How did financial markets react to the COVID-19 vaccine rollout? Fresh evidence from Australia

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2025

How did financial markets react to the COVID-19 vaccine rollout? Fresh evidence from Australia

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Abstract

We provide the first study on how COVID-19 vaccine rollout affects Australian financial markets. To examine the heterogeneous and asymmetric effects of vaccination rate on financial markets, we adopt the quantile-on-quantile regression (QQR). We also use the novel quantile copula coherency developed by Baruník and Kley (2019) to detect longer (e.g. monthly or yearly) reactions of financial markets or distinguish the mixed market reactions to short- and long-persistent impacts from vaccine rollout. We find that relative short-term impacts of lagged vaccination rates on quantiles of the returns of the ASX200 stock price and foreign exchange (FX) are stable against fluctuations of the Dow Jones stock price index or FX return at various quantiles. Therefore, the vaccination policy implemented in Australia homogeneously affects financial markets at quantiles. Moreover, our study properly detects short- and long-lived significant reactions of the stock price index and FX returns to the vaccine rate variation.

Keywords: Financial markets; COVID-19 vaccine; Quantile-on-quantile regression; 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

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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 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., 2022), exchange rate market (Iyke and Ho, 2021; Narayan, 2021; Zhou, 2021), and macroeconomic policy (Elgin et al., 2021; Gholipour and Arjomandi, 2022). 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 large and persistent the 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 analyse 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.

[1]https://www.rba.gov.au/education/resources/snapshots/economy-composition-snapshot/
[2]Most of the education companies whose shares are publicly listed on the Australian Securities Exchange (ASX) are categorised under the consumer discretionary sector.
[3]Mining 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.

The other difference is in our empirical strategy, which is also related to the second contribution. In particular, the novelty of our paper lies in the analysis of the entire dependence structure of the quantile of different financial market data series and that of vaccination rate, thereby extending the quantile regression to a quantile-on-quantile regression (QQR) developed by Sim and Zhou (2015). Tail events such as financial crises and the current global pandemic 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. The conventional methods to examine the financial markets such as vector autoregressive (VAR) method and ordinary least squares (OLS) or quantile regression, fail to capture the complex inter-dependent relationship at different quantiles for our data series. The QQR approach, however, combines quantile regression and nonparametric estimation techniques, which can show the nonlinear relationship between vaccine rollout and financial markets in an ad hoc fashion. Moreover, the QQR analysis enables us to explore the impact that the quantiles of global stock market returns have on the relationship between vaccination rates and quantiles of financial market series, thus presenting a more comprehensive picture of the overall inter-dependence between them.

To detect longer (e.g. monthly or yearly) reactions of the financial markets or identify the mixed signals of short- and long-lived responses of one variable to another, we also adopt the novel quantile copula coherency developed by Baruník and Kley (2019). We detect the shortest (daily) to the longest (yearly) responses based on this framework. 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.

The remainder of this paper is organised as follows. In Section 2, we discuss the data set and present the empirical strategy undertaken in this study. Section 3 reports empirical findings. Section 4 concludes.

2 Data and Empirical Strategy

2.1 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 administrated 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/ASX200) 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/ASX200 Healthcare, S&P/ASX200 Consumer Discretionary, S&P/ASX200 Materials, and S&P/ASX200 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.

2.2 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 a benchmark exercise. For the regressors, the lagged vaccination rates ($t-1 \sim t-5$), ASX200 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. Our model using the ASX200 stock price return as a regressand is as follows.

$$\text{ASX200}_t = \alpha^\tau + \sum_{i=1}^{5} \beta_i^\tau \text{Vaccine}_{t-i} + \gamma^\tau \text{FX}_t + \delta^\tau \text{DJ}_t + \zeta^\tau \text{VIX}_t + v_t^\tau \tag{1}$$

where ASX200, Vaccine, FX, DJ, and VIX represent ASX200 stock price return, vaccination rate, FX return, Dow Jones industrial average index return, and VIX, respectively. The parameters α^τ, β^τ, γ^τ, δ^τ, and ζ^τ vary with τ. v_t^τ is an error term that has a zero τ-quantile. When we use the FX return or each sectoral stock price return as a regressand, the ASX200 stock return is replaced.

[4] We excluded the data for weekends and holidays.

2.3 Quantile-on-quantile regression

The tails of the distribution of the ASX200 stock price return (or sectoral stock price return or FX return) may more sensitively respond to the tail behaviours of the US stock return. Particularly in crisis periods such as the COVID-19, the upper quantile (e.g. 0.95%) or lower quantile (e.g., 0.05%) of the stock/FX return seems to be more dependent on the 0.95- or 0.05-quantiles of the Dow Jones return. If so, the quantile regression explained in Section 2.2 may not fully capture such dependence in its entirety. Moreover, the coefficients of the lagged vaccination rate series may change with different quantiles of the Dow Jones return in the quantile regression. To consider these possibilities and confirm the robustness of the coefficients of the vaccination rate in this case, we utilize a quantile-on-quantile (QQR) regression proposed by Sim and Zhou (2015), which is able to examine how the quantiles of one variable affect the conditional quantiles of another variable. We briefly describe the QQR method below.

Let τ_1 denote the quantile of the ASX200 stock return and rewrite Equation (1) as follows:

$$\begin{aligned}\text{ASX200}_t &= \alpha^{\tau_1} + \sum_{i=1}^{5} \beta_i^{\tau_1}\text{Vaccine}_{t-i} + \gamma^{\tau_1}\text{FX}_t + \delta^{\tau_1}\text{DJ}_t + \zeta^{\tau_1}\text{VIX}_t + v_t^{\tau_1} \\ &= \alpha^{\tau_1} + \delta^{\tau_1}\text{DJ}_t + \boldsymbol{\beta}'\boldsymbol{x_t} + v_t^{\tau_1} \end{aligned} \tag{2}$$

where $\boldsymbol{\beta}' = (\beta_1^{\tau_1}, \beta_2^{\tau_1}, \beta_3^{\tau_1}, \beta_4^{\tau_1}, \beta_5^{\tau_1}, \gamma^{\tau_1}, \zeta^{\tau_1})'$ and $\boldsymbol{x}_t' = (\text{Vaccine}_{t-1}, \text{Vaccine}_{t-2}, \text{Vaccine}_{t-3}, \text{Vaccine}_{t-4}, \text{Vaccine}_{t-5}, \text{FX}_t, \text{VIX}_t)'$. To study the relationship between the τ_1-quantile of ASX200 return and the quantile (τ_2) of Dow Jones return, which is denoted as $\text{DJ}_t^{\tau_2}$, we treat $\delta^{\tau_1}(\cdot)$ as an unknown function of DJ_t. We then take a first order Taylor expansion of $\delta^{\tau_1}(\text{DJ}_t)$ around $\text{DJ}_t^{\tau_2}$.

$$\delta^{\tau_1}(\text{DJ}_t) \approx \delta^{\tau_1}(\text{DJ}^{\tau_2}) + \delta^{\tau_1'}(\text{DJ}^{\tau_2})(\text{DJ}_t - \text{DJ}^{\tau_2})$$

Sim and Zhou (2015) define $\delta^{\tau_1}(\text{DJ}^{\tau_2})$ and $\delta^{\tau_1'}(\text{DJ}^{\tau_2})$ as $\delta_0(\tau_1, \tau_2)$ and $\delta_1(\tau_1, \tau_2)$, respectively. Hence,

$$\delta^{\tau_1}(\text{DJ}_t) \approx \delta_0(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) \tag{3}$$

By substituting Equation (3) into (2), we obtain:

$$\begin{aligned}\text{ASX200}_t &= \alpha(\tau_1) + \delta_0(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) + \boldsymbol{b}'\boldsymbol{x_t} + v_t^{\tau_1} \\ &= \alpha(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) + \boldsymbol{b}'\boldsymbol{x_t} + v_t^{\tau_1} \end{aligned} \tag{4}$$

where $\alpha^{\tau_1} \equiv \alpha(\tau_1)$, $\boldsymbol{\beta}' \equiv \boldsymbol{b}' = (\beta_1(\tau_1), \beta_2(\tau_1), \beta_3(\tau_1), \beta_4(\tau_1), \beta_5(\tau_1), \gamma(\tau_1), \zeta(\tau_1))'$, and $\alpha(\tau_1, \tau_2) \equiv \alpha(\tau_1) + \delta_0(\tau_1, \tau_2)$.

Equation (4) can be estimated by quantile regression at a given value of τ_1. Sim and Zhou (2015), instead, solve the weighted equation as follows.

$$\min_{\delta_0,\delta_1} \rho_{\tau_1}[\text{ASX200}_t - \alpha(\tau_1,\tau_2) - \delta_1(\tau_1,\tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) - \boldsymbol{b}'\boldsymbol{x_t}]K(\frac{F_n(\text{DJ}_t) - \tau_2}{h}) \quad (5)$$

where ρ_{τ_1} corresponds to the absolute value function that gives the τ_1-conditional quantile of ASX200_t as a solution. We use a normal kernel function as $K(\cdot)$ to weight observations according to a normal probability distribution with the bandwidth h.[5] Theses weights are inversely related to the distance of DJ_t from DJ^{τ_2}; in other words, the distance of the empirical distribution function $F_n(\text{DJ}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\text{DJ}_k < \text{DJ}_t)$ from τ_2, where τ_2 is the value of the distribution function that refers to DJ^{τ_2}.

2.4 Quantile copula coherency

To investigate how large and persistent the Australian financial markets reacted to vaccine rollout, we adopt the novel quantile copula coherency proposed by Baruník and Kley (2019).

Let $\{X_t\}_{t\in\mathbb{Z}}$ be a d-variate strictly stationary process, with components $X_{t,l}$, $l = 1,...,d$; that is, $X_t = (X_{t,1},...,X_{t,d})'$. $X_{t,l}$ has a marginal distribution function $F_l(q)$ and inverse function $q_1(\tau) := F_l^{-1}(\tau) := \inf\{q \in \mathbb{R} : \tau \leq F_l(q)\}$, where $\tau \in [0,1]$. The matrix of quantile cross-covariance, $\Gamma_k(\tau_1,\tau_2) := (\gamma_k^{l_1 l_2}(\tau_1,\tau_2))_{l_1,l_2=1,...,d}$, where $\gamma_k^{l_1 l_2}(\tau_1,\tau_2)$ represents the cross-covariance of a pair (X_{t,l_1}, X_{t,l_2}), which is specified as follows:

$$\gamma_k^{l_1 l_2}(\tau_1,\tau_2) := Cov(I\{X_{t,l_1} \leq q_{l_1}(\tau_1)\}, I\{X_{t-k,l_2} \leq q_{l_2}(\tau_2)\}) \quad (6)$$

where $l_1, l_2 \in \{1,...,d\}, k \in \mathbb{Z}$, 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:

$$f_{q_{\tau_1},q_{\tau_2}}(\omega) := (f^{l_1 l_2}_{q_{\tau_1},q_{\tau_2}}(\omega))_{l_1,l_2=1,...,d} \quad (7)$$

where

$$f^{l_1 l_2}_{q_{\tau_1},q_{\tau_2}}(\omega) := \frac{1}{2\pi}\sum_{k=-\infty}^{\infty} \gamma_k^{l_1 l_2}(\tau_1,\tau_2)e^{-ik\omega} \quad (8)$$

[5] h is given by the Silverman optimal bandwidth $h = 3.49\sigma T^{1/3}$, where $\sigma = \min(\frac{\text{IQR}}{1.34}, \text{std}(\text{DJ}))$, where IQR and std denote the inter-quantile range and standard deviation, respectively; T is the sample size.

and ω is the frequency, with $\omega \in \mathbb{R}$. Each quantile cross-spectral density, i.e. $f^{l_1 l_2}_{q_{\tau_1}, q_{\tau_2}}(\omega)$ 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:

$$\mathcal{R}^{l_1 l_2}_{q_{\tau_1}, q_{\tau_2}}(\omega) := \frac{f^{l_1 l_2}_{q_{\tau_1}, q_{\tau_2}}(\omega)}{(f^{l_1 l_1}_{q_{\tau_1}, q_{\tau_1}}(\omega) f^{l_2 l_2}_{q_{\tau_2}, q_{\tau_2}}(\omega))^{1/2}} \tag{9}$$

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

$$I^{l_1 l_2}_{n,R}(\omega; \tau_1, \tau_2) := \frac{1}{2\pi n} d^{l_1}_{n,R}(\omega; \tau_1) d^{l_2}_{n,R}(-\omega; \tau_2) \tag{10}$$

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

$$d^{l}_{n,R}(\omega; \tau) := \sum_{t=0}^{n-1} I\{\hat{F}_{n,l}(X_{t,l}) \leq \tau\} e^{-i\omega t} = \sum_{t=0}^{n-1} I\{R^{(n)}_{t,l} \leq n\tau\} e^{-i\omega t} \tag{11}$$

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

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

$$\hat{G}^{l_1 l_2}_{n,R}(\omega; \tau_1, \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_n(\omega - 2\pi s/n) I^{l_1 l_2}_{n,R}(\frac{2\pi s}{n}; \tau_1, \tau_2) \tag{12}$$

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 $(I\{F_{l_1}(X_{t,l_1}) \leq \tau_1\}, I\{F_{l_2}(X_{t,l_2}) \leq \tau_2\})(t = 0, ..., n-1)$. 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:

$$\hat{\mathcal{R}}^{l_1 l_2}_{n,R,q\tau_1,q\tau_2} := \frac{\hat{G}^{l_1 l_2}_{n,R}(\omega;\tau_1,\tau_2)}{(\hat{G}^{l_1 l_1}_{n,R}(\omega;\tau_1,\tau_1)\hat{G}^{l_2 l_2}_{n,R}(\omega;\tau_2,\tau_2))^{1/2}} \tag{13}$$

The difference between this coherency and $\mathcal{R}^{l_1 l_2}_{q\tau_1,q\tau_2}(\omega)$ 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 Quantile regression results

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 sector. 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 ASX200, healthcare, consumer discretionary, materials, and finance sectors. The overall significant impact is negative only for ASX200.[6] At the 0.95-quantile, which is the upper tail of the 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.[7]

3.2 Quantile-on-quantile regression results

Figures 1 to 3 display the selected estimated coefficient values of lagged vaccination rates over quantiles of the ASX200 return (sectoral stock price return) and Dow Jones return in a quantile-on-quantile regression.[8] In each figure, the 3D plot shows coefficient values over pairs of their quantiles. Figure 1 shows the estimated coefficients of vaccine rates $(t-1)$ and $(t-3)$, which are found significant in the quantile regression shown in Table 1. Panel A of Figure 1 reveals the relative stability of the coefficient of vaccine rate $(t-1)$, though some outliers occur at around 0.9-quantile of ASX200 and 0.05-quantile of Dow Jones. Panel B of Figure 1 also shows stable coefficient values except for some

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

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

[8]We have conducted a quantile-on-quantile regression in more cases. The results omitted here are available upon request.

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

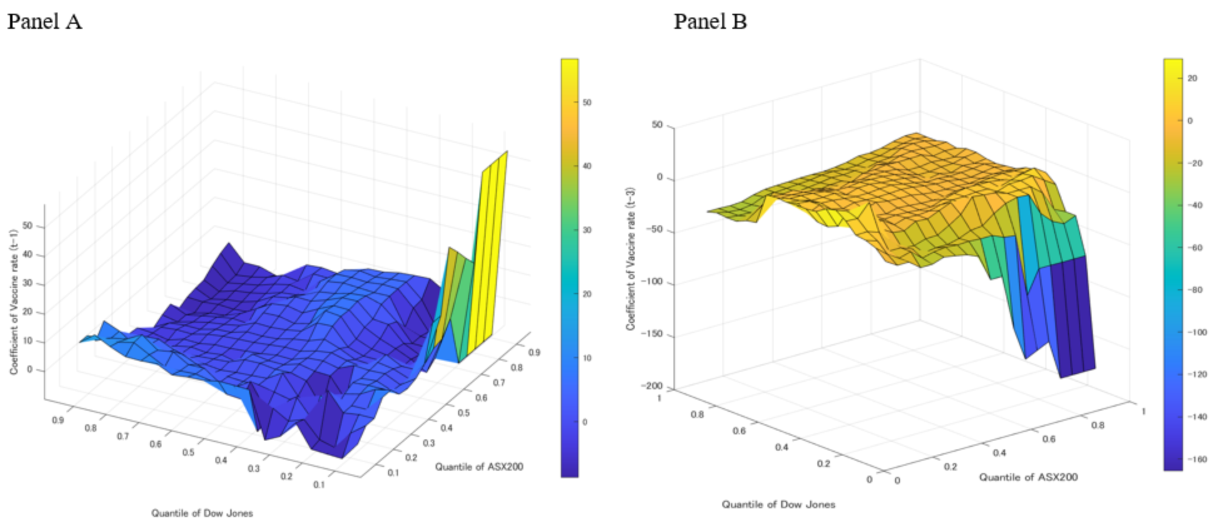
	ASX200			FX			Healthcare			Consumer discretionary			Materials			Finance		
Variable	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$	$\tau = 0.50$	$\tau = 0.05$	$\tau = 0.95$
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	0.104	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	0.048	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	0.046	0.425	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	0.275	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				-0.127	-0.211	**-0.316**	0.015	-0.082	-0.021	**0.360**	0.142	0.055	0.066	0.245	-0.110
	0.140	0.134	0.523				0.274	0.138	0.087	0.865	0.573	0.859	0.002	0.136	0.641	0.509	0.100	0.603
Dow Jones (return)	0.107	**0.310**	-0.215	0.151	**0.471**	-0.120	0.155	**0.286**	0.049	0.141	-0.163	-0.060	0.090	-0.041	-0.077	-0.035	0.137	-0.008
	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
VIX	**-0.106**	**-0.156**	0.008	0.014	-0.007	**-0.101**	-0.028	**-0.141**	-0.034	-0.048	**-0.096**	0.046	**-0.081**	**-0.204**	-0.013	-0.070	**-0.051**	0.107
	0.007	0.005	0.956	0.743	0.913	0.029	0.635	0.005	0.656	0.365	0.066	0.431	0.085	0.000	0.800	0.265	0.387	0.359
ASX 200 (return)				**0.233**	**0.638**	0.093												
				0.010	0.003	0.549												
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.

outliers. In Panel A of Figure 2, the estimated coefficient of vaccine rate $(t-1)$ slightly fluctuates except for 0.05- and 0.10-quantiles of Dow Jones. Panel B of Figure 2 depicts a flat surface of the coefficient values of vaccine rate $(t-1)$, which is also significant in Table 1, with one exceptional case of 0.05-quantile of Dow Jones and 0.5∼1.0-quantiles of Healthcare sector stock price returns. Figure 3 shows the estimated coefficient values of vaccine rate $(t-2)$ over pairs of quantiles of Materials sector stock price return and FX return. In this case, the estimated coefficient crosses a zero line and takes positive or negative values corresponding to various pairs of quantiles. Therefore, the coefficient does not seem to be robust to changes of quantile pairs.

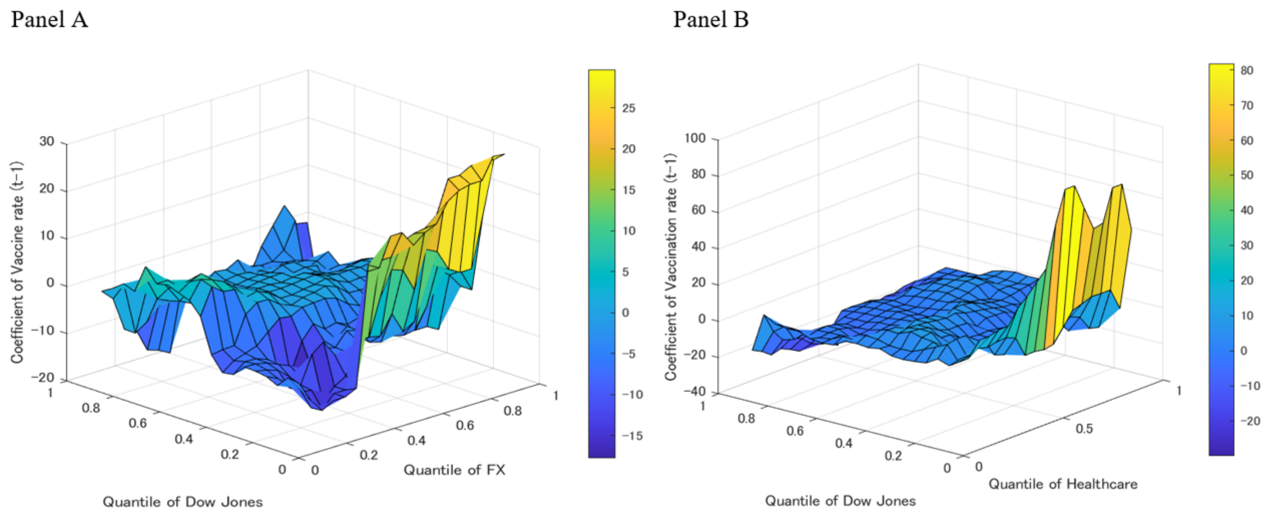
As shown above, the time domain approach is effective in investigating whether the vaccination rate change has significant short-lived (i.e. daily or weekly) impacts on stock price and FX returns. However, we cannot detect longer (e.g. monthly or yearly) reactions occurring in the stock and FX markets 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, next, we estimate the quantile copula coherency between the vaccination rate and each stock price/FX return.

Figure 1: 3D plots of selected coefficients in the quantile-on-quantile estimation for ASX200



Note: Panel A and Panel B respectively show the estimated parameters, $\beta_1(\tau_1)$ and $\beta_3(\tau_1)$, of the regression equation $\mathrm{ASX200}_t = \alpha(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\mathrm{DJ}_t - \mathrm{DJ}^{\tau_2}) + \beta_1(\tau_1)\mathrm{Vaccine}_{t-1} + \beta_2(\tau_1)\mathrm{Vaccine}_{t-2} + \beta_3(\tau_1)\mathrm{Vaccine}_{t-3} + \beta_4(\tau_1)\mathrm{Vaccine}_{t-4} + \beta_5(\tau_1)\mathrm{Vaccine}_{t-5} + \gamma(\tau_1)\mathrm{FX}_t + \zeta(\tau_1)\mathrm{VIX}_t + v_t^{\tau_1}$. Both of the estimated slope coefficients are placed on the z-axis against the quantiles of the ASX200 on the y-axis and the quantiles of Dow Jones on the x-axis.

Figure 2: 3D plots of selected coefficients in the quantile-on-quantile estimation for FX and Healthcare



Note: Panel A shows the estimated parameters $\beta_1(\tau_1)$ of the regression equation: $\text{FX}_t = \alpha(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) + \beta_1(\tau_1)\text{Vaccine}_{t-1} + \beta_2(\tau_1)\text{Vaccine}_{t-2} + \beta_3(\tau_1)\text{Vaccine}_{t-3} + \beta_4(\tau_1)\text{Vaccine}_{t-4} + \beta_5(\tau_1)\text{Vaccine}_{t-5} + \gamma(\tau_1)\text{ASX200}_t + \zeta(\tau_1)\text{VIX}_t + v_t^{\tau_1}$. In Panel A, the estimated slope coefficients are placed on the z-axis against the quantiles of the FX on the y-axis and the quantiles of Dow Jones on the x-axis. Panel B shows the estimated parameters $\beta_1(\tau_1)$ of the regression equation: $\text{Healthcare}_t = \alpha(\tau_1, \tau_2) + \delta_1(\tau_1, \tau_2)(\text{DJ}_t - \text{DJ}^{\tau_2}) + \beta_1(\tau_1)\text{Vaccine}_{t-1} + \beta_2(\tau_1)\text{Vaccine}_{t-2} + \beta_3(\tau_1)\text{Vaccine}_{t-3} + \beta_4(\tau_1)\text{Vaccine}_{t-4} + \beta_5(\tau_1)\text{Vaccine}_{t-5} + \gamma(\tau_1)\text{ASX200}_t + \zeta(\tau_1)\text{FX}_t + v_t^{\tau_1}$. In Panel B, the estimated slope coefficients are placed on the z-axis against the quantiles of the Healthcare on the y-axis and the quantiles of Dow Jones on the x-axis.

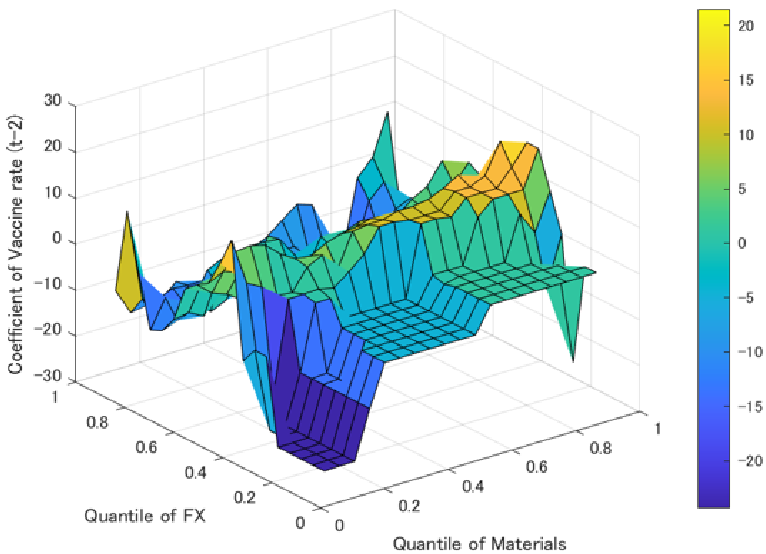
3.3 Quantile copula coherency estimates

We estimate the quantile copula coherency (shown in Equation (13)) 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.[9] 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 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

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

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.

Figure 3: 3D plot of selected coefficients in the quantile-on-quantile estimation for Materials



Note: This figure shows the estimated parameters $\beta_2(\tau_1)$ of the regression equation: $\text{Materials}_t = \alpha(\tau_1, \tau_2) + \gamma_1(\tau_1, \tau_2)(\text{FX}_t - \text{FX}^{\tau_2}) + \beta_1(\tau_1)\text{Vaccine}_{t-1} + \beta_2(\tau_1)\text{Vaccine}_{t-2} + \beta_3(\tau_1)\text{Vaccine}_{t-3} + \beta_4(\tau_1)\text{Vaccine}_{t-4} + \beta_5(\tau_1)\text{Vaccine}_{t-5} + \delta(\tau_1)\text{DJ}_t + \zeta(\tau_1)\text{VIX}_t + v_t^{\tau_1}$. The estimated slope coefficients are placed on the z-axis against the quantiles of the Materials on the y-axis and the quantiles of FX on the x-axis.

Figures 4(a), 4(b), and 4(c) show the quantile copula coherency estimates between the vaccination rate and the ASX200 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 4(a) and 4(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 4(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.

Figure 4: The quantile coherency estimates between the vaccination rate and ASX200 return

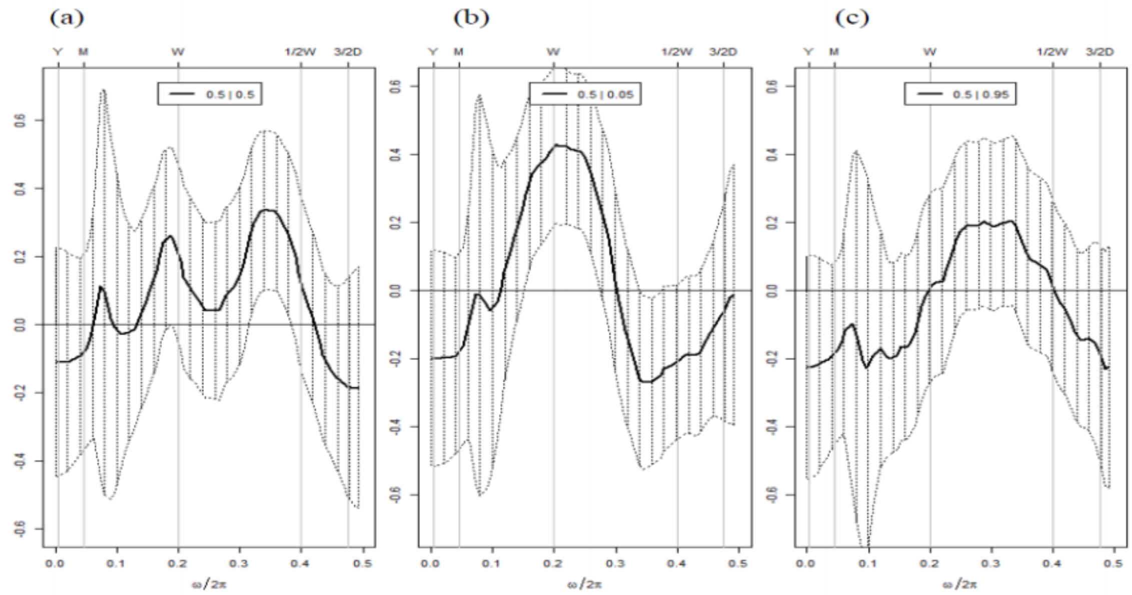
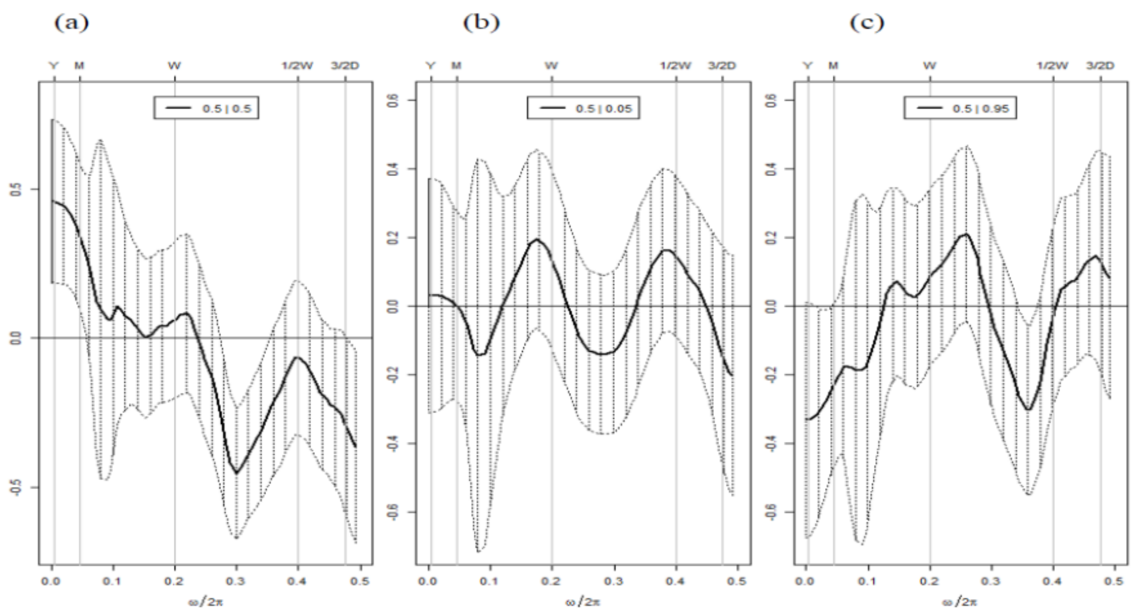


Figure 5: The quantile coherency estimates between the vaccination rate and FX return



Figures 5(a), 5(b), and 5(c) show the quantile copula coherency estimates between the vaccination rate and FX return. At the 0.5|0.5-quantile, Figure 5(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.

Figure 6: The quantile coherency estimates between the vaccination rate and sectoral stock return (healthcare)

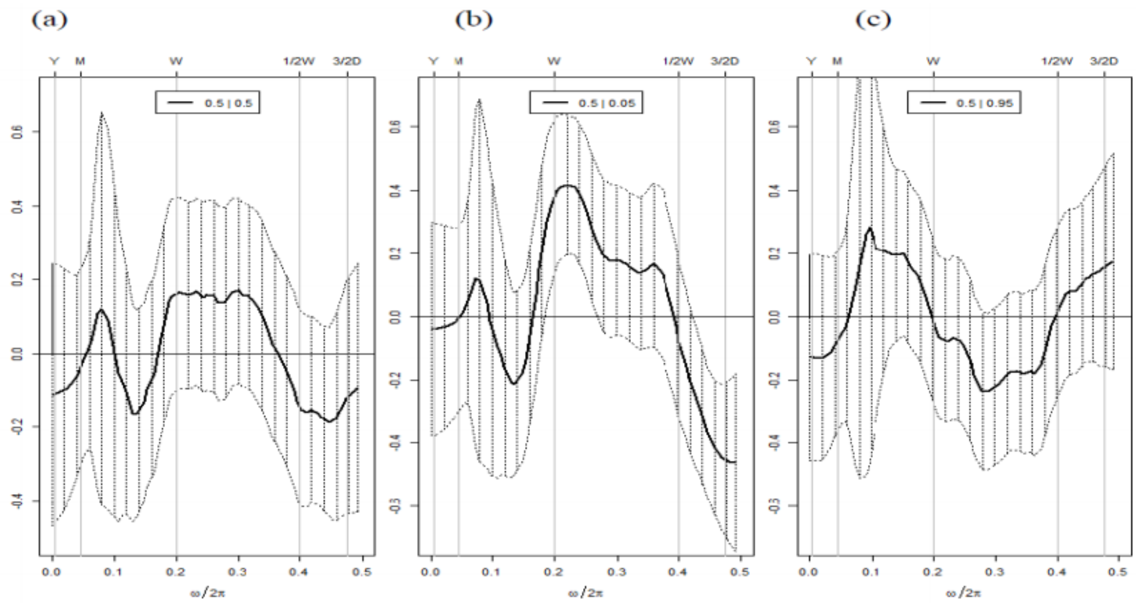


Figure 7: The quantile coherency estimates between the vaccination rate and sectoral stock return (consumer discretionary)

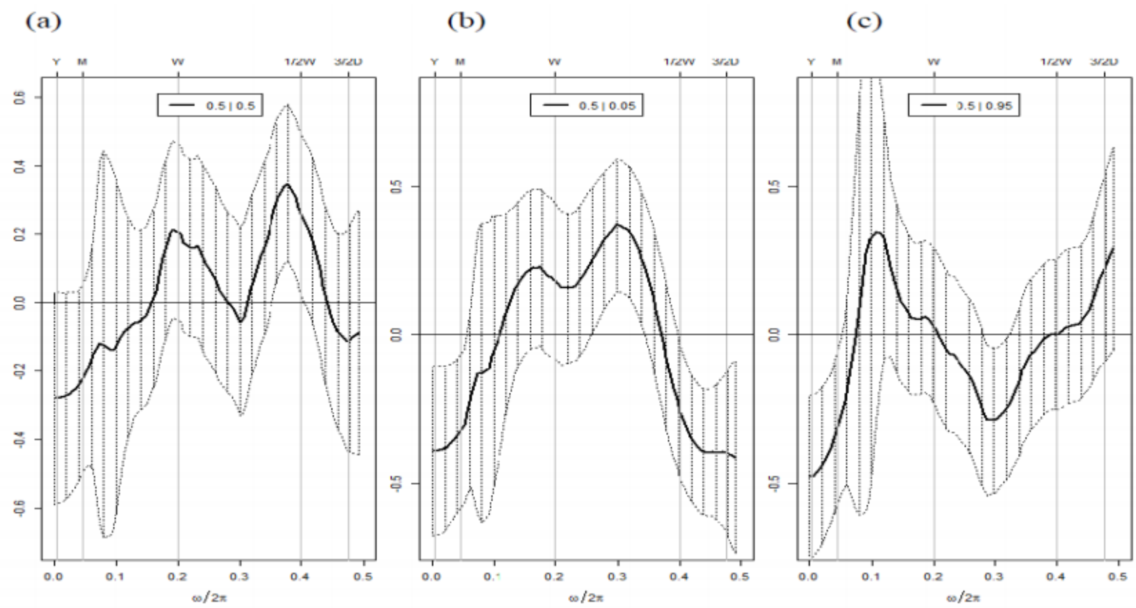
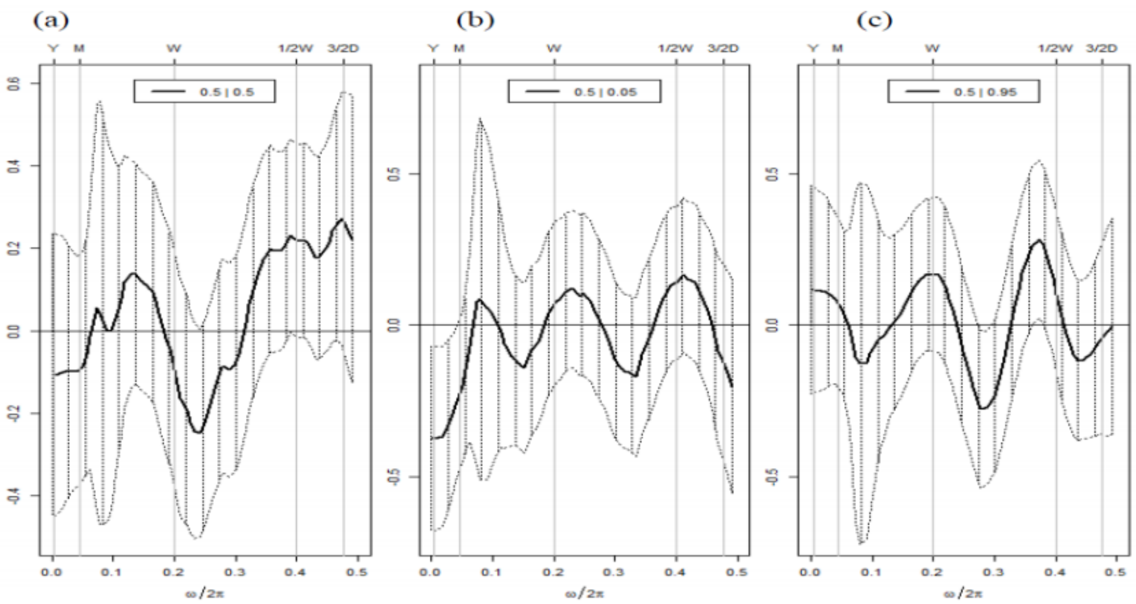
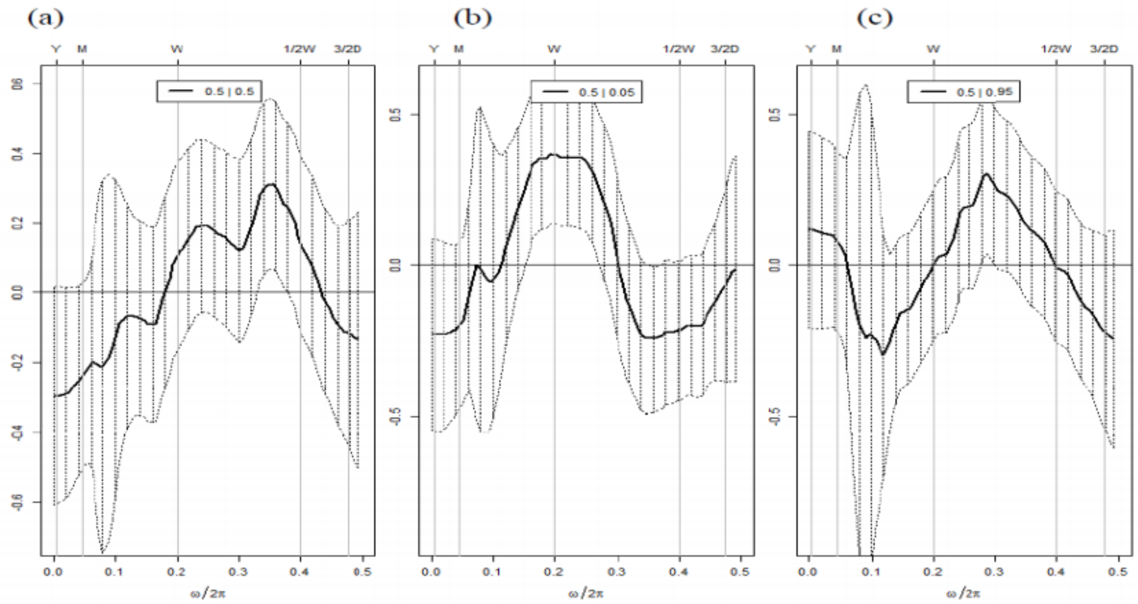


Figure 8: The quantile coherency estimates between the vaccination rate and sectoral stock return (materials)



In Figures 6 to 9, 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.

Figure 9: The quantile coherency estimates between the vaccination rate and sectoral stock return (finance)



4 Concluding Remarks

This study provides early evidence on how vaccine rollout affects Australian financial markets. Specifically, to examine the impacts of vaccination rate on different quantiles of financial markets, we use the QQR approach developed by Sim and Zhou (2015). The QQR method allows us to capture the quantile-specific relationship between two data series and obtain a more comprehensive picture of the overall dependence structure, compared with traditional techniques such as OLS or quantile regression. Furthermore, to investigate how large and persistent Australian financial markets react to the COVID-19 vaccine rollout, we also adopt the novel quantile copula coherency estimation developed by Baruník and Kley (2019). Our empirical evidence points out two main findings. First, the results of QQR approach suggest that relative short-term impacts of lagged vaccination rates on quantiles of the returns of the ASX200 stock price and FX are stable against fluctuations of the Dow Jones stock price index or FX return at various quantiles. Therefore, the vaccination policy implemented in Australia homogeneously affects financial markets at quantiles. Second, 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 are successfully uncovered in the quantile coherency estimation.

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