Money-Income Granger-Causality in Quantiles*

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ABSTRACT

The causal relationship between money and income (output) has been an important topic that has been extensively studied. However, those empirical studies are almost entirely on Granger-causality in the conditional mean. Compared to conditional mean, conditional quantiles give a broader picture of a variable in various scenarios. In addition, under some asymmetric loss functions, conditional quantiles (rather than conditional mean) may be optimal forecasts. In this paper, we explore whether forecasting the conditional quantile of output growth may be improved using money. We compare the check (tick) loss functions of the quantile forecasts of output growth with and without using the past information on money growth, and assess the statistical significance of the loss-differential of the unconditional and conditional predictive abilities. As conditional quantiles can be inverted to the conditional distribution, we also test for Granger-causality in the conditional distribution (via using a nonparametric copula function). Using U.S. monthly series of real personal income and industrial production for income, and M1 and M2 for money, for 1959-2001, we find that out-of-sample quantile forecasting for output growth, particularly in tails, is significantly improved by accounting for money. On the other hand, money-income Granger-causality in the conditional mean is quite weak and unstable. These empirical findings in this paper have never seen in the money-income literature. The new results have an important implication on monetary policy, showing that the effectiveness of monetary policy has been underestimated by merely testing Granger-causality in mean. Money does Granger-cause income more strongly than it has been known and therefore the information on money growth can (and should) be more utilized in implementing monetary policy.

Keywords : Money-income Granger-causality, Conditional mean, Conditional quantile, Conditional distribution
JEL Classification : C2, C5, E4, E5

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1 Introduction

Granger-causality (GC), introduced by Granger (1969, 1980, 1988), is one of the important issue that has been much studied in empirical macroeconomics and empirical finance. Particularly the study on money and income is one of the most studied subject in economics. In this paper, we extend the literature in two ways. The literature on money-income causality is studies for the conditional *mean* and most papers have used the *in-sample* significance of money variable in the output growth equation. (In this paper, the terms, income and output, will be used interchangeably.) First, we go beyond the conditional mean, and examine the conditional distribution and conditional *quantiles*. Second, we examine the *out-of-sample* predictive contents of money variable for forecasting output growth.

While GC is naturally defined in terms of the conditional distribution (see Granger and Newbold 1986), almost all the papers in this literature have focused on GC in mean (GCM). The GC in distribution (GCD) has been less studied empirically perhaps because it is in fact about independence and so it may be too broad to be useful for its policy implication. More useful may be the particular quantiles of the conditional distribution as inverting the conditional distribution we obtain the conditional quantile. Hence, we may examine directly the GC in distribution, or indirectly via GC in conditional quantiles (GCQ). Granger (2003) notes that the study of the time series of quantiles is relevant as the predictive distribution can be expressed in terms of the CDF, the density, the characteristic function, or quantiles.

Vast empirical literature on the money-income causality has very mixed results on GCM – usually quite unstable and sensitive to the sample periods, data sets and choice of variables (e.g., M1 or M2 for money, personal income (PI) or industrial production (IP) for income, with or without including some other variables such as interest rates and business cycle indicators in the regression, different countries, etc.). Different countries, sample periods and variables are analyzed in those empirical studies, but no consensus has been reached. The results in this paper for GCD and GCQ are much more stable and stronger.

The aim of this paper is to study the GC beyond the conditional mean between money and income, which is in line with the suggested directions of Granger (2003, 2005, 2006).[1] Forecasting conditional quantiles is important in economic policy when a concern is a particular scenario of the

[1] Granger (2006) remarks, "For most of its history time series theory considered conditional means, but later conditional variances. The next natural development would be conditional quantiles, but this area is receiving less attention than I expected. The last stages are initially conditional marginal distributions, and finally conditional multivariate distributions. Some interesting theory is starting in these areas but there is enormous amount to be done."

economy. For instance, in asset valuation, different scenarios of output growth are extremely useful in sensitivity analysis, scenario analysis, and risk management. For industries greatly influenced by overall macroeconomic conditions, forecasting output growth helps to evaluate the industry exposure in different scenarios. The fan chart of Bank of England for different quantile forecasts of inflation rate is another example.

