebounds that are exploitable through simple trading rules, the contrarian trading strategies with the data at hand do not perform satisfactorily even under these relaxed conditions.[15]

5. Conclusion

The present study is the first to investigate the quantile dependence of overnight and intraday returns in the Australian stock market. We employ the newly introduced cross-quantilogram, a multivariate version of the quantilogram, which allows us to assess the magnitude and significance of the directional predictability between two time series to be assessed.

The results suggest the presence of reversal effects following non-trading periods that are characterised by very low returns. The cross-quantilograms are significant in most cases for the 95% quantiles of subsequent intraday returns, suggesting that, after particularly low overnight returns, the returns in the intraday periods at the beginning of the trading day are likely to rebound and, after very high overnight returns, the reversal effects are weaker. Extending the analysis to the stock returns over the whole day (open-to-close returns) shows that the rebound effects smooth away in the course of the trading day and do not dominate the overall daily performance. The reversals appear to occur with a short delay of at least five minutes at the beginning of the trading day and are discernible throughout the trading day. The weakening of the observed reversals related to widening the intraday period is accompanied by occasional continuation effects. In some cases, especially at the daily frequency, the cross-quantilograms for both very low and very high quantiles are significant, with signs indicating that the likelihood of both rebound and continuation effects increases.

Studies that discuss explanations for potential short-term predictability focus on under-/overreaction and microstructure effects. Here, the bid-ask spread as the source of potential rebounds can be ruled out for two reasons. First, the stocks in our sample are highly liquid and so are unlikely to be prone to bid-ask spreads that are large enough to result in a rebound from the lowest 5% quantile to the highest 5%. Second, reversals tend to be statistically significant for longer intraday periods but not usually for the first five minutes of the trading day. Since the focus of the current study is to quantify short-term reactions and to measure quantile dependence, placing the intraday returns in the perspective of their own empirical distribution, we do not run tests on the under/overreaction hypothesis but explore the economic significance of our findings. A trading simulation based on a contrarian

[15] Trading simulations were also conducted for the opposite case - that is, shorting a stock at a bid price and exiting the position at the end of the holding period at an ask price whenever its overnight return exceeds the historical 95%. As expected, the findings based on the cross-quantilogram (i.e., inconsistent pattern across stocks) are confirmed but are not reported here in order to limit the number of tables.

rule that takes bid-ask spreads into account is shown to be incapable of consistently generating excess returns or revealing a discernible pattern. Overall, despite the persistence of significant reversal effects throughout the first hours of the trading day, the Australian market for large stocks appears to be comfortingly efficient in the short term.

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