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Fresh evidence from quantile copula
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Matsuki, Takashi and Pan, Lei

Faculty of Economics, Osaka Gakuin University, School of
Accounting, Economics and Finance, Curtin University

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How Did Australian Financial Markets React to the COVID-19 Vaccine Rollout? Fresh Evidence from Quantile Copula Spectrum Analysis

Takashi Matsuki
Faculty of Economics
Osaka Gakuin University

Lei Pan*
School of Accounting, Economics and Finance
Curtin University

Abstract

We provide the first study of how the large and persistent Australian financial markets reacted to the COVID-19 vaccine rollout. Using the novel quantile copula coherency estimation developed by [Baruník and Kley \(2019\)](#), our study properly detects short- and long-lived significant reactions of the stock price index and foreign exchange returns to the vaccine rate variation.

Keywords: Australia; Financial markets; COVID-19 vaccine; Quantile copula spectrum; Quantile coherency

JEL Classification: G1; H51; I18

1 Introduction

Although many hoped that by this point of time the coronavirus (COVID-19) would be spoken of in the past tense, the pandemic continues to pose challenges in many parts of the world. A large body of literature has documented the effects of the spread of COVID-19, especially on the stock market (see e.g. [Jebabli et al., 2021](#); [Liu et al., 2021](#); [Rahman](#)

*Corresponding author. Email: lei.pan@curtin.edu.au

et al., 2021), commodity markets (e.g. Amar et al., 2021; Bakas and Triantafyllou, 2020), cryptocurrency markets (e.g. Corbet et al., 2020; Kakinaka and Umeno, 2021; Rubbaniy et al., 2021), derivative markets (Hanke et al., 2020; Li et al., 2021), exchange rate market (Iyke and Ho, 2021; Narayan, 2021; Zhou, 2021), and macroeconomic policy (Elgin et al., 2021; Gholipour and Arjomandi, 2021). However, the empirical relationships between COVID-19 vaccine rollout and financial markets have been underexplored. In this study, we aim to fill this research gap.

There is great anticipation of the world economy returning to its pre-pandemic status. The implementation of vaccination policy may provide hope achieving this. The main objective of this paper is to provide early evidence on how the large and persistent Australian financial markets respond to the COVID-19 vaccination rate. We focus on Australia for two reasons: First, although having a slow start, the latest vaccination rate figures put Australia in a leading position worldwide to stop the spread of the pandemic. In early November 2021, Australia overtook the UK in terms of the percentage of the population of any age who had received two vaccine doses, making the country an international leader in the vaccination rollout. Second, Australian financial markets are one of the most affected markets in the world. Therefore, it can provide insights into market reactions during the vaccine implementation period. We consider two crucial markets in the Australian financial system: stock and foreign exchange markets. According to the Reserve Bank of Australia (RBA),¹ the four key sectors of the Australian economy are: health and education, mining, finance, and construction. Therefore, to further understand the reaction of major Australian industries to COVID-19 vaccine rollout, we specifically focus on the performance of these four sectors: healthcare, consumer discretionary,² materials,³ and financial.

Our study contributes to the literature in two ways. First, to the best of our knowledge, this study is the first attempt to analysis the reaction of financial markets to COVID-19 vaccine rollout. The only similar study is Rouatbi et al. (2021), who investigated the role of mass COVID-19 vaccination programs on stock market volatility. Our study differs from theirs in at least two aspects. Specifically, we not only explore the response of the stock market at the aggregate level, but also at the sector level, and consider other financial markets. Hence, our study provides a more comprehensive understanding of the linkage between the progress of vaccination policies and financial markets. The other difference is in our empirical strategy, which is also related to the second contribution. In particular, we adopt the novel quantile copula coherency developed by Baruník and Kley (2019). Tail events such as financial crisis and the current global pandemic

¹ <https://www.rba.gov.au/education/resources/snapshots/economy-composition-snapshot/>

²Most of the education companies whose shares are publicly listed on the Australian Securities Exchange (ASX) are categorised under the consumer discretionary sector.

³Mining and construction companies such as BHP Group Limited and Rio Tinto whose share are publicly listed on the ASX are categorised under the materials segment.

can cause financial markets to react differently to non-volatile periods. It is therefore crucial to understand the importance of tail behaviours in macroeconomic and financial data series. [Baruník and Kley's \(2019\)](#) approach utilises the dependence measure based on a quantile spectrum, which is more robust to extreme events, strong asymmetries and nonlinear dynamics of data series. In addition, the dependence structure between data captured from a copula-based quantile cross-periodogram is invariant to outliers. Moreover, such a frequency-domain approach helps to find and identify the mixed signals of short- and long-lived responses of one variable to another. We detect the shortest (daily) to the longest (yearly) responses based on this framework.

The remainder of this paper is organised as follows. In [Section 2](#), we present our empirical strategy, followed by our results in [Section 3](#). [Section 4](#) concludes.

2 Quantile Copula Coherency

In this section, we define the quantile copula coherency of our data series developed by [Baruník and Kley \(2019\)](#).