Although it is not stable in the U.S. data whether money growth helps to improve forecasting of the conditional mean of output growth, we find that there is much stronger evidence whether it helps to improve forecasting of its conditional quantiles. Forecasting the conditional quantiles of output growth depends on its conditional distribution, so we also GCD, for which we extend Hong and Li (2005) and Egorov, Hong, and Li (2006), by using a nonparametric copula function to test for independent copula. Hong and Li's (2005) test evaluates a model by testing whether the out-of-sample probability integral transforms (PIT) of forecasts follow an i.i.d. U[0, 1] distribution.

GCD implies GCQ in some quantiles, although GCD does not necessarily imply GCQ in each quantile. GCQ in a specific quantile exists if the lagged money variables helps to improve forecasting the output growth at that quantile. Two quantile regression models for output growth with and without money growth information are estimated and the out-of-sample average of the "check" loss values of the two quantile models are compared. Because these two quantile forecasting models are nested, the unconditional predictive ability test proposed by Diebold and Mariano (1995) and West (1996) fails in that its asymptotic distribution degenerates. We therefore utilize the *conditional* predictive ability test proposed by Giacomini and White (2005).

Our empirical study using several different data sets over various sample periods find the following results. First, for the causality in the conditional mean, differently from Chao, Corradi and Swanson (2001) who test out-of-sample Granger-causality in mean using moment conditions, we compare the squared forecast error loss values of the two conditional mean forecasts of output growth with and without money. The result is very weak for the GCM (as expected from the existing literature). We find that the predictive ability of a model with including money as a predictor for the conditional mean of output growth may be even worse than a model without money, and the result varies sensitively over time as pointed out by Eichenbaum and Singleton (1986), Stock and Watson (1996), Swanson (1998) and Thoma (1994). Second, for the money-income GC in the conditional distribution, we use a nonparametric copula function, and find a more stable and significant result for GCD in many subsamples even when there exists no significant GCM. Third, for the GCQ, two quantile regression models with and without money are estimated and their quantile forecasts are compared for their out-of-sample check loss values. We find that GCQ is significant in tail quantiles in most subsamples and most data sets, while it is not significant in the center of the distribution. Forth, comparing results across different data sets (which consist of different variables for money and income), it seems that GCQ between money and industrial production (IP) is more significant that between money and real personal income (PI).

The structure of this paper is as follows. In Section 2, we discuss GC in mean, GC in distribution, and GC in quantiles. Section 3 reports the empirical findings. Section 4 concludes.

2 Granger-causality

We use the following notation. Let R denote the sample size for estimation (for which we use a rolling scheme), P the size of the out-of-sample period for forecast evaluation, and $T = R + P$. Let x be money growth and y the output growth. Consider the distribution functions conditional on the information set $\mathcal{F}_t$ as $F_{t+1}(x|\mathcal{F}_t) = \Pr(x_{t+1} < x|\mathcal{F}_t)$, $G_{t+1}(y|\mathcal{F}_t) = \Pr(y_{t+1} < y|\mathcal{F}_t)$, and $H_{t+1}(x, y|\mathcal{F}_t) = \Pr(x_{t+1} < x \text{ and } y_{t+1} < y|\mathcal{F}_t)$. Let $f_{t+1}(x|\mathcal{F}_t)$, $g_{t+1}(y|\mathcal{F}_t)$, and $h_{t+1}(x, y|\mathcal{F}_t)$ be the corresponding densities. Let $u = F_{t+1}(x|\mathcal{F}_t)$ and $v = G_{t+1}(y|\mathcal{F}_t)$. Let $C_{t+1}(u, v|\mathcal{F}_t)$ and $c_{t+1}(u, v|\mathcal{F}_t)$ be the conditional copula function and the conditional copula density function respectively. See Appendix for a brief introduction on the copula theory. Let the conditional mean of y_{t+1} be denoted $E(y_{t+1}|\mathcal{F}_t)$. Let $X_t = (x_t, \ldots, x_{t+1-q})'$ and $\mathcal{G}_t$ be the information set excluding X_t, i.e., $\mathcal{G}_t = \mathcal{F}_t/\{X_t\}$.

2.1 Money-Income Granger-causality in Mean

Starting with Friedman (1956) the debate about role of money on income attract attention of a lot of economists. Numerous studies have been devoted to the interaction between money and income. To entangle this interaction, theoretical models are constructed to explore the roles of aggregate demand fluctuation and money demand fluctuation, such as in Kaldor (1970), Modigliani (1977), Meltzer (1963), among others. Along with the theoretical development, many empirical studies have been made following the seminal research of Sims (1972, 1980). Sims (1972) shows money Granger-causes income, but his result was criticized due to the bias caused by hidden factors. Sims (1980) applies a VAR model to handle a vector of variables and reports that money does not Granger cause income after the World War II. After Sims, Granger-causality and VAR models become the generally accepted instruments for studying the money and income relationship. Stock and Watson (1989) contend that the deterministic trend plays important roles and uses detrended money in the analysis. They find more significant money-income causality with the detrended money growth rate. Friedman and Kuttner (1992, 1993) and Thoma (1994) also report limited evidence for the money-income causality, however, they find out varying money-income causality with regard different sample period or with regard to different variables.[2] Swanson (1998) tests money-income Granger-causality in an error-correction model. Dufour and Renault (1998) and Dufour *et al.* (2002) test the long horizon causality.

Definition 1. (Non Granger-causality in mean, NGCM): *X_t does not Granger-cause y_{t+1} in mean if and only if $E(y_{t+1}|X_t, \mathcal{G}_t) = E(y_{t+1}|\mathcal{G}_t)$ almost surely (a.s.).*

To test for Granger-causality in mean (GCM), we can utilize either an in-sample test or an out-of-sample test. In the literature, most tests of money-income causality focus on in-sample conditional mean in a Vector Autoregressive (VAR) model. The in-sample Granger-causality test is to test the joint hypothesis that coefficients of money are all insignificant in the output equation. A Wald-type test is often used in an in-sample test of GCM. Following Ashley, Granger, and Schmalensee (1980), we conduct an out-of-sample test for Granger-causality. An out-of-sample test for GCM is based on two nested models. The first model does not account for money-income GCM (referred as Model 1 or "NGCM") and the second does (referred as Model 2 or "GCM"):

$$\begin{aligned} \text{Model 1 (NGCM)} &: \quad y_{t+1} = E(y_{t+1}|\mathcal{G}_t) + \varepsilon_{1,t+1} = V_t'\theta_1 + \varepsilon_{1,t+1}, \quad (1) \\ \text{Model 2 (GCM)} &: \quad y_{t+1} = E(y_{t+1}|X_t, \mathcal{G}_t) + \varepsilon_{2,t+1} = W_t'\theta_2 + \varepsilon_{2,t+1}, \quad (2) \end{aligned}$$

where $V_t \in \mathcal{G}_t$ and $W_t = (X_t' \; V_t')$ are vectors of regressors. V_t includes a constant term. The parameters θ_i are estimated by minimizing the squared error loss using the rolling sample of the most recent R observations at time t $(t = R, \ldots, T-1)$:

$$\begin{aligned} \hat{\theta}_{1,t} &= \arg\min_{\theta_1} \sum_{s=t-R+1}^{t} (y_s - V_{s-1}'\theta_1)^2, \quad (3) \\ \hat{\theta}_{2,t} &= \arg\min_{\theta_2} \sum_{s=t-R+1}^{t} \rho_\alpha(y_s - W_{s-1}'\theta_2)^2. \quad (4) \end{aligned}$$

Denote $\hat{y}_{1,t+1}(\hat{\theta}_{1,t}) = V_t'\hat{\theta}_{1,t}$ and $\hat{y}_{2,t+1}(\hat{\theta}_{2,t}) = W_t'\hat{\theta}_{2,t}$, the forecasts of y_{t+1} from Model 1 and Model 2 respectively, and let $\hat{\varepsilon}_{i,t+1}(\hat{\theta}_{i,t}) = y_{t+1} - \hat{y}_{i,t+1}(\hat{\theta}_{i,t})$ for the forecast error of Model i. In

[2]For instance, by replacing the three month T-bill rate by commercial paper rate, the money-income causality become less significant. But in general, those empirical studies give us relatively controversial results on the money-income causality.

Section 3 for the empirical analysis, we choose $X_t = (x_t, \ldots, x_{t+1-q})'$ and $V_t = (Y_t', I_t, B_t)'$ where $Y_t = (y_t, \ldots, y_{t+1-q})'$, $q = 12$, I_t is the 3 month T-bill interest rate, and B_t is the business cycle coincident index. See Table 1, Panel A.

As the models are nested, we may not use the tests of Diebold and Mariano (1995) and West (1996). A test for Granger-causality is to compare the loss functions of forecasts conditional on two information sets, $\mathcal{G}_t$ and $\mathcal{F}_t$. As we are interested in comparing the loss of forecasting output growth y_{t+1} without and with using the information on past money growth X_t, we use the conditional predictive ability test of Giacomini and White (GW, 2005) as follows. Let $L_{t+1}(\cdot)$ be a loss function. The null hypothesis of NGCM is therefore

$$H_0 : E[L_{t+1}(y_{t+1}, \hat{y}_{1,t+1}) - L_{t+1}(y_{t+1}, \hat{y}_{2,t+1})|\mathcal{F}_t] = 0, \qquad t = R, \ldots, T-1. \tag{5}$$

Under the H_0 the loss differential $\Delta L_{t+1} \equiv L_{t+1}(y_{t+1}, \hat{y}_{1,t+1}) - L_{t+1}(y_{t+1}, \hat{y}_{2,t+1})$ is a martingale difference sequence (MDS), which implies $E(h_t \Delta L_{t+1}) = 0$ for any h_t that is $\mathcal{F}_t$-measurable. Denoting $Z_{t+1} = h_t \Delta L_{t+1}$, the GW (2005) statistic is

$$GW_{R,P} = P \bar{Z}_{R,P}' \hat{\Omega}_P^{-1} \bar{Z}_{R,P}, \tag{6}$$

where $\bar{Z}_{R,P}' = \frac{1}{P}\sum_{t=R}^{T-1} h_t \Delta L_{t+1}$ and $\hat{\Omega}_P = \frac{1}{P}\sum_{t=R}^{T-1} Z_{t+1} Z_{t+1}'$. Under some regularity conditions, $GW_{R,P} \to^d \chi_q^2$ as $P \to \infty$ under H_0 (GW 2005, Theorem 1).[3]

We choose the "test" function, h_t, such that it is $\mathcal{F}_t$-measurable but not $\mathcal{G}_t$-measurable. For simplicity, we choose $h_t = X_t = (x_t, \ldots, x_{t+1-q})'$.[4]

We choose the loss function, $L_{t+1}(y_{t+1}, \hat{y}_{i,t+1}) = \hat{\varepsilon}_{i,t+1}^2$ $(i = 1, 2)$, the squared error loss, to test money-income Granger-causality in *mean*, for the out-of-sample forecast evaluation because the conditional mean is the optimal forecast under the squared error loss. We also minimize the same loss for in-sample parameter estimation as shown in (3) and (4). Therefore, $Z_{t+1} = h_t \Delta L_{t+1} = h_t(\hat{\varepsilon}_{1,t+1}^2 - \hat{\varepsilon}_{2,t+1}^2)$. To be consistent with the literature using monthly series, we choose h_t using 12 lags of money growth rate, i.e., $h_t = X_t = (x_t \ \ldots \ x_{t-11})'$ with $q = 12$.

[3] Chao, Corradi and Swanson (2003) propose an out-of-sample test using following test statistic

$$CCS_{R,P} = \frac{1}{P}\sum_{t=R}^{T-1} \hat{\varepsilon}_{1,t+1} h(X_t),$$

which follows zero-mean normal distribution asymptotically with its asymptotic variance affected by estimation error.

[4] Two possible ways to improve the power of the test are (i) to choose q in a way to maximize the test power and (ii) to choose h_t from transforms of X_t as suggested in Bierens (1990), Stinchcombe and White (1998), or Hong (1999). We do not consider these extensions in this paper for simplicity and also to match the choice of h_t with the vast literature on GCM. Following Lee *et al.* (1993) and Stinchcombe and White (1998), h_t will be called a *test* function.

Because the GW statistic is for *equal* conditional predictive ability, the rejection of the null hypothesis only implies that the two models are not equal in conditional predictive ability. To choose one model over the other, we follow the decision rule suggested by GW (2005) to construct a statistic as

$$I_P = \frac{1}{P}\sum_{t=R}^{T-1} \mathbf{1}(\hat{\alpha}_P' h_t < 0), \tag{7}$$

where $\mathbf{1}(\cdot)$ is the indicator function and $\hat{\alpha}_P$ is the coefficient of h_t by regressing ΔL_{t+1} on h_t $(t = R, \ldots, T-1)$. As the rejection of H_0 occurs when the test function h_t can *predict* the loss difference ΔL_{t+1} in out-of-sample, $\hat{\alpha}_P' h_t \approx E(\Delta L_{t+1}|\mathcal{F}_t)$ will be the out-of-sample *predicted* loss differences. If I_P is greater than 0.5, Model 1 (NGCM) will be selected; otherwise Model 2 (GCM) will be selected.

2.2 Asymmetric GCM vs GCQ

Hayo (1998) nicely summarizes five stylized facts found in the empirical literature on the existence and strength of GCM between money and output using U.S. data: (a) In a model with only two variables, money Granger-causes output (Sims 1972). (b) The statistical significance of the effect of money on output will be lower when including other variables in a multivariate test such as prices and interest rates (Sims 1980). (c) The use of narrow money is less likely to support GC from money to output than broad money (King and Plosser 1984). (d) Assuming that variables are trend stationary and modelling them in (log-) levels with a deterministic trend is more likely to lead to significant test results than assuming difference stationary and employing growth rates (Christiano and Ljungquist 1988, Stock and Watson 1989, Hafer and Kutan 1997). (e) Allowing asymmetric effects of money on output growth and including the business cycle greatly influences results and strengthens the causal effect of money (Cover 1992, Thoma 1994, Weise 1999, Lo and Piger 2005, Ravn and Sola 2004, Psaradakis, Ravn, and Sola 2005).

Hayo (1998) revisited the above U.S. stylized facts using a broad data base of 14 EU-countries plus Canada and Japan. It is found that very few of the above, particularly (b) and (d), can be sustained. Also found in the literature is that GCM is unstable, change with the sample periods, data to use (variables and frequency), and countries. Psaradakis, Ravn, and Sola (2004, pp. 666-667) provide some summary on this instability evidence from the literature. Davis and Tanner (1997) finds the instability of the GCM across countries.

What appears to be robust is (e). Thoma (1994) shows for monthly data on M1 that the state of business cycle has considerable influence on the results and strengthens the GCM of money.

When real activity declines the effect of money on output becomes stronger, while the opposite takes place during a recovery. Numerous papers in the literature have found that the evidence for the GCM becomes more evident when some asymmetry has been introduced. Weise (1999) and Lo and Piger (2005) classify the three forms of asymmetry studies in a large body of empirical literature on money-income causality.

A1 (sign asymmetry): asymmetry related to the direction of the monetary policy action (Cover 1992, Dolado et al 2004)

A2 (size asymmetry): asymmetry related to the size of the policy action. (Ravn and Sola 2004, Dolado et al 2004)

A3 (business cycle asymmetry): asymmetry related to the existing business cycle business cycle phase (Thoma 1994, Weise 1999, Lo and Piger 2005, Garcia and Schaller 2002)

Weise (1999) find no evidence for A1, some evidence for A2, and strong evidence for A3. Bernanke and Gertler (1995) and Galbraith (1996) explains A3 via credit rationing and its threshold effects in the relationship between money and output. Lo and Piger (2005) examine A3 using a regime switching model in the response of U.S. output to monetary policy and find that policy actions during recessions have larger output effects than those taken during expansions. To deal with the instability and the asymmetry in GCM between money and income, many researchers have used split subsamples or rolling samples or nonlinear models such as regime switching models and threshold models.

The objective of this paper is to study GCQ, which is useful for scenario analysis in implementing monetary policy. Our empirical results (in Section 3) for GCQ is "symmetric", in that GCQ is insignificant in or near the center of the predicted distribution of the output growth while it is strongly significant in both tails. (The results of Section 3 shows that GCQ is strong in both tails.) The difference between the asymmetric GCM and GCQ is that the former refers to the empirical fact that the predictive power of past money growth to predict the mean of output growth is stronger when the *past output growth* is negative (in recession), while the (symmetric) GCQ refers to the fact the predictive power of past money growth to predict the quantiles of output growth is stronger when the scenario of our interest is the *future output growth* in tails of its predicted distribution. Hence, the asymmetric GCM prescribes a monetary policy based on the past information, while the GCQ enables a monetary policy to be based on the forward looking scenarios of output growth. The GCQ can indicate how/whether the past and current money growth affects the various future *states* (i.e., quantiles) of the output growth. Now we turn to GCD and GCQ in the next two subsections.

2.3 Money-Income Granger-causality in Distribution

Most empirical studies on money-income causality focus on Granger-causality in mean. As discussed above, in many cases, one may care about conditional distribution of output growth. Even without significant Granger-causality in mean, Granger-causality in distribution (GCD) may be significant.

Definition 2. (Non Granger-causality in distribution, NGCD): *X_t does not Granger-cause y_{t+1} in distribution if and only if* $\Pr(y_{t+1} < y|X_t, \mathcal{G}_t) = \Pr(y_{t+1} < y|\mathcal{G}_t)$ *a.s. for all* y.

Remark: Note that we can write for $y \in \mathbb{R}$,

$$G_{t+1}(y|\mathcal{F}_t) = \Pr(y_{t+1} < y|\mathcal{F}_t) = E[\mathbf{1}(y_{t+1} < y|\mathcal{F}_t] = E(z_{t+1}|\mathcal{F}_t), \quad (8)$$

$$G_{t+1}(y|\mathcal{G}_t) = \Pr(y_{t+1} < y|\mathcal{G}_t) = E[\mathbf{1}(y_{t+1} < y|\mathcal{G}_t] = E(z_{t+1}|\mathcal{G}_t), \quad (9)$$

where $z_{t+1} = \mathbf{1}(y_{t+1} < y)$. Therefore, Definition 2 is equivalent to

$$E(z_{t+1}|\mathcal{F}_t) = E(z_{t+1}|\mathcal{G}_t) \ a.s. \text{ for all } y. \quad (10)$$

Hong, Liu, and Wang (2005) use this to test for Granger-causality in risk for a fixed value of y between two financial markets (X_t and y_{t+1}). The GCD between X_t and y_{t+1} can be viewed as GCM between X_t and z_{t+1}. □

There is GCD if $\Pr(y_{t+1} < y|X_t, \mathcal{G}_t) \neq \Pr(y_{t+1} < y|\mathcal{G}_t)$ for some y. X_t does not Granger-cause y_{t+1} in distribution if $G_{t+1}(y|X_t, \mathcal{G}_t) = G_{t+1}(y|\mathcal{G}_t)$ *a.s.* or $g_{t+1}(y|X_t, \mathcal{G}_t) = g_{t+1}(y|\mathcal{G}_t)$ *a.s.* We use the latter in density form to test for GCD by testing the null hypothesis that

$$H_0 : g_{t+1}(y|X_t, \mathcal{G}_t) = g_{t+1}(y|\mathcal{G}_t) \ \ a.s. \quad (11)$$

The null hypothesis H_0 in (11) that $X_t = (x_t, \ldots, x_{t+1-q})'$ does not Granger-cause y_{t+1} in distribution implies the following q hypotheses:

$$H_0^{(l)} : g_{t+1}(y|x_{t+1-l}, \mathcal{G}_t) = g_{t+1}(y|\mathcal{G}_t) \ \ a.s. \qquad l = 1, \ldots, q. \quad (12)$$

Denote $F_{t+1}^{(l)}(x|\mathcal{G}_t) = \Pr(x_{t+1-l} < x|\mathcal{G}_t)$, $G_{t+1}(y|\mathcal{G}_t) = \Pr(y_{t+1} < y|\mathcal{G}_t)$, and $H_{t+1}^{(l)}(x, y|\mathcal{G}_t) = \Pr(x_{t+1-l} < x \text{ and } y_{t+1} < y|\mathcal{G}_t)$. Let $f_{t+1}^{(l)}(x|\mathcal{G}_t)$, $g_{t+1}(y|\mathcal{G}_t)$, and $h_{t+1}^{(l)}(x, y|\mathcal{G}_t)$ be the corresponding densities. Denote the PITs as $u_{t+1}^{(l)} = F_{t+1}^{(l)}(x_{t+1-l}|\mathcal{G}_t)$ and $v_{t+1} = G_{t+1}(y_{t+1}|\mathcal{G}_t)$. Let $C_{t+1}^{(l)}(u^{(l)}, v|\mathcal{G}_t)$

and $c^{(l)}_{t+1}(u^{(l)}, v|\mathcal{G}_t)$ be the conditional copula function and the conditional copula density function respectively. Then, from equation (31) in Appendix,

$$g_{t+1}(y|x_{t+1-l}, \mathcal{G}_t) = h^{(l)}_{t+1}(x, y|\mathcal{G}_t)/f^{(l)}_{t+1}(x|\mathcal{G}_t) \tag{13}$$

$$= g_{t+1}(y|\mathcal{G}_t) \times c^{(l)}_t(F^{(l)}_{t+1}(x|\mathcal{G}_t), G_t(y|\mathcal{G}_t)|\mathcal{G}_t), \;\; l = 1, \ldots, q. \tag{14}$$

Hence, $H^{(l)}_0$ can be written as

$$H^{(l)}_0 : c^{(l)}_{t+1}(F^{(l)}_{t+1}(x|\mathcal{G}_t), G_t(y|\mathcal{G}_t)|\mathcal{G}_t) = 1, \qquad l = 1, \ldots, q. \tag{15}$$

Hence, a test of GCD is equivalent to a test of whether this copula density function is an independent copula for $l = 1, \ldots, q$. To test for this, we extend Hong and Li (2005) to testing for independence between one variable y_{t+1} and a set of variables X_t. In our test of money-income Granger-causality in distribution, $H^{(l)}_0$ is based on the independence between PIT value of y_{t+1} and PIT value of x_{t+1-l}. We test $H^{(l)}_0$ using a nonparametric copula density $\hat{c}^{(l)}_P(u, v)$ estimated by a product kernel function based on the out-of-sample PIT values of $\{x_{t+1-l}, y_{t+1}\}^{T-1}_{t=R}$, i.e.,

$$\hat{c}^{(l)}_P(u, v) = \frac{1}{P}\sum^{T-1}_{t=R} K(u, \hat{u}^{(l)}_{t+1})K(v, \hat{v}_{t+1}), \tag{16}$$

where $K(\cdot)$ is the kernel function in the product kernel, and

$$\hat{u}^{(l)}_{t+1} = \hat{F}^{(l)}_{t+1}(x_{t+1-l}) = \frac{1}{R+1}\sum^{t}_{s=t-R+1} \mathbf{1}(x_s \leq x_{t+1-l}), \tag{17}$$

$$\hat{v}_{t+1} = \hat{G}_{t+1}(y_{t+1}) = \frac{1}{R+1}\sum^{t}_{s=t-R+1} \mathbf{1}(y_s \leq y_{t+1}), \qquad t = R, \ldots, T-1, \tag{18}$$

are the out-of-sample PIT values for x_{t+1-l} and y_{t+1} respectively calculated with respect to the marginal empirical distribution functions (EDF) that have been estimated using the rolling samples of the most recent R observations at each time t ($t = R, \ldots, T-1$). To circumvent the boundary problem (as the PITs are bounded on [0 1]), we apply the boundary-modified kernel used by Hong and Li (2005):

$$K_h(x, y) = \begin{cases} h^{-1}k\left(\frac{x-y}{h}\right) \Big/ \int^1_{-(x/h)} k(u)du, & \text{if } x \in [0, h), \\ h^{-1}k\left(\frac{x-y}{h}\right), & \text{if } x \in [h, 1-h), \\ h^{-1}k\left(\frac{x-y}{h}\right) \Big/ \int^{(1-x)/h}_{-1} k(u)du, & \text{if } x \in (1-h, 1], \end{cases} \tag{19}$$

where $k(\cdot)$ is a symmetric kernel function and h is the bandwidth. For the null hypothesis $H^{(l)}_0$, the test statistic is based on a quadratic form[5]

$$\hat{M}_P(l) = \int^1_0 \int^1_0 [\hat{c}^{(l)}_P(u, v) - 1]^2 du dv. \tag{20}$$

[5]See Granger (2003, p. 695) for a similar but different statistic based on the Hellinger entropy between two densities. See also Hong and Li (2005, footnote 12) on the comments on their test using the Hellinger entropy.

The test statistic $\hat{Q}_P(l)$ is centered and scaled based on $\hat{M}_P(l)$, i.e.,

$$\hat{Q}_P(l) = [Ph\hat{M}_P(l) - A_h^0]/V_0^{1/2}, \qquad l = 1, \ldots, q, \tag{21}$$

where A_h^0 is the nonstochastic centering factor and V_0 is the nonstochastic scale factor. Specifically,

$$A_h^0 \equiv \left[(h^{-1} - 2) \int_{-1}^{1} k^2(u)du + 2 \int_0^1 \int_{-1}^{b} k_b^2(u)dudb \right]^2 - 1, \tag{22}$$

$$V_0 \equiv 2 \left[\int_{-1}^{1} \left[\int_{-1}^{1} k(u+v)k(v)dv \right]^2 du \right]^2, \tag{23}$$

in which $k_b(\cdot) = k(\cdot)/\int_{-1}^{b} k(v)dv$. Hong and Li (2005) show, under some regularity conditions, $\hat{Q}_P(l)$ follows the standard normal distribution asymptotically as $P \to \infty$ under $H_0^{(l)}$. As in Hong and Li (2005) and Egorov *et al.* (2006), we also compute the test statistic $W_P = q^{-1/2} \sum_{l=1}^{q} \hat{Q}_P(l)$, which follows the standard normal distribution asymptotically as $P \to \infty$ under H_0, for any fixed q. For the empirical analysis in Section 3, $\hat{Q}_P(l)$ $(l = 1, \ldots, q)$ and W_P are reported with $q = 12$ in Table 3.

2.4 Money-Income Granger-causality in Quantile

Let the conditional quantile of y_{t+1} be denoted $q_\alpha(y_{t+1}|\mathcal{F}_t)$ such that $G_{t+1}(q_\alpha(y_{t+1}|\mathcal{F}_t)|\mathcal{F}_t) = \alpha$. The conditional quantile $q_\alpha(y_{t+1}|X_t, \mathcal{G}_t)$ can be obtained by inverting the conditional distribution $G_{t+1}(y|\mathcal{F}_t) = \alpha$. Recall that $\mathcal{G}_t$ is the information set excluding X_t, i.e., $\mathcal{G}_t = \mathcal{F}_t/\{X_t\}$. We now define GC in conditional quantile (GCQ).

Definition 3. (Non Granger-causality in quantile): *X_t does not Granger-cause y_{t+1} in α-quantile if and only if $q_\alpha(y_{t+1}|X_t, \mathcal{G}_t) = q_\alpha(y_{t+1}|\mathcal{G}_t)$ a.s.*

GC in conditional quantