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Causality in Quantiles and Dynamic Stock Return-Volume

Relations

Chia-Chang Chuang, Chung-Ming Kuan and Hsin-Yi Lin

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Institute of Economics
Academia Sinica
Taipei 115, TAIWAN
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中央研究院 經濟研究所

INSTITUTE OF ECONOMICS, ACADEMIA SINICA
TAIWAN

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Chia-Chang Chuang

Department of International Business
National Taipei College of Business

Chung-Ming Kuan

Institute of Economics
Academia Sinica

Hsin-yi Lin

Department of Economics
National Chengchi University

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† Author for correspondence: Chung-Ming Kuan, Institute of Economics, Academia Sinica, Taipei 115, Taiwan; E-mail address: ckuan@econ.sinica.edu.tw., phone: +886 2 2782-2791 ext. 646.

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Causality in Quantiles and Dynamic Stock Return-Volume Relations

Abstract

This paper investigates the causal relations between stock return and volume based on quantile regressions. We first define Granger non-causality in all quantiles and propose testing non-causality by a sup-Wald test. Such a test is consistent against any deviation from non-causality in distribution, as opposed to the existing tests that check only non-causality in certain moment. This test is readily extended to test non-causality in different quantile ranges, and the testing results enable us to identify the quantile range for which causality is relevant. In the empirical studies of 3 major stock market indices, we find that, while the conventional test suggests no causality in mean, there are strong evidences that lagged volume Granger causes return in all but some middle quantiles. In particular, the causal effects have opposite signs at lower and upper quantiles and are stronger at more extreme quantiles. These relations form (symmetric) V shapes across quantiles. They also show that the dispersion of the return distribution increases with volume so that volume has a positive effect on return volatility. It is also shown that the quantile causal effects of lagged return on volume are mainly negative.

JEL Classification No: C12, G14

Keywords: Granger non-causality in quantiles, quantile causal effect, quantile regression, return-volume relation, sup-Wald test

1 Introduction

The relationship between financial asset return and trading volume, henceforth the return-volume relation, is important for understanding operational efficiency and information dynamics in asset markets. Models related to this topic include, e.g., the sequential information arrival model (Copeland, 1976; Jennings, Starks, and Fellingham, 1981; Jennings and Barry, 1983) and mixture of distributions model (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983). There are also equilibrium models that emphasize on the information content of volume, e.g., Harris and Raviv (1993), Blume, Easley, and O'Hara (1994), Wang (1994), and Suominen (2001). For instance, Blume, Easley, and O'Hara (1994) stressed that volume carries information that is not contained in price statistics and hence is useful for interpreting the price (return) behavior. On the empirical side, there have been numerous studies on contemporaneous return-volume relation since Granger and Morgenstern (1963) and Ying (1966); see Gallant, Rossi, and Tauchen (1992) and also Karpoff (1987) for a review. Yet, as far as prediction and risk management are concerned, the dynamic (causal) relation between return and volume is more informative.

Causal relations between variables are typically examined by testing Granger non-causality. While Granger non-causality is defined in terms of conditional distribution, it is more common to test non-causality in conditional mean based on a linear model (Granger, 1969, 1980). Granger, Robins, and Engle (1986) and Cheung and Ng (1996) considered testing non-causality in conditional variance, whereas Hiemstra and Jones (1994) derived a test for nonlinear causal relations. These tests have been widely used in the literature (e.g., Fujihara and Mougoué, 1997; Silvapulle and Choi, 1999; Chen, Firth, and Rui, 2001; Ciner, 2002; Lee and Rui, 2002). A serious limitation of this approach is that non-causality in mean (or in variance) need not carry over to other distribution characteristics or different parts of the distribution. Diks and Panchenko (2005) also gave examples that the test of Hiemstra and Jones (1994) may not test Granger non-causality. We are therefore motivated to characterize and test causal relations in a different way.

This paper investigates causal relations from the perspective of conditional quantiles. We first define Granger non-causality in *all* quantiles. The quantile causal effects are estimated by means of quantile regressions (Koenker and Baseett 1978; Koenker, 2005), and the hypothesis of non-causality is tested by the sup-Wald test of Koenker and Machado (1999). This test checks significance of the entire parameter process in quantile regression models and hence is consistent against any deviation from non-causality in distribution, as opposed to the conventional tests of non-causality in a moment and other tests such as

Lee and Yang (2006) and Hong, Liu, and Wang (2006). This test is readily extended to evaluate non-causality in different quantile ranges and enables us to identify the quantile range for which causality is relevant. Our approach thus provides a detailed description of the causal relations between return and volume.

In the empirical study we analyze three stock market indices: New York Stock Exchange (NYSE), Stand&Poor 500 (S&P 500), and Financial Times-Stock Exchange 100 (FTSE 100). Despite that the conventional test suggests no causality in mean for these indices, we find strong evidences that lagged volume Granger causes return at all but some middle quantiles. In particular, the causal effects are heterogeneous across return quantiles, and these effects have opposite signs at lower and upper quantiles and are stronger at more extreme quantiles. For NYSE and S&P 500, such effects are also symmetric about the median. Our results reveal a vivid pattern of quantile causal effects. By putting lagged volume on the vertical axis and return on the horizontal axis, the causal effects form (symmetric) V shapes across quantiles, where the V shapes at tail quantiles have wider opening than those at middle quantiles. This helps to explain why the least-squares regression usually leads to an insignificant estimate, as the opposite effects at two sides of the distribution cancel out each other in “averaging.”

The spectrum of V shapes found in this paper generalizes the existing V -shape results, such as Karpoff (1987), Gallant, Rossi, and Tauchen (1992), and Blume, Easley, and O’Hara (1994). While the previous results were usually obtained by regressing absolute return on volume and hence represent an “average” relation between return and volume, our result gives more details of the conditional return distribution. Our finding of causality is very different from some equilibrium results, such as the nonlinear mean relation derived in Campbell, Grossman, and Wang (1993), because volume is shown to play only an insignificant role in determining the returns at middle quantiles, including the mean. Moreover, the fact that the distribution dispersion increases with volume is also an evidence that volume has a positive effect on return volatility, analogous to the conclusion based on conditional variance (e.g., Lamoureux and Lastrapes, 1990; Gallant, Rossi, and Tauchen, 1992).

This paper is organized as follows. We introduce the notion of Granger (non-)causality in quantiles in Section 2 and discuss the sup-Wald test of non-causality in quantiles in Section 3. The empirical results of different causal models are presented in Section 4. Section 5 concludes the paper.

2 Causality in Mean and Quantiles

Following Granger (1969, 1980), we say that the random variable x does not Granger cause the random variable y if

$$F_{y_t}(\eta | (\mathcal{Y}, \mathcal{X})_{t-1}) = F_{y_t}(\eta | \mathcal{Y}_{t-1}), \quad \forall \eta \in \mathbb{R}, \quad (1)$$

where $F_{y_t}(\cdot | \mathcal{F})$ is the conditional distribution of y_t , and $(\mathcal{Y}, \mathcal{X})_{t-1}$ is the information set generated by y_i and x_i up to time $t - 1$. That is, Granger non-causality requires that the past information of x does not alter the conditional distribution of y_t . The variable x is said to Granger causes y when (1) fails to hold. In what follows, Granger non-causality defined by (1) will be referred to as Granger non-causality in distribution.