Let $\{X_t\}_{t \in \mathbb{Z}}$ be a d -variate strictly stationary process, with components $X_{t,l}$, $l = 1, \dots, d$; that is, $X_t = (X_{t,1}, \dots, X_{t,d})'$. $X_{t,l}$ has a marginal distribution function $F_l(q)$ and inverse function $q_l(\tau) := F_l^{-1}(\tau) := \inf\{q \in \mathbb{R} : \tau \leq F_l(q)\}$, where $\tau \in [0, 1]$. The matrix of quantile cross-covariance, $\Gamma_k(\tau_1, \tau_2) := (\gamma_k^{l_1 l_2}(\tau_1, \tau_2))_{l_1, l_2=1, \dots, d}$, where $\gamma_k^{l_1 l_2}(\tau_1, \tau_2)$ represents the cross-covariance of a pair (X_{t,l_1}, X_{t-k,l_2}) , which is specified as follows:

$$\gamma_k^{l_1 l_2}(\tau_1, \tau_2) := Cov(I\{X_{t,l_1} \leq q_{l_1}(\tau_1)\}, I\{X_{t-k,l_2} \leq q_{l_2}(\tau_2)\}) \quad (1)$$

where $l_1, l_2 \in \{1, \dots, d\}$, $k \in \mathbb{Z}$, and $\tau_1, \tau_2 \in [0, 1]$. $I(\cdot)$ is an indicator function. The quantile-based quantities are functions of τ_1 and τ_2 , which are quantiles of a quantile regression. In the frequency domain, under approximate mixing conditions, the quantile cross-spectral densities are:

$$f_{q_{\tau_1}, q_{\tau_2}}(\omega) := (f_{q_{\tau_1}, q_{\tau_2}}^{l_1 l_2}(\omega))_{l_1, l_2=1, \dots, d} \quad (2)$$

where

$$f_{q_{\tau_1}, q_{\tau_2}}^{l_1 l_2}(\omega) := \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_k^{l_1 l_2}(\tau_1, \tau_2) e^{-ik\omega} \quad (3)$$

and ω is the frequency, with $\omega \in \mathbb{R}$. Each quantile cross-spectral density, i.e., $f_{q_{\tau_1}, q_{\tau_2}}^{l_1 l_2}(\omega)$ is a complex-valued function. As in conventional spectral analysis, its real and imaginary parts are known as the quantile cospectrum and quantile quadrature spectrum.

To measure the dynamic dependence structure of the two data series $\{X_{t,l_1}\}_{t \in \mathbb{Z}}$ and $\{X_{t,l_2}\}_{t \in \mathbb{Z}}$, the quantile coherency is defined as follows:

$$\mathcal{R}_{q\tau_1, q\tau_2}^{l_1 l_2}(\omega) := \frac{f_{q\tau_1, q\tau_2}^{l_1 l_2}(\omega)}{(f_{q\tau_1, q\tau_1}^{l_1 l_1}(\omega) f_{q\tau_2, q\tau_2}^{l_2 l_2}(\omega))^{1/2}} \quad (4)$$

where $(\tau_1, \tau_2) \in [0, 1]^2$. The modulus squared of this quantile coherency, for instance, $|\mathcal{R}_{q\tau_1, q\tau_2}^{l_1 l_2}(\omega)|^2$, is the quantile coherence.

When we use the empirical distribution function of $X_{t,l}$, i.e., $\hat{F}_{n,l}(X) := n^{-1} \sum_{t=0}^{n-1} I\{X_{t,l} \leq x\}$, the rank-based copula cross-periodograms (CCR periodograms) are:

$$I_{n,R}^{l_1 l_2}(\omega; \tau_1, \tau_2) := \frac{1}{2\pi n} d_{n,R}^{l_1}(\omega; \tau_1) d_{n,R}^{l_2}(-\omega; \tau_2) \quad (5)$$

where $l_1, l_2 \in \{1, \dots, d\}$, $\omega \in \mathbb{R}$, $(\tau_1, \tau_2) \in [0, 1]^2$, and

$$d_{n,R}^l(\omega; \tau) := \sum_{t=0}^{n-1} I\{\hat{F}_{n,l}(X_{t,l}) \leq \tau\} e^{-i\omega t} = \sum_{t=0}^{n-1} I\{R_{t,l}^{(n)} \leq n\tau\} e^{-i\omega t} \quad (6)$$

where $l = 1, \dots, d$, $\omega \in \mathbb{R}$, $\tau \in [0, 1]$, and $R_{t,l}^{(n)}$ refers to the rank of $X_{t,l}$ among $X_{0,l}, \dots, X_{t-1,l}$.

As shown in [Kley et al. \(2016\)](#), when estimating the quantile cross-spectral density $f_{q\tau_1, q\tau_2}^{l_1 l_2}(\omega)$, the CCR periodogram is not consistent. By correcting biases, the smoothed versions (i.e. smoothed CCR periodogram as below) are consistent (see [Kley et al., 2016](#), Theorem 3.5).

$$\hat{G}_{n,R}^{l_1 l_2}(\omega; \tau_1, \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_n(\omega - 2\pi s/n) I_{n,R}^{l_1 l_2}\left(\frac{2\pi s}{n}; \tau_1, \tau_2\right) \quad (7)$$

where W_n refers to a sequence of weight functions. The smoothed CCR periodogram also maintains asymptotic normality. It is noteworthy that when fixing l_1, l_2 and τ_1, τ_2 , the smoothed CCR periodogram is asymptotically equivalent to the conventional smoothed periodogram determined from the unobservable bivariate time series $(I\{F_{l_1}(X_{t,l_1}) \leq \tau_1\}, I\{F_{l_2}(X_{t,l_2}) \leq \tau_2\})(t = 0, \dots, n-1)$. Utilising the property of asymptotic normality, we can calculate the pointwise asymptotic confidence intervals for the real and imaginary parts of the spectrum for a pair of (τ_1, τ_2) .

The consistent estimators of quantile coherency are defined as follows:

$$\hat{\mathcal{R}}_{n,R,q\tau_1,q\tau_2}^{l_1 l_2} := \frac{\hat{G}_{n,R}^{l_1 l_2}(\omega; \tau_1, \tau_2)}{(\hat{G}_{n,R}^{l_1 l_1}(\omega; \tau_1, \tau_1) \hat{G}_{n,R}^{l_2 l_2}(\omega; \tau_2, \tau_2))^{1/2}} \quad (8)$$

The difference between this coherency and $\mathcal{R}_{q\tau_1, q\tau_2}^{l_1 l_2}(\omega)$ together with the bias correction terms asymptotically converges to a normal distribution, indicating asymptotic consistency (see [Baruník and Kley, 2019](#), Theorem 4.1).

3 Empirical Results

3.1 Data

The data used in this study comprise daily observations of the COVID-19 vaccination rate in Australia (measured as the total number of vaccination doses administered per 100 people in the total population), the equilibrium value of AUD (measured as Australia’s real effective exchange rate (REER)), and Standard & Poor’s Australian Securities Exchange 200 (S&P/ASX 200) index as a benchmark for the Australian stock market. To investigate the response of Australian industries to the COVID-19 vaccination rate, we also use four sector indices: S&P/ASX 200 Healthcare, S&P/ASX 200 Consumer Discretionary, S&P/ASX 200 Materials, and S&P/ASX 200 Financial. All data series were gathered from Datastream. The sample period is from 22 February 2021 to 5 November 2021.⁴ The vaccination rate is first-differenced to show its increase per day, and then 5-day moving averaged to remove the day bias of the reported number of vaccination doses. All data series are converted into natural logarithms except for the vaccination rate and first-differenced. To control for the day-of-the-week effect and the time-varying variances in these stock price indices and foreign exchange rate return series, they are first regressed on dummy variables that represent the weekdays from Tuesday to Friday in a GARCH (1, 1) model. The standardised residuals are used as adjusted return series for our analysis.

3.2 Quantile regression

To examine the tail behaviours of the stock price and FX returns to the vaccination rate change based on the time domain approach, we first estimate the quantile regression proposed by [Koenker and Bassett \(1978\)](#). As the regressors, the lagged vaccination rates ($t - 1 \sim t - 5$), ASX 200 stock price return or FX return, Dow Jones industrial average index return, and Chicago Board Options Exchange’s Volatility Index (VIX) are used. We assume that the Dow Jones industrial average index return represents the global stock market trend, and the VIX represents the global volatility of financial markets. [Table 1](#) presents the estimation results. At the mean level ($\tau = 0.5$), one or two of the lagged vaccination rates are significant in the FX and consumer discretionary sectors. At the 0.05-quantile, which is the lower tail of the regressand (return) series, the significance of the lagged vaccination rates is observed in more cases, such as the ASX 200, healthcare, consumer discretionary, materials, and finance sectors. The overall significant impact is negative only for ASX 200.⁵ At the 0.95-quantile, which is the upper tail of the

⁴ We excluded the data for weekends and holidays.

⁵ The overall impacts are $8.976 - 19.877 = -10.901$ for the ASX200, 6.198 for the healthcare, and 4.938 for the materials.

series, the FX, healthcare, consumer discretionary, and materials sectors have significant coefficients of the lagged vaccination rates in the regression models. The material sector only experiences an overall negative impact from the vaccination rate change.⁶

As shown above, the time domain approach is effective in investigating whether the vaccination rate change has significant short-lived (i.e. daily or weekly) impacts on stock price and FX returns. However, we cannot detect longer (e.g. monthly or yearly) reactions occurring in the stock and FX markets or distinguish the mixed market reactions to short- and long-lasting impacts from vaccination policy implementation. In this case, the frequency-domain approach helps to find a mixture of signals and identify each. Therefore, in the next subsection, we estimate the quantile copula coherency between the vaccination rate and each stock price/FX return.

3.3 Quantile copula coherency estimates

We estimate the quantile copula coherency (shown in Equation (8)) between the vaccination rate and each stock/FX return series. Because the real parts of the quantile coherency estimates reveal frequency dynamics in quantiles of the joint distribution of the data pairs, we calculate them for three combinations of quantile levels: 0.5|0.5, 0.5|0.05, and 0.5|0.95.⁷ For example, the quantile pair of 0.5|0.05 means that the vaccination rate at the 0.5-quantile (mean) and a return series at the lower 0.05-quantile of the data distribution are used for calculation. To investigate how large and persistent stock prices and FX returns react at their lower/upper quantiles and the mean of the distributions under the progress of the nationwide vaccination policy, we focus on the data variation of the vaccination rate at its mean and the return series at their lower/upper tails and mean. To confirm the persistence of the cycles of the data pairs being investigated, we present the quantile coherency estimates for $\omega \in 2\pi\{1/2.1, 1/2.5, 1/5, 1/22, 1/250\}$, which correspond to 3/2 daily, half weekly, weekly, monthly, and yearly cycles of coherency, respectively. The estimate for each ω shows how long the variation cycle of data pairs persists; for example, significantly higher/lower quantile coherency for $\omega = 2\pi(1/5)$ implies that the variation of data pairs significantly positively/negatively persists for a week. The same consideration holds for $\omega = 2\pi(1/2.1), 2\pi(1/2.5), 2\pi(1/22)$, or $2\pi(1/250)$, which means that the data variation persists for one and a half days, a half week, a month, or a year.

⁶ The overall impacts are 1.660 for the FX, 2.603 for the consumer discretionary, and -3.338 for the materials.

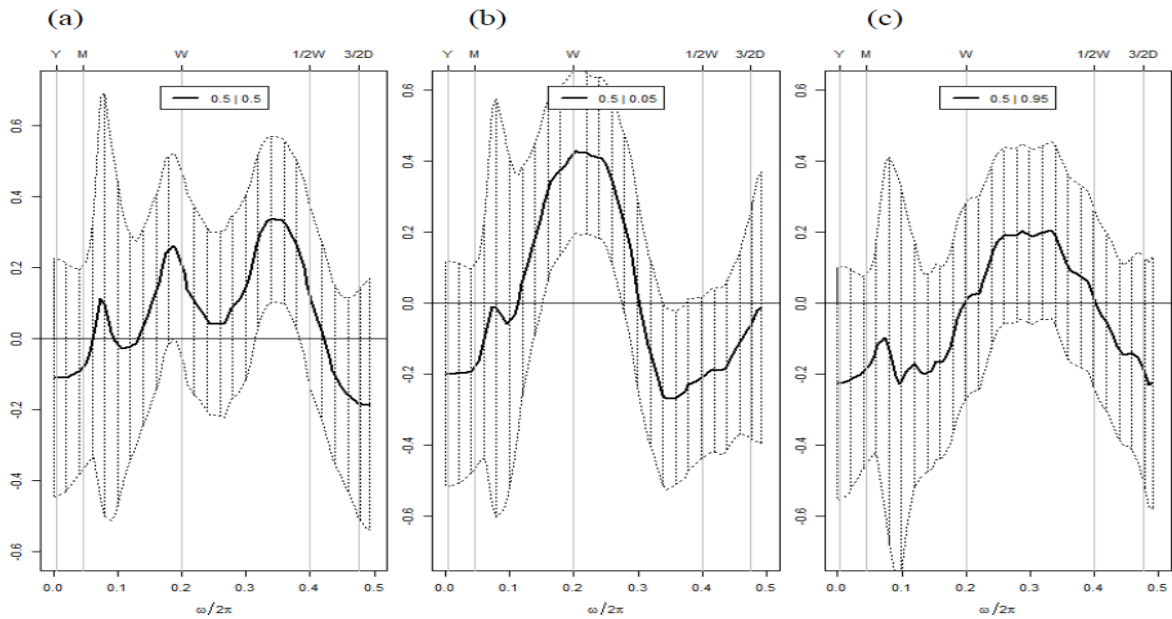
⁷ We compute the estimates using Epanechnikov kernel and a bandwidth of $0.5n^{1/4}$.

Table 1: Quantile regression results (sample size = 172)

Variable	ASX200						FX						Healthcare						Consumer discretionary						Materials						Finance						
	$\tau = 0.50$		$\tau = 0.05$		$\tau = 0.95$		$\tau = 0.50$		$\tau = 0.05$		$\tau = 0.95$		$\tau = 0.50$		$\tau = 0.05$		$\tau = 0.95$		$\tau = 0.50$		$\tau = 0.05$		$\tau = 0.95$		$\tau = 0.50$		$\tau = 0.05$		$\tau = 0.95$								
	τ		τ		τ		τ		τ		τ		τ		τ		τ		τ		τ		τ		τ		τ		τ								
Constant	2.227	1.613	1.491	-0.482	-1.842	3.661	0.534	1.255	2.172	1.169	0.570	0.715	1.626	2.908	1.649	1.379	-0.546	-0.674	0.003	0.153	0.554	0.560	0.149	0.001	0.642	0.221	0.179	0.256	0.581	0.537	0.073	0.000	0.102	0.220	0.699	0.773	
Vaccine rate (t-1)	-0.380	8.976	-0.933	-1.941	0.065	-7.994	-0.414	-9.512	2.032	0.535	-1.323	-5.047	1.865	-5.737	6.930	0.711	13.164	2.207	0.881	0.059	0.800	0.453	0.988	0.080	0.907	0.013	0.701	0.862	0.808	0.015	0.547	0.049	0.840	0.049	0.468		
Vaccine rate (t-2)	1.489	2.864	5.283	-2.737	-3.909	9.654	0.809	15.710	-3.514	0.174	-0.553	7.650	0.782	10.675	-4.151	0.885	-9.558	-2.702	0.693	0.690	0.441	0.477	0.636	0.046	0.892	0.006	0.598	0.972	0.943	0.045	0.867	0.028	0.498	0.871	0.529	0.748	
Vaccine rate (t-3)	-1.100	-19.877	-7.281	6.695	10.319	1.809	1.761	-4.862	-1.473	-8.694	9.061	-6.541	-4.646	-5.995	-11.240	-3.785	-13.154	1.681	0.776	0.000	0.337	0.099	0.131	0.747	0.807	0.328	0.867	0.052	0.025	0.288	0.259	0.149	0.408	0.490	0.883		
Vaccine rate (t-4)	-1.027	6.761	0.569	-4.397	-2.438	-6.548	-6.330	0.689	9.201	9.222	-6.873	3.392	3.139	2.524	7.902	0.356	9.969	0.640	0.824	0.238	0.905	0.242	0.639	0.646	0.298	0.885	0.042	0.448	0.454	0.618	0.064	0.952	0.483	0.876			
Vaccine rate (t-5)	0.723	0.904	2.172	2.729	-3.572	2.925	4.167	-2.295	-6.234	-1.418	-0.941	0.423	-1.378	-2.028	0.573	1.716	-0.605	-1.653	0.788	0.842	0.551	0.285	0.789	0.186	0.516	0.233	0.654	0.906	0.908	0.633	0.493	0.871	0.676	0.928	0.638		
FX (return)	0.153	0.188	0.134	0.140	0.134	0.523	-0.127	-0.211	-0.316	0.015	-0.082	-0.021	0.360	0.142	0.055	0.066	0.245	-0.110	0.107	0.310	-0.215	0.151	0.471	-0.120	0.155	0.049	0.141	-0.163	0.090	-0.041	-0.077	-0.035	0.137	-0.008			
Dow Jones (return)	0.298	0.077	0.534	0.125	0.021	0.514	0.281	0.043	0.776	0.158	0.255	0.705	0.416	0.628	0.570	0.745	0.383	0.976	-0.106	-0.156	0.008	0.014	-0.007	-0.101	-0.028	-0.141	-0.034	-0.048	0.046	0.046	0.431	0.085	0.000	0.800	0.265	0.387	0.359
VIX	0.007	0.005	0.956	0.233	0.638	0.093	0.635	0.005	0.656	0.365	0.066	0.431	0.085	0.000	0.800	0.265	0.387	0.359	0.010	0.003	0.549	0.010	0.003	0.549	0.025	0.158	0.090	0.071	0.099	0.072	0.101	0.304	0.075	0.033	0.202	0.063	
ASX 200 (return)	0.088	0.254	0.090	0.091	0.147	0.072	0.025	0.158	0.090	0.071	0.099	0.072	0.101	0.304	0.075	0.033	0.202	0.063	Pseudo R-squared	0.088	0.254	0.090	0.091	0.147	0.072	0.025	0.158	0.090	0.071	0.099	0.072	0.101	0.304	0.075	0.033	0.202	0.063

Note: For each variable, the estimated coefficients and their p -values are reported in the upper and lower rows, respectively. The coefficient written in the bold letter shows statistical significance at least at the 10% significance level.

Fig.1: The quantile coherency estimates between the vaccination rate and ASX 200 return



Figures 1(a), 1(b), and 1(c) show the quantile copula coherency estimates between the vaccination rate and the ASX 200 return. The dotted regions represent 95% confidence intervals. The vertical lines of Y , M , W , $1/2W$, and $3/2D$ represent the yearly, monthly, weekly, half-weekly, and one-and-a-half daily cycles of coherency at frequency scales. Figures 1(a) and 1(b) illustrate significant positive cycles of the vaccination rate and Australian stock index return at the 0.5|0.5- and 0.5|0.05-quantiles, which implies that weekly or less than weekly positive variations exist between the vaccination rate and stock return at the mean and mean|lower tail of the joint distribution. In addition, at the lower tail of the return distribution, a short-lived negative cycle was observed at around frequency = 0.35. Figure 1(c) shows no significant cycle of 0.5|0.95-quantile coherency. This may suggest that the Australian stock return at the upper tail of the distribution is not related to the implementation of the national vaccination policy, which is consistent with the quantile regression results shown in Table 1.

Figures 2(a), 2(b), and 2(c) show the quantile copula coherency estimates between the vaccination rate and FX returns. At the 0.5|0.5-quantile, Figure 2(a) shows a positive year-long cycle of quantile coherency, while a significant drop appears at frequency = 0.3 (less than a week and more than a half week). Interestingly, the foreign exchange rate market shows long positive and short negative reactions to vaccination rate variation. This was not found in the quantile regression. In addition, the 0.5|0.95-quantile coherency presents a significantly short negative cycle. This means that the upper 5% tail of the FX return series negatively reacts to the national vaccination rate movement for a short time. The 0.5|0.05-quantile coherency cycle was not significant for all frequencies. This also corresponds to the findings presented in Table 1.

Fig.2: The quantile coherency estimates between the vaccination rate and FX return

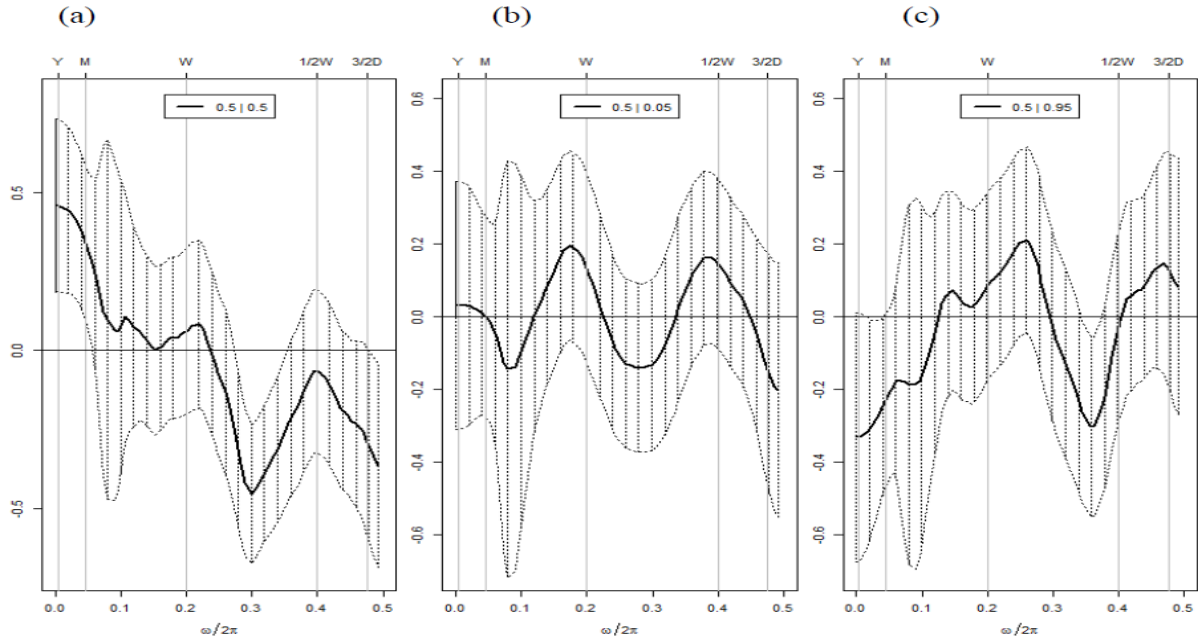
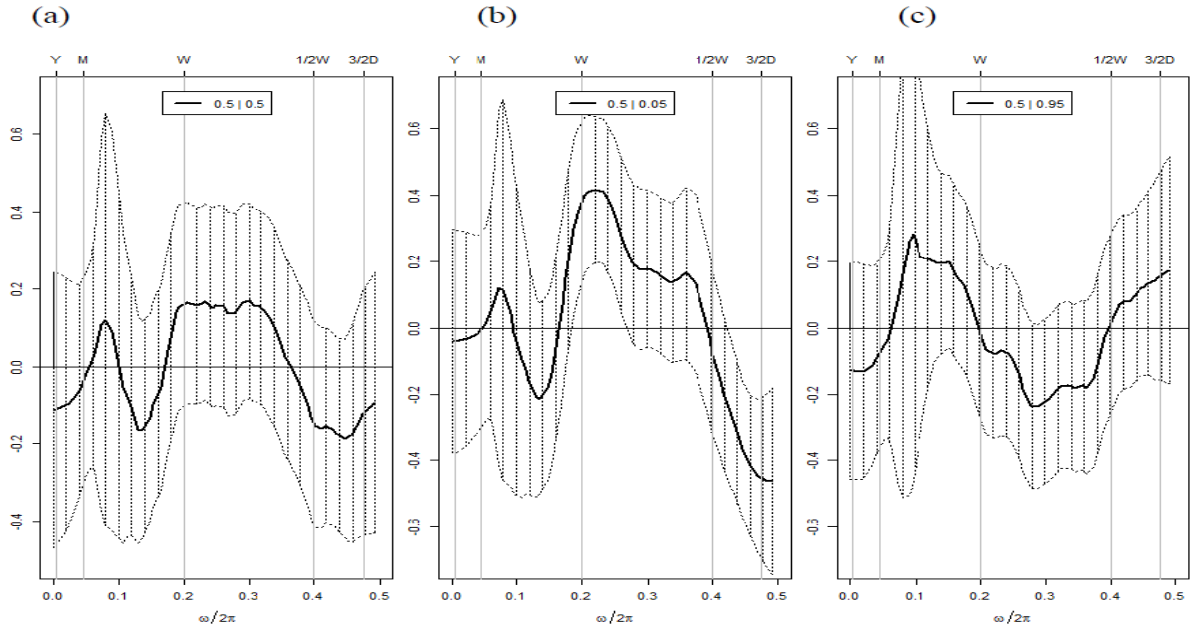


Fig.3: The quantile coherency estimates between the vaccination rate and sectoral stock return (healthcare)



In Figures 3 to 6, the quantile coherency estimates of the vaccination rate and sectoral stock price index returns are plotted. At the mean level, the consumer discretionary and financial sectors have significant positive variations for frequency = 0.35, which suggests (less than weekly) short-term positive reactions to the vaccination rate increase. At the 0.5|0.05-quantile, all sectors showed significant cycles at various frequencies. The cycles of the healthcare, consumer discretionary, and finance sectors are significantly positive around the weekly frequency or less. The longest (yearly) cycles are observed

in the consumer discretionary and materials sectors while the shortest one is done in the healthcare and consumer discretionary sectors. The consumer discretionary and materials sectors also have negative 0.5|0.95-quantile coherency cycles; on the other hand, the finance sector shows a positive cycle. Notably, the consumer discretionary and finance sectors are more sensitive to the vaccination rate variations, namely, the reactions at all pairs of quantiles are significant. In light of these findings, the reactions of the consumer discretionary sector imply mixed perspectives on the effects of the vaccination policy progress on this sector. Short-term positive and negative cycles of quantile coherency exist for all quantile pairs. At the same time, due to the high uncertainty of this sector, negative yearly cycles at both tails of the return cast a pessimistic view of its full recovery. The stock return in the financial sector, which has weekly or half-weekly variations with the vaccination rate change, may reflect stock traders' present growth predictions in this sector, created by the expansionary monetary policies of the Reserve Bank of Australia.

Fig.4: The quantile coherency estimates between the vaccination rate and sectoral stock return (consumer discretionary)

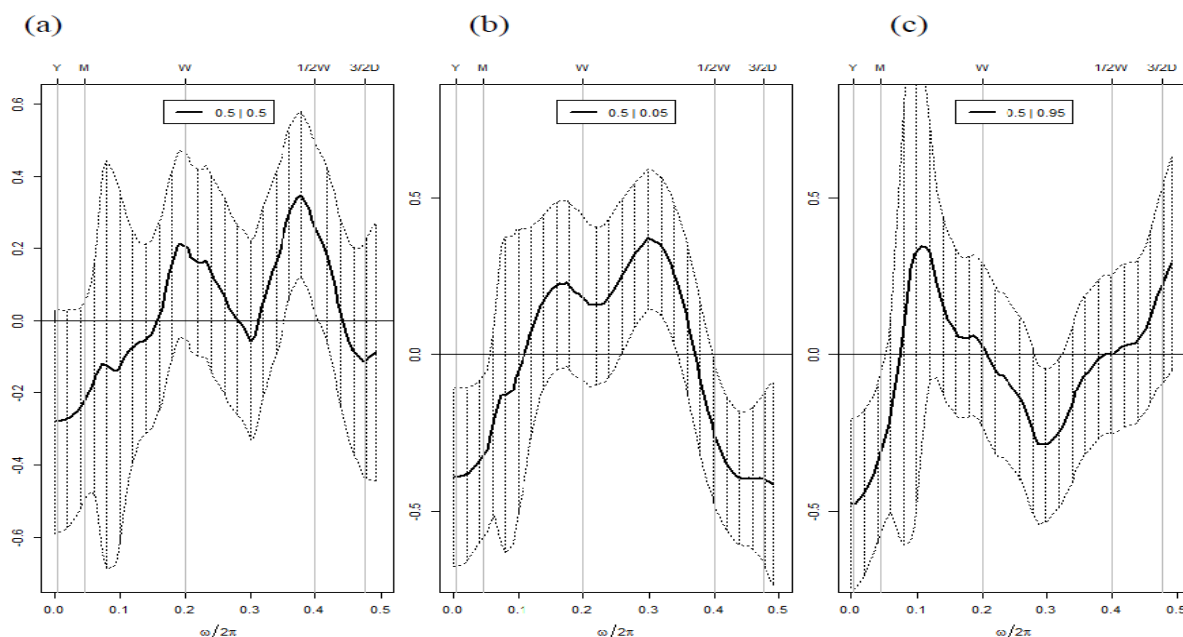


Fig.5: The quantile coherency estimates between the vaccination rate and sectoral stock return (materials)

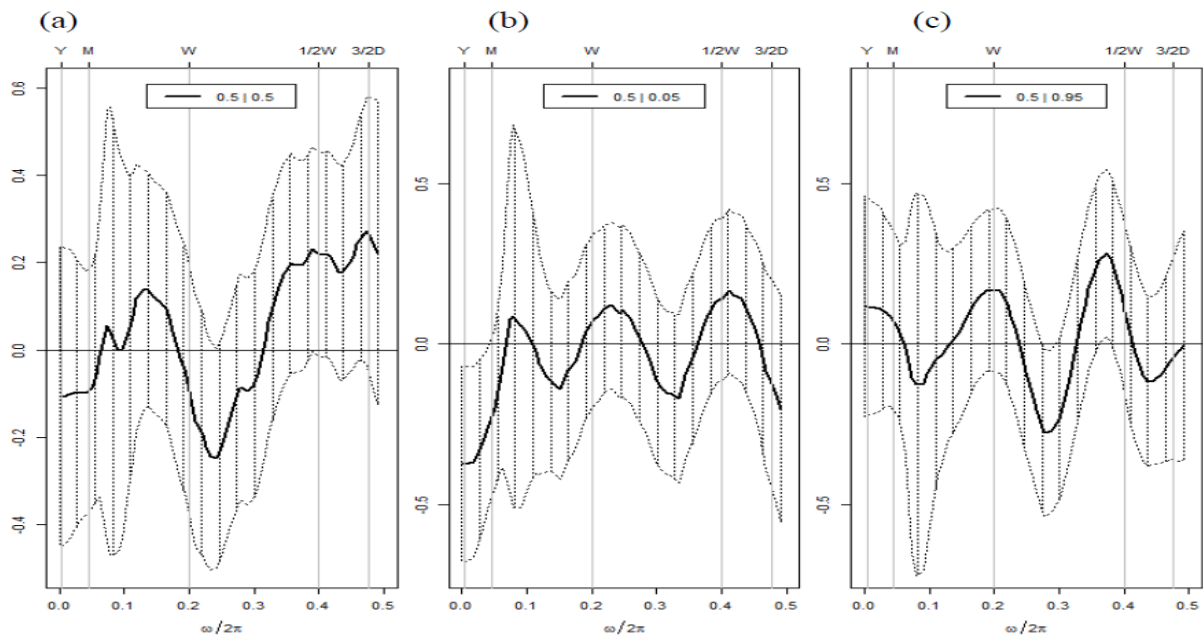
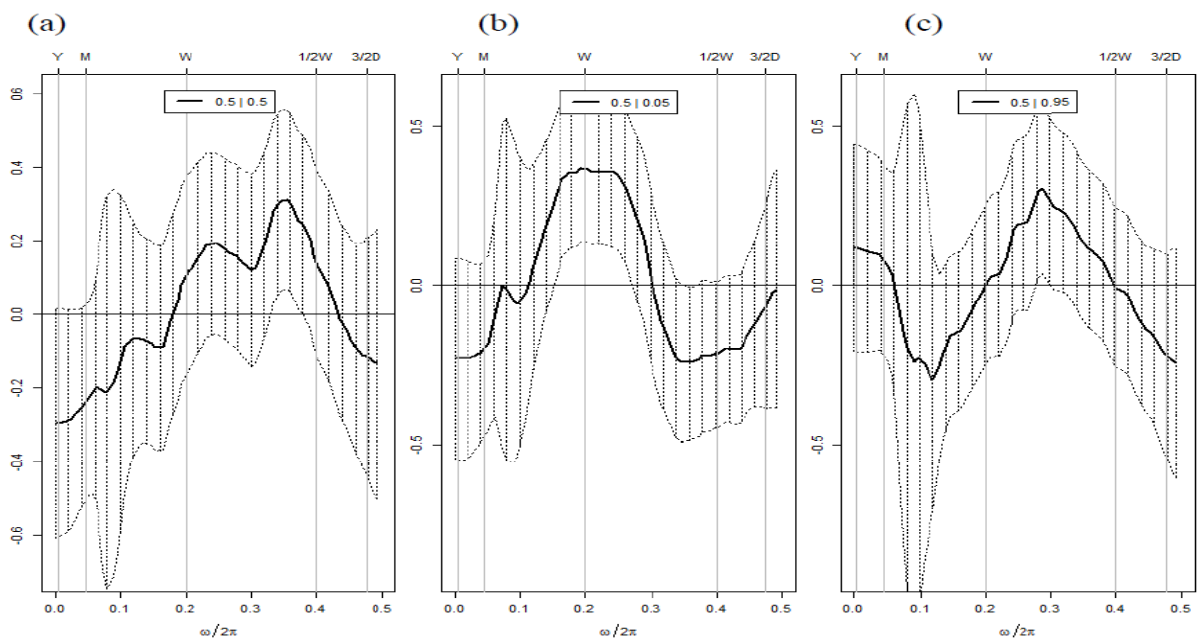


Fig.6: The quantile coherency estimates between the vaccination rate and sectoral stock return (finance)



4 Concluding Remarks

This study examines how large and persistent Australian financial markets react to the COVID-19 vaccine rollout. Based on the time domain and frequency domain approaches such as quantile regression (Koenker and Bassett, 1978) and quantile copula

coherency estimation (Baruník and Kley, 2019), our study properly detects short- and long-lived significant reactions of the stock price index and FX returns to the vaccination rate variation. The results reveal both positive and negative reactions of the stock and foreign exchange rate markets to the progress of vaccination policy implementation. Relatively shorter (daily or weekly) tail responses are obtained from the quantile regression; moreover, longer (monthly or yearly) tail responses were successfully uncovered in the quantile coherency estimation.

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