As estimating and testing conditional distributions are practically cumbersome, it is more common to test a necessary condition of (1), namely,

$$\mathbb{E}[y_t | (\mathcal{Y}, \mathcal{X})_{t-1}] = \mathbb{E}(y_t | \mathcal{Y}_{t-1}), \quad (2)$$

where $\mathbb{E}(y_t | \mathcal{F})$ is the mean of $F_{y_t}(\cdot | \mathcal{F})$. We say that x does not Granger cause y in mean if (2) holds; otherwise, x Granger causes y in mean. Similarly, we may define non-causality in variance (Granger, Robins, and Engle, 1986; Cheung and Ng, 1996) and non-causality in other moments. Hong, Liu, and Wang (2006) considered “non-causality in risk,” a special case of (1) in which η is the negative of the Value at Risk. Note that these notions of non-causality are only necessary conditions of Granger non-causality in distribution.

The hypothesis (2) is usually tested by evaluating a linear model of $\mathbb{E}[y_t | (\mathcal{Y}, \mathcal{X})_{t-1}]$:

$$\alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{j=1}^q \beta_j x_{t-j},$$

which depends on the past information of $y_{t-1}, \dots, y_{t-p}$ and $x_{t-1}, \dots, x_{t-q}$. Testing (2) now amounts to testing the null hypothesis that $\beta_j = 0$, $j = 1, \dots, q$, in the postulated model; that is, whether any lagged x has a significant impact on the conditional mean of y_t . Rejecting this null hypothesis suggests that x Granger causes y . Yet, failing to reject the null is compatible with non-causality in mean but says nothing about causality in other moments or other distribution characteristics.

Given that a distribution is completely determined by its quantiles, Granger non-causality in distribution can also be expressed in terms of conditional quantiles. Letting $Q_{y_t}(\tau | \mathcal{F})$ denote the τ -th quantile of $F_{y_t}(\cdot | \mathcal{F})$, (1) is equivalent to

$$Q_{y_t}(\tau | (\mathcal{Y}, \mathcal{X})_{t-1}) = Q_{y_t}(\tau | \mathcal{Y}_{t-1}), \quad \forall \tau \in (0, 1). \quad (3)$$

We say that x does not Granger cause y in all quantiles if (3) holds. We may also define Granger non-causality in a quantile range $[a, b] \subset (0, 1)$ as

$$Q_{y_t}(\tau | (\mathcal{Y}, \mathcal{X})_{t-1}) = Q_{y_t}(\tau | \mathcal{Y}_{t-1}), \quad \forall \tau \in [a, b]. \quad (4)$$

Note that Lee and Yang (2006) considered only non-causality in a particular quantile, i.e., the equality in (3) holds for a given τ .

3 Testing Non-Causality in Quantiles

This paper proposes to verify causal relations by testing (3), rather than testing non-causality in a moment (mean or variance) or non-causality in a given quantile. To this end, we postulate a model for the conditional quantile function $Q_{y_t}(\tau | (\mathcal{Y}, \mathcal{X})_{t-1})$ and estimate the model by the quantile regression method of Koenker and Bassett (1978). Writing $\mathbf{y}_{t-1,p} = [y_{t-1}, \dots, y_{t-p}]'$, $\mathbf{x}_{t-1,q} = [x_{t-1}, \dots, x_{t-q}]'$, and $\mathbf{z}_{t-1} = [1, \mathbf{y}_{t-1,p}', \mathbf{x}_{t-1,q}']'$, the model for the τ -th conditional quantile is

$$y_t = \alpha_0(\tau) + \mathbf{y}_{t-1,p}' \boldsymbol{\alpha}(\tau) + \mathbf{x}_{t-1,q}' \boldsymbol{\beta}(\tau) + e_t(\tau) = \mathbf{z}_{t-1}' \boldsymbol{\theta}(\tau) + e_t(\tau),$$

where $\boldsymbol{\theta}(\tau) = [\alpha_0(\tau), \boldsymbol{\alpha}(\tau)', \boldsymbol{\beta}(\tau)']'$ is the k -dimensional parameter vector with $k = 1 + p + q$, and $e_t(\tau)$ is the corresponding error. For a given τ , the parameter vector $\boldsymbol{\theta}(\tau)$ is estimated by minimizing an asymmetrically weighted absolute deviations:

$$\min_{\boldsymbol{\theta}} \sum_{t=1}^T (\tau - \mathbf{1}_{\{y_t < \mathbf{z}_{t-1}' \boldsymbol{\theta}\}}) |y_t - \mathbf{z}_{t-1}' \boldsymbol{\theta}|.$$

The solution to this problem, denoted as $\hat{\boldsymbol{\theta}}_T(\tau)$, can be computed using a linear programming algorithm. Under suitable regularity conditions, $\hat{\boldsymbol{\theta}}_T(\tau)$ is consistent and asymptotically normally distributed. For a thorough discussion of quantile regression and its properties we refer to Koenker (2005).

Given a linear model for conditional quantiles, testing (3) amounts to testing

$$H_0 : \boldsymbol{\beta}(\tau) = \mathbf{0}, \quad \forall \tau \in (0, 1). \quad (5)$$

To this end, we must check significance of the entire parameter process $\boldsymbol{\beta}(\cdot)$. Let $\boldsymbol{\Psi}$ be a $q \times k$ selection matrix such that $\boldsymbol{\Psi} \boldsymbol{\theta}(\tau) = \boldsymbol{\beta}(\tau)$. Then by the asymptotic normality of $\hat{\boldsymbol{\theta}}_T$, $\hat{\boldsymbol{\beta}}_T(\tau) = \boldsymbol{\Psi} \hat{\boldsymbol{\theta}}_T$ is such that

$$\sqrt{T} \left[\hat{\boldsymbol{\beta}}_T(\tau) - \boldsymbol{\beta}(\tau) \right] \xrightarrow{D} [\tau(1 - \tau)]^{1/2} \boldsymbol{\Omega}^{1/2} \mathcal{N}(\mathbf{0}, \mathbf{I}_q), \quad (6)$$

where $\xrightarrow{D}$ stands for convergence in distribution, $\mathbf{\Omega} = \mathbf{\Psi} \mathbf{D}(\tau)^{-1} \mathbf{M}_{zz} \mathbf{D}(\tau)^{-1} \mathbf{\Psi}'$, $\mathbf{M}_{zz} := \lim_{T \rightarrow \infty} T^{-1} \sum_{t=1}^T \mathbf{z}_{t-1} \mathbf{z}_{t-1}'$, and

$$\mathbf{D}(\tau) := \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T f_t(F_t^{-1}(\tau)) \mathbf{z}_{t-1} \mathbf{z}_{t-1}',$$

with f_t and F_t being, respectively, the conditional density and distribution functions of y_t given $\mathbf{z}_{t-1}$. For a given τ , the Wald statistic of $\boldsymbol{\beta}(\tau) = \mathbf{0}$ is

$$\mathcal{W}_T(\tau) := T \hat{\boldsymbol{\beta}}_T(\tau)' \hat{\mathbf{\Omega}}^{-1} \hat{\boldsymbol{\beta}}_T(\tau) / [\tau(1 - \tau)],$$

where $\hat{\mathbf{\Omega}}$ is a consistent estimator of $\mathbf{\Omega}$. In the special case that $f_t(\cdot) = f(\cdot)$, the unconditional density of y_t , $\mathbf{\Omega} = f(F^{-1}(\tau))^{-2} \mathbf{\Psi} \mathbf{M}_{zz}^{-1} \mathbf{\Psi}'$, and the Wald statistic becomes

$$\mathcal{W}_T(\tau) = T \hat{\boldsymbol{\beta}}_T(\tau)' (\mathbf{\Psi} \mathbf{M}_{zz}^{-1} \mathbf{\Psi}')^{-1} \hat{\boldsymbol{\beta}}_T(\tau) \hat{f}^2 / [\tau(1 - \tau)],$$

where $\hat{f}$ is an estimate of f . To test (5), Koenker and Machado (1999) suggested using a sup-Wald test, i.e., the supremum of $\mathcal{W}_T(\tau)$.

In what follows, let $\mathbf{B}_q$ denote a vector of q independent Brownian bridges, $\Rightarrow$ denote weak convergence (of associated probability measures) and $\|\cdot\|$ denote the Euclidean norm. Clearly, $\mathbf{B}_q(\tau)$ equals $[\tau(1 - \tau)]^{1/2} \mathcal{N}(\mathbf{0}, \mathbf{I}_q)$ in distribution, and (6) can be expressed as

$$\sqrt{T} \left[\hat{\boldsymbol{\beta}}_T(\tau) - \boldsymbol{\beta}(\tau) \right] \xrightarrow{D} \mathbf{\Omega}^{1/2} \mathbf{B}_q(\tau). \quad (7)$$

Under suitable conditions, (7) holds uniformly on a closed interval $\mathcal{T} \subset (0, 1)$; see Koenker and Machado (1999) for details. We then have, under the null hypothesis (5),

$$\mathcal{W}_T(\tau) \Rightarrow \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1 - \tau)}} \right\|^2, \quad \tau \in \mathcal{T},$$

where the weak limit is the sum of squares of q independent Bessel processes. This immediately leads to the following result:

$$\sup_{\tau \in \mathcal{T}} \mathcal{W}_T(\tau) \Rightarrow \sup_{\tau \in \mathcal{T}} \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1 - \tau)}} \right\|^2. \quad (8)$$

It should be noted that $\|\mathbf{B}_q(\tau)/\sqrt{\tau(1 - \tau)}\|$ tends to infinity when $\tau \rightarrow 0$ or 1 (Andrews, 1993). Thus, the right-hand side of (8) would be a well defined limit provided that $\mathcal{T}$ is a closed interval in $(0, 1)$.

In practice, we may set $\mathcal{T} = [\epsilon, 1 - \epsilon]$ for some small ϵ in $(0, 0.5)$ and choose n points ($\epsilon = \tau_1 < \dots < \tau_n = 1 - \epsilon$). The sup-Wald test for (5) is computed as

$$\sup\text{-}\mathcal{W}_T = \sup_{i=1, \dots, n} \mathcal{W}_T(\tau_i).$$

Table 1: Critical values of the sup-Wald test ($q = 1$) on different quantile ranges.

level	[0.05, 0.95]	[0.05, 0.25]	[0.25, 0.5]	[0.5, 0.75]	[0.75, 0.95]
1%	13.01	11.25	10.54	10.20	10.96
5%	9.84	7.63	6.96	6.91	7.61
10%	8.19	6.13	5.45	5.40	6.10

level	[0.52, 0.69]	[0.48, 0.61]	[0.63, 0.78]	[0.07, 0.14]	[0.25, 0.41]
1%	9.65	9.43	9.57	9.60	9.85
5%	6.29	5.96	6.28	6.27	6.38
10%	4.87	4.55	4.85	4.88	4.91

When n is large, the right-hand side of (8) with $\mathcal{T} = [\epsilon, 1 - \epsilon]$ ought to be a good approximation to the null limit of $\sup \mathcal{W}_T$. Similarly, we may test the null hypothesis:

$$H_0 : \beta(\tau) = \mathbf{0}, \quad \forall \tau \in [a, b]. \quad (9)$$

by the supremum of $\mathcal{W}_T(\tau_i)$ with $a = \tau_1 < \dots < \tau_n = b$. It is clear that the limit in (8) carries over to $\mathcal{T} = [a, b]$. The results of the sup-Wald test on various $[a, b]$ may be used to identify the quantile range from which causality arises. For example, if the null hypothesis (5) is rejected but (9) is not rejected for some interval $[a, b]$, one may infer that causality mainly arises from the quantiles outside $[a, b]$.

To determine the critical values for the sup-Wald test, we note that, for $s = \tau/(1 - \tau)$, the one-dimensional Bessel process $B(\tau)/\sqrt{\tau(1 - \tau)}$ and the normalized, one-dimensional Brownian motion $W(s)/\sqrt{s}$ are equal in distribution. It follows that

$$\mathbb{P} \left\{ \sup_{\tau \in [a, b]} \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1 - \tau)}} \right\|^2 < c \right\} = \mathbb{P} \left\{ \sup_{s \in [1, s_2/s_1]} \left\| \frac{\mathbf{W}_q(s)}{\sqrt{s}} \right\|^2 < c \right\},$$

with $s_1 = a/(1 - a)$, $s_2 = b/(1 - b)$, and $\mathbf{W}_q$ a vector of q independent Brownian motions. That is, the critical values c are determined by the sum of squared normalized Brownian motions. The critical values for some q and s_2/s_1 have been tabulated in DeLong (1981) and Andrews (1993); other critical values can be easily computed via simulations. The simulated critical values of the sup-Wald test (with $q = 1$) on $[0.05, 0.95]$ and other sub-intervals considered in Section 4.1 are summarized in Table 1.¹

¹Our simulation approximates the standard Brownian motion using a Gaussian random walk with 3000 i.i.d. $\mathcal{N}(0, 1)$ innovations; the number of replications is 20,000.

Table 2: Summary statistics for stock returns r_t and volume v_t .

	NYSE		S&P 500		FTSE 100	
	r_t	v_t	r_t	v_t	r_t	v_t
mean	0.03	769.43	0.04	863.18	0.02	778.10
SD	0.89	541.27	1.02	761.37	1.02	662.77
median	0.05	609.31	0.05	494.88	0.04	426.80
skewness	-0.23	0.53	-0.09	0.61	-0.11	0.94
kurtosis	4.15	-0.96	3.74	-1.07	3.11	-0.07
minimum	-6.79	31.64	-7.25	2.08	-5.89	26.36
maximum	5.18	2767.75	5.61	3345.21	5.90	4461.01
number	4135	4135	4161	4161	4166	4166

4 Empirical Study

Our empirical study focuses on 3 stock market indices: NYSE, S&P 500 and FTSE 100. The daily data from the beginning of 1990 (Jan. 2 or Jan. 4) to June 30, 2006 are taken from *DataStream* database, and there are 4135, 4161 and 4166 observations for NYSE, S&P 500 and FTSE 100, respectively.² Returns are calculated as $r_t = 100 \times (\ln(p_t) - \ln(p_{t-1}))$, where p_t is index at time t . Volumes v_t are the traded share volumes of these indices times 10^{-6} . The summary statistics of r_t and v_t are collected in Table 2.

It can be seen that the mean and median returns are all close to zero and their standard deviations are close to one. Also, the return series behave similarly to what we usually observe in the literature: they fluctuate around their respective mean levels and exhibit volatility clustering and excess kurtosis. For volume, the mean and median are quite different, and the standard deviations are larger. To conserve space, we plot only v_t in the upper panel of Figure 1. These series appear to have a quadratic trend prior to 2001 but a more complex pattern afterwards. Following Gallant, Rossi, and Tauchen (1992), we remove the deterministic trend in log volume series by regressing $\log v_t$ on a constant, t and t^2 . This is a common exercise in the empirical studies that involve trading volume; see, e.g., Chen, Firth, Rui (2000) and Lee and Rui (2002). The residuals (i.e., detrended log volumes) are plotted in the lower panel of Figure 1. These residuals will also be referred to as volumes and still denoted as v_t . Our subsequent analysis of return-volume relations

²Our results are quite robust to the sample period; the same analysis on various sub-samples yields qualitatively similar conclusions.

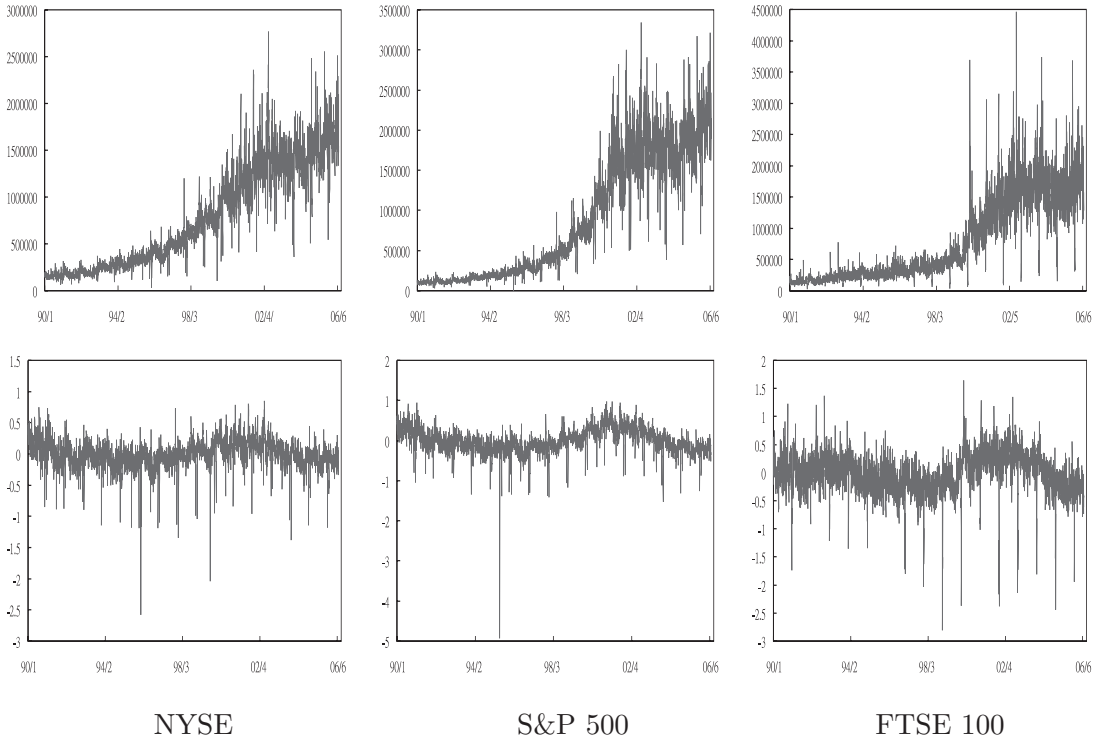


Figure 1: The series of volume (upper panel) and detrended log volume (lower panel).

is based on r_t and (detrended log) volumes v_t .

4.1 Models with One Lag

For each return-volume relation, we consider the following model:

$$y_t = \alpha_0(\tau) + \sum_{i=1}^q \alpha_i(\tau) y_{t-i} + \sum_{j=1}^q \beta_j(\tau) x_{t-j} + e_t. \quad (10)$$

To determine whether volume Granger causes return, y is return and x is volume; for reversed causal relations, y is volume and x is return. This model specification allows us to investigate whether lagged x delivers information (about y) that is not contained in lagged y (Blume, et al., 1994). Model estimation is based on the R program (version 2.4.0) with the “quantreg” package (version 4.01) written by R. Koenker.³

To illustrate, we first estimate model (10) with $q = 1$. For each y , 91 quantile regressions (with $\tau = 0.05, 0.06, \dots, 0.94, 0.95$) and least-squares regression are computed. In

³The R program and “quantreg” package are available from the CRAN website: <http://cran.r-project.org/>.

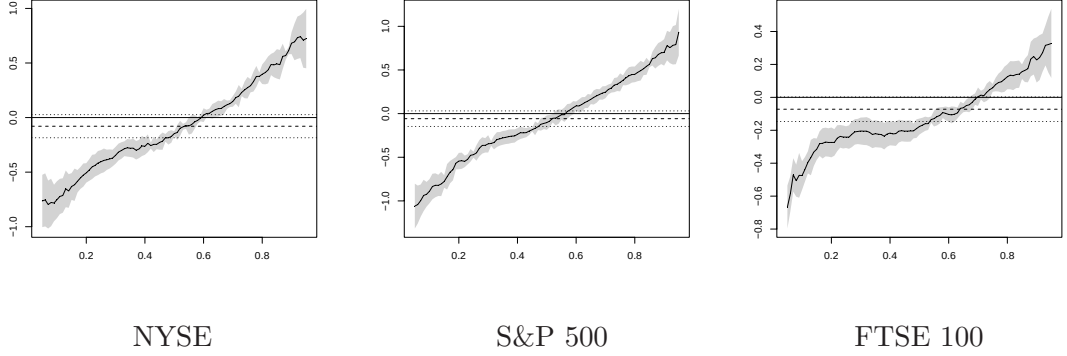


Figure 2: Quantile and least-squares estimates of the causal effects of volume on return.

Figure 2, we plot the estimated $\beta_1(\tau)$ from the regressions of r_t on r_{t-1} and v_{t-1} and their 95% confidence intervals (in shaded area) against τ , together with the least-squares estimate (dashed line) and its 95% confidence interval (dotted lines). For readers' information, the estimated coefficients of 9 quantile regressions ($\tau = 0.05, 0.1, 0.25, 0.4, 0.5, 0.6, 0.75, 0.9, 0.95$) are summarized in Table A.1 in Appendix.

It can be seen from Figure 2 that the causal effects of volume, i.e., the regression estimates of $\beta_1(\tau)$, vary with quantiles and exhibit a similar pattern: They are significantly negative (positive) for lower (upper) quantiles but insignificant at some middle quantiles (τ in $[0.52, 0.69]$ for NYSE, $[0.48, 0.61]$ for S&P 500, and $[0.63, 0.78]$ for FTSE 100). Further, the magnitude of these estimates increases when τ move toward zero and one. Thus, lagged volume exerts opposite and heterogeneous effects on the two sides of the return distribution, and such effects become stronger at more extreme quantiles. In contrast, the least-squares estimates of the causal effects are all negative but insignificant, suggesting *no* causality in mean. This is a clear evidence that non-causality in mean may convey little information about non-causality in other quantiles of the distribution.

To be sure, we apply the sup-Wald test to check joint significance of $\beta_1(\tau)$ on $[0.05, 0.95]$ and the subintervals divided by quartiles: $[0.05, 0.25]$, $[0.25, 0.5]$, $[0.5, 0.75]$ and $[0.75, 0.95]$. We also test $\beta_1(\tau) = 0$ on $\mathcal{T}^\dagger$, the range of quantiles at which the estimates of $\beta_1(\tau)$ are insignificant individually. As shown in the upper panel of Table 3, these statistics overwhelmingly reject the null of non-causality in all quantile ranges at 1% level but can not reject non-causality in $\mathcal{T}^\dagger$ at 5% or even 10% level. We thus conclude that, for the indices being tested, volume Granger causes return at the quantiles outside $\mathcal{T}^\dagger$. This conclusion is in contrast with many existing results (e.g., Kocagil and Shachmurove, 1998; Chen,

Table 3: The sup-Wald tests of non-causality in different quantile ranges.

	Index	[0.05, 0.95]	[0.05, 0.25]	[0.25, 0.5]	[0.5, 0.75]	[0.75, 0.95]	$\mathcal{T}^\dagger$
r_t on	NYSE	39.14**	38.84**	27.41**	13.77**	39.14**	3.83
r_{t-1}, v_{t-1}	S&P 500	108.02**	108.02**	43.47**	31.95**	64.54**	4.91
	FTSE 100	33.18**	33.18**	23.56**	14.94**	11.61**	4.38
v_t on	NYSE	17.02**	8.19*	17.02**	11.38**	12.05**	5.85
v_{t-1}, r_{t-1}	S&P 500	53.32**	13.10**	15.36**	45.55**	53.32**	15.36**
	FTSE 100	6.34	0.63	4.09	3.47	6.34	N/A

Note: ** and * denote significance at 1% and 5% levels, respectively. In the upper panel, $\mathcal{T}^\dagger$ is [0.52, 0.69] for NYSE, [0.48, 0.61] for S&P 500, and [0.63, 0.78] for FTSE 100; In the lower pannel, $\mathcal{T}^\dagger$ is [0.07, 0.14] for NYSE and [0.25, 0.11] for S&P 500. The corresponding critical values are in Table 1.

Firth, and Rui, 2001; Lee and Rui, 2002) which are based on a test for linear causality in mean. Yet, our results of no causality in some middle quantiles (including the mean) do not support the nonlinear mean relations given in Gallant, Rossi, and Tauchen (1992) and Campbell, Grossman, and Wang (1993).

Following Buchinsky (1998), we also test whether the causal effects at the τ -th and $(1 - \tau)$ -th quantiles are symmetric about the median, i.e., $\beta_1(\tau) + \beta_1(1 - \tau) = 2\beta_1(0.5)$; This amounts to checking whether

$$\hat{\gamma}_T(\tau) = \hat{\beta}_{1,T}(\tau) + \hat{\beta}_{1,T}(1 - \tau) - 2\hat{\beta}_{1,T}(0.5)$$

is sufficiently close to zero. We compute a $\chi^2(1)$ test based on the square of the normalized $\hat{\gamma}_T(\tau)$ for the τ pairs: (0.05, 0.95), (0.1, 0.9), ..., (0.45, 0.55), where the standard error of $\hat{\gamma}_T(\tau)$ is obtained via design matrix bootstrap; the testing results are summarized in Table 4. From this table we find that, for NYSE and S&P 500, the null of symmetric causal effects can not be rejected at 5% level for all τ pairs, but for FTSE 100, these effects are not symmetric for (0.15, 0.85), (0.2, 0.8), (0.25, 0.75) and (0.3, 0.7). The symmetry of these quantile causal effects also helps to explain why the conventional methods, such as correlation coefficient and least-squares estimation, usually yield an insignificant estimate of causal effect, as the positive and negative effects at corresponding upper and lower quantiles tend to cancel out each other in “averaging.”

These results together show that, by putting lagged volume on vertical axis and return

Table 4: Testing symmetry of quantile causal effects: Model with one lag.

τ pair	NYSE	S&P 500	FTSE 100
(0.05, 0.95)	1.215	0.254	0.019
(0.10, 0.90)	2.236	0.058	1.063
(0.15, 0.85)	1.366	0.005	5.117*
(0.20, 0.80)	3.112	1.390	7.859**
(0.25, 0.75)	3.273	1.019	7.631**
(0.30, 0.70)	1.386	2.238	6.916**
(0.35, 0.65)	1.959	2.492	2.001
(0.40, 0.60)	0.760	1.508	0.801
(0.45, 0.55)	0.071	0.070	0.408

Note: Each entry is a test statistic for the hypothesis that the quantile causal effects are symmetric about the median. ** and * denote significance at 1% and 5% levels, respectively; the corresponding critical values are 6.63 and 3.84.

on the horizontal axis, the relations between return and lagged volume exhibit (symmetric) V shapes across return quantiles, and a V shape at more extreme quantiles has wider opening. Thus, an increase in lagged volume results in a larger return in either sign, and such effect is stronger for return with larger magnitude. This complements the findings of Karpoff (1987), Gallant, Rossi, and Tauchen (1992), and Blume, Easley, and O'Hara (1994). Compared with the V -shape results obtained from least-squares regression of absolute return on lagged volume, the V shapes based on quantile regressions constitute a vivid pattern of the causal effects. Moreover, the V -shape relations imply that the dispersion of the return distributions increases with volume. This is an alternative evidence that return volatility depends positively on volume, analogous to the results in the context of conditional variance, e.g., Lamoureux and Lastrapes (1990), Gallant, Rossi, and Tauchen (1992), Moosa and Al-Loughani (1995), Kocagil and Shachmurove (1998), Chen, Firth, and Rui (2001), and Xu, Chen, and Wu (2006).

For the regressions of v_t on v_{t-1} and r_{t-1} , we plot the estimated $\beta_1(\tau)$, the quantile causal effects of r_{t-1} on v_t , in Figure 3. Similar to Table A.1, we summarize the estimated coefficients of 9 quantile regressions in Table A.2 in Appendix. In Figure 3, the least-squares estimates are all significantly negative, showing causality in mean in these series. The estimated $\beta_1(\tau)$ for NYSE are quite stable and close to the least-squares estimate, and they are significantly negative at most quantiles, except for $\tau = 0.05, 0.07\text{--}0.14$,

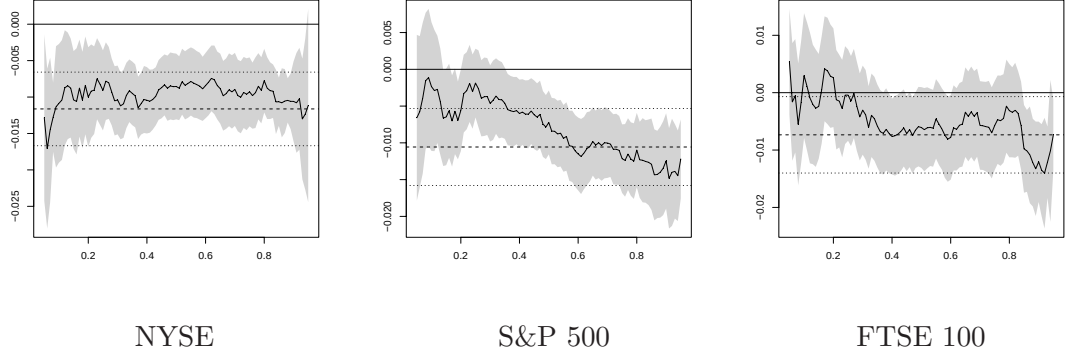


Figure 3: Quantile and least-squares estimates of the causal effects of return on volume.

0.17 and 0.19. For S&P 500, these estimates are negative and significant at middle and upper quantiles ($\tau > 0.41$), and the magnitude of these estimates increases with τ . For FTSE 100, these estimates are mostly insignificant, except at a few right tail quantiles (τ in $[0.88, 0.93]$).

We also conduct the sup-Wald test and summarize the results in the lower panel of Table 3, where $\mathcal{T}^\dagger = [0.07, 0.14]$ for NYSE and $\mathcal{T}^\dagger = [0.25, 0.41]$ for S&P 500. We do not consider any $\mathcal{T}^\dagger$ for FTSE 100 because the individual tests are mostly insignificant. From this table we find that, for NYSE, causality arises from all quantiles but those in $[0.07, 0.14]$. For S&P 500, we can not identify a quantile range on which there is no causality. Thus, for NYSE and S&P 500, volume is negatively associated with lagged return at most quantiles. An increase in lagged return tends to pull volume toward the trend function when detrended volume is positive (volume is above the trend) but push volume further below the trend function when detrended volume is negative (volume is below the trend). These results agree with many existing findings, e.g., Moosa and Al-Loughani (1995), Silvapulle and Choi (1999), Chen, Firth, and Rui (2001), and Lee and Rui (2002).

The results based on the significance tests and the sup-Wald test are quite interesting. Observe that, while the estimated $\beta_1(\tau)$ for S&P 500 are insignificant individually at lower quantiles ($\tau \leq 0.41$), the sup-Wald test is able to reject the null of non-causality in the quantile ranges $[0.05, 0.25]$ and $[0.25, 0.41]$ at 1% level. Note also that, for FTSE 100, the estimated $\beta_1(\tau)$ are significant on $[0.88, 0.93]$, but the sup-Wald test on $[0.75, 0.95]$ fails to reject the null of non-causality in this quantile range. This shows that it may be inappropriate to draw conclusions on non-causality in quantiles from the individual tests

of parameter significance. A sup-Wald test is to be preferred for this purpose.

To summarize, what we find here are two-way quantile causal relations between return and volume for NYSE and S&P 500 but only one-way causality in quantiles from volume to return for FTSE 100. Moreover, the causal effects of volume on return are of different V shapes across quantiles, whereas the effects of return on volume, if exist, are mainly negative. The presence of these causal effects indicates that lagged volume (return) indeed carries information that is not contained in the past return (volume).

4.2 Models with Multiple Lags

We further investigate whether more lagged x have causal effects on y . To this end, we estimate the model (10) with $q \geq 1$; the resulting model is referred to as a lag q model. To determine an appropriate lag order q^* , we apply the sup-Wald test to the last coefficient of x_{t-q} in each lag q model and check if $\beta_q(\tau) = 0$ with τ in $[0.05, 0.95]$. If such sup-Wald test does not reject the null for a lag q model but rejects the null for a lag $q - 1$ model, it suggests that x_{t-q} does not Granger cause y_t in all quantiles but x_{t-q+1} does. Thus, the desired lag order is set to $q^* = q - 1$.

Consider first the regressions of return on q lagged returns and volumes. For NYSE, the sup-Wald test of $\beta_4(\tau)$ in the lag 4 model is 12.124 and that of $\beta_3(\tau)$ in the lag 3 model is 17.147. The latter is significant at 1% level, but the former is not. For S&P 500, the sup-Wald test of $\beta_3(\tau)$ in the lag 3 model is insignificant (with the statistic 10.270), but that of $\beta_2(\tau)$ is significant at 1% level (with the statistics 23.175). We therefore consider the model (10) with $q^* = 3$ for NYSE and $q^* = 2$ for S&P 500. For FTSE 100, the sup-Wald test of $\beta_2(\tau)$ in the lag 2 model is 9.827 which is insignificant at 5% level. Thus, $q^* = 1$ for FTSE 100, and the model estimated in the preceding sub-section suffices.⁴

For NYSE, the least-squares and quantile estimates of $\beta_1(\tau)$, $\beta_2(\tau)$ and $\beta_3(\tau)$ in the lag 3 model are plotted in Figure 4. As the least-squares estimates of these coefficients are also insignificant, conventional causality tests would still yield the conclusion of no causality in mean, even when more lagged r_t and v_t are included. Also, the quantile causal effects of lagged volume seem to possess a similar pattern as that displayed in Figure 2, i.e., opposite causal effects at the lower and upper quantiles of the return distribution. The estimated $\beta_1(\tau)$ are, however, insignificant for most upper quantiles (except for $\tau = 0.51, 0.77, 0.80, 0.82-0.84$, and 0.88), and the estimates at lower quantiles are significant with a smaller

⁴At 5% level, we find that $q^* = 6$ for NYSE, $q^* = 5$ for S&P 500, and $q^* = 1$ for FTSE. To ease our illustration, we focus on the simpler models with $q^* = 3$ and $q^* = 2$ for NYSE and S&P 500, respectively.

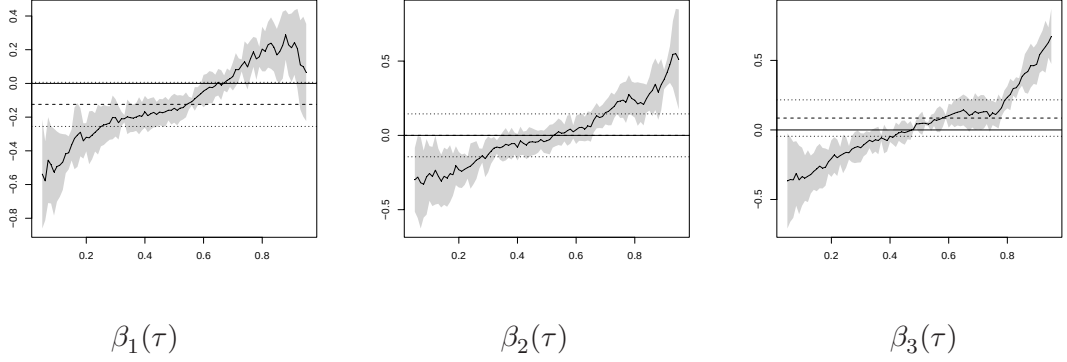


Figure 4: Quantile and least-squares estimates of the causal effects of volume on return: Models with multiple lags for NYSE.

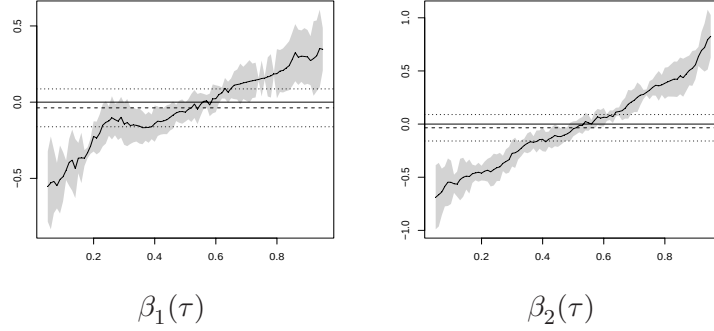


Figure 5: Quantile and least-squares estimates of the causal effects of volume on return: Models with multiple lags for S&P 500.

magnitude than those in the lag 1 model. That is, the effect of v_{t-1} on r_t are weaker when more lagged terms are included in the model. Moreover, the quantile regression estimates of $\beta_2(\tau)$ and $\beta_3(\tau)$ are insignificant at middle quantiles ($\tau = 0.28$ and $[0.30, 0.71]$ for $\beta_2(\tau)$ and τ in $[0.27, 0.64]$ and $[0.66, 0.77]$ for $\beta_3(\tau)$). The sup-Wald test on $[0.30, 0.71]$ and $[0.27, 0.77]$ yields respective statistics 6.06 and 6.54, which are insignificant at 5% level.⁵ These results suggest that the causal effects of more remote v_t are mainly on the quantiles outside the interquartile range.

For S&P 500, the least-squares and quantile estimates of $\beta_1(\tau)$ and $\beta_2(\tau)$ in the lag 2

⁵On $[0.30, 0.71]$, the critical values of the sup-Wald test are 11.27 (1%), 7.44 (5%), 5.92 (10%); on $[0.27, 0.77]$, the critical values are 11.53 (1%), 7.86 (5%), 6.28 (10%).

Table 5: Testing symmetry of quantile causal effects: Models with multiple lags.

τ pair	NYSE			S&P 500	
	β_1	β_2	β_3	β_1	β_2
(0.05, 0.95)	0.564	1.416	1.344	0.105	0.692
(0.10, 0.90)	0.002	1.464	0.110	0.157	0.311
(0.15, 0.85)	0.485	0.240	0.023	0.087	0.126
(0.20, 0.80)	1.738	0.465	0.295	0.574	0.008
(0.25, 0.75)	1.492	1.318	1.633	2.084	0.000
(0.30, 0.70)	2.103	0.908	0.882	1.615	0.144
(0.35, 0.65)	1.428	0.517	0.031	0.719	0.110
(0.40, 0.60)	1.380	0.275	0.208	0.053	0.016
(0.45, 0.55)	0.028	0.755	0.327	0.090	0.087

Note: Each entry is a test statistic for the hypothesis that the quantile causal effects are symmetric about the median. This table shows that no test is significant at 5% level.

model are plotted in Figure 5. Similar to the case of NYSE, these estimates also exhibit opposite causal effects at the two sides of the return distribution, and the estimated $\beta_1(\tau)$ have a smaller magnitude than those in the lag 1 model. For $\beta_1(\tau)$ and $\beta_2(\tau)$, there are more insignificant estimates (at the quantiles in, respectively, $[0.22, 0.66]$ and $[0.35, 0.67]$), whereas the causal effects in the lag one model are insignificant only at $[0.48, 0.61]$. The sup-Wald test on $[0.22, 0.66]$ and $[0.35, 0.67]$ yields respective statistics 5.22 and 6.02, which are insignificant at 10% and 5% levels.⁶ Thus, remote volumes also have causal effects on tail returns in S&P 500. Table 5 summarizes the results of testing symmetry of the pairwise quantile causal effects. It shows that, for both indices, these effects are all symmetric about the median at 5% level.

Consider now the reversed regressions of v_t on multiple lagged v_t and r_t . For NYSE, the sup-Wald test of $\beta_4(\tau)$ in the lag 4 model is 3.56 and that of $\beta_3(\tau)$ in the lag 3 model is 14.44. The latter is significant at 1% level, but the former is insignificant even at 10% level. For S&P 500, the sup-Wald test of $\beta_3(\tau)$ in the lag 3 model is insignificant (with the statistic 9.69) at 5% level, but that of $\beta_2(\tau)$ is significant at 1% level (with the statistics 17.45). We therefore consider the model (10) with $q^* = 3$ for NYSE and $q^* = 2$ for S&P

⁶On $[0.22, 0.66]$, the critical values of the sup-Wald test are 11.22 (1%), 7.77 (5%), 6.20 (10%); on $[0.35, 0.67]$, the critical values are 10.61 (1%), 7.14 (5%), 5.64 (10%).

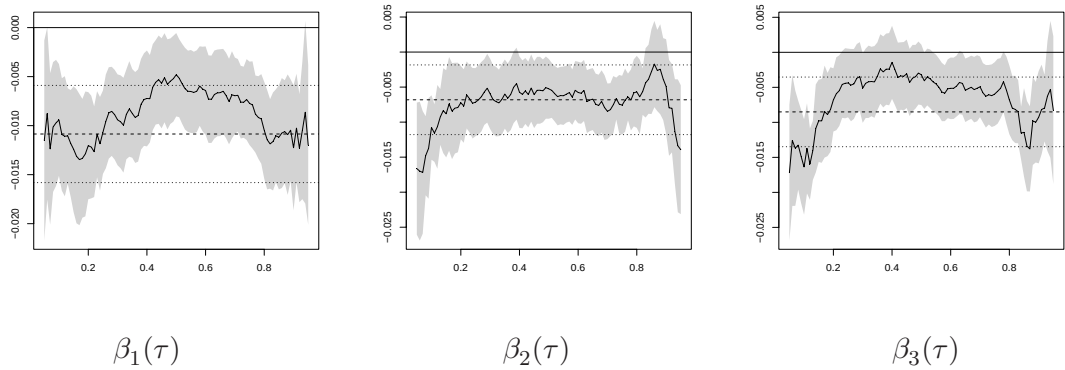


Figure 6: Quantile and least-squares estimates of the causal effects of return on volume: Models with multiple lags for NYSE.

500 in reversed regressions. For FTSE 100, the sup-Wald test of $\beta_2(\tau)$ in the lag 2 model is 9.827 which is insignificant at 5% level. This shows that, for FTSE 100, there is still no causality of return on volume when more lagged terms are included in the model.

The estimated β coefficients of NYSE and S&P 500 are plotted in, respectively, Figure 6 and Figure 7. For both indices, the least-squares estimates are all significantly negative and verify that there is causality in mean. The quantile regression estimates are also significantly negative at most quantiles, showing negative relations between volume and lagged returns across quantiles. It can be seen that the quantile regression estimates are basically within the confidence interval of the least-squares estimates and that the causal effects of r_{t-1} on v_t are similar to those in the lag 1 model but with a smaller magnitude.

We summarize this section by noting that, for NYSE and S&P 500, there are more lagged volumes that Granger cause return and also more lagged returns that Granger cause volume. It is quite interesting to note that remote volumes have the causal effects only on more extreme returns, such as those outside the interquartile range. Similar to the lag 1 model, the causal effects of lagged volumes also exhibit symmetric V shapes, so that lagged volumes have positive effects on return volatility. Also, the causal effects of lagged returns on volume are negative in general. It is interesting to note that the effect of v_{t-1} on r_t and that of r_{t-1} on v_t are attenuated when additional lagged terms are included in the model.

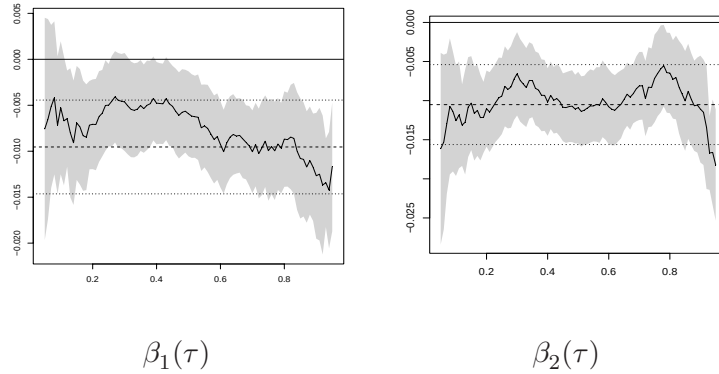


Figure 7: Quantile and least-squares estimates of the causal effects of return on volume: Models with multiple lags for S&P 500.

5 Concluding Remarks

In this paper we estimate quantile causal effects and test Granger non-causality in quantiles based on the results of quantile regression. We show that the causal relations between variables may be far more complicated than what can be described using a least-squares regression, in that the causal effects may be heterogeneous across quantiles. In particular, the effects at tail quantiles may be much different from those at middle quantiles. Our finding provides a detailed description of the conditional distribution and hence the causal relations. Without knowing causality in quantiles, the conclusion on non-causality based solely on a conventional test may be misleading.

The empirical results of causality in quantiles, however, can not be explained by existing equilibrium models (e.g., Campbell, Grossman, and Wang, 1993). These models typically yield implications on the conditional mean but say little about the behaviors at various quantiles. Therefore, different models are needed to account for the quantile causal patterns found in this paper. It is also interesting to note that quantile causal relations provide detailed information about distribution dispersion and hence can complement conventional volatility measures, such as conditional variance. How to incorporate such information to improve on the evaluation of volatility and related assets (e.g., VIX option) is an interesting topic and currently being investigated.

Appendix

Table A.1 Estimated coefficients of quantile regressions of return on lagged return and volume.

τ	NYSE			S&P 500			FTSE 100		
	α_0	α_1	β_1	α_0	α_1	β_1	α_0	α_1	β_1
0.05	-1.38*	0.21*	-0.76*	-1.55*	0.13*	-1.06*	-1.57*	0.06	-0.67*
	(0.035)	(0.039)	(0.082)	(0.039)	(0.042)	(0.086)	(0.041)	(0.032)	(0.085)
0.1	-1.01*	0.19*	-0.75*	-1.14*	0.13*	-0.89*	-1.14*	0.08*	-0.48*
	(0.027)	(0.037)	(0.093)	(0.027)	(0.032)	(0.078)	(0.029)	(0.027)	(0.069)
0.25	-0.42*	0.11*	-0.40*	-0.51*	0.08*	-0.47*	-0.54*	0.03	-0.24*
	(0.017)	(0.023)	(0.067)	(0.021)	(0.025)	(0.073)	(0.019)	(0.022)	(0.058)
0.4	-0.12*	0.05*	-0.26*	-0.15*	0.01	-0.24*	-0.17*	0.00	-0.22*
	(0.014)	(0.019)	(0.063)	(0.017)	(0.019)	(0.062)	(0.017)	(0.021)	(0.050)
0.5	0.04*	0.02	-0.15*	0.05*	-0.02	-0.10	0.03	-0.01	-0.18*
	(0.014)	(0.019)	(0.067)	(0.016)	(0.019)	(0.064)	(0.017)	(0.021)	(0.049)
0.6	0.20*	-0.01	0.02	0.24*	-0.04*	0.09	0.24*	-0.02	-0.10*
	(0.014)	(0.017)	(0.071)	(0.017)	(0.019)	(0.053)	(0.017)	(0.022)	(0.049)
0.75	0.51*	-0.03	0.27*	0.59*	-0.05*	0.36*	0.59*	-0.01	0.06
	(0.017)	(0.020)	(0.076)	(0.019)	(0.019)	(0.067)	(0.019)	(0.022)	(0.052)
0.9	1.04*	-0.04	0.68*	1.17*	-0.04	0.70*	1.16*	-0.03	0.23*
	(0.024)	(0.027)	(0.077)	(0.027)	(0.027)	(0.083)	(0.027)	(0.027)	(0.060)
0.95	1.39*	-0.01	0.72*	1.63*	-0.03	0.93*	1.59*	-0.01	0.33*
	(0.033)	(0.035)	(0.118)	(0.045)	(0.043)	(0.124)	(0.042)	(0.032)	(0.073)

Note: The estimated model is $r_t = \alpha_0(\tau) + \alpha_1(\tau)r_{t-1} + \beta_1(\tau)v_{t-1} + e_t(\tau)$. For each estimated coefficient, the number in the parentheses is its standard error. ** and * denote significance at 1% and 5% levels, respectively.

Table A.2 Estimated coefficients of regressions of volume on lagged volume and return.

τ	NYSE			S&P 500			FTSE 100		
	α_0	α_1	β_1	α_0	α_1	β_1	α_0	α_1	β_1
0.05	-0.24*	0.63*	-0.01	-0.27*	0.74*	-0.01	-0.42*	0.75*	0.01
	(0.006)	(0.028)	(0.010)	(0.007)	(0.027)	(0.008)	(0.010)	(0.035)	(0.010)
0.1	-0.18*	0.63*	-0.01	-0.20*	0.76*	0.00	-0.31*	0.68*	0.00
	(0.004)	(0.024)	(0.006)	(0.005)	(0.021)	(0.006)	(0.008)	(0.030)	(0.008)
0.25	-0.08*	0.64*	-0.01*	-0.10*	0.78*	0.00	-0.15*	0.63*	0.00
	(0.003)	(0.019)	(0.004)	(0.003)	(0.016)	(0.004)	(0.005)	(0.018)	(0.005)
0.4	-0.03*	0.64*	-0.01*	-0.04*	0.78*	-0.01	-0.05*	0.63*	-0.01
	(0.003)	(0.018)	(0.003)	(0.003)	(0.014)	(0.003)	(0.005)	(0.015)	(0.004)
0.5	0.00	0.63*	-0.01*	0.00	0.78*	-0.01*	0.00	0.63*	-0.01
	(0.003)	(0.017)	(0.003)	(0.003)	(0.013)	(0.003)	(0.005)	(0.015)	(0.004)
0.6	0.04*	0.64*	-0.01*	0.04*	0.78*	-0.01*	0.06*	0.62*	-0.01
	(0.003)	(0.017)	(0.003)	(0.003)	(0.013)	(0.003)	(0.005)	(0.015)	(0.004)
0.75	0.09*	0.63*	-0.01*	0.11*	0.78*	-0.01*	0.16*	0.63*	-0.01
	(0.003)	(0.018)	(0.003)	(0.003)	(0.013)	(0.003)	(0.005)	(0.015)	(0.005)
0.9	0.17*	0.55*	-0.01*	0.20*	0.74*	-0.01*	0.30*	0.61*	-0.01*
	(0.004)	(0.021)	(0.003)	(0.005)	(0.015)	(0.003)	(0.006)	(0.020)	(0.005)
0.95	0.26*	0.46*	-0.01*	0.29*	0.65*	-0.01*	0.39*	0.56*	-0.01
	(0.008)	(0.022)	(0.004)	(0.010)	(0.027)	(0.004)	(0.008)	(0.024)	(0.006)

Note: The estimated model is $v_t = \alpha_0(\tau) + \alpha_1(\tau)v_{t-1} + \beta_1(\tau)r_{t-1} + e_t(\tau)$. For each estimated coefficient, the number in the parentheses is its standard error. ** and * denote significance at 1% and 5% levels, respectively.

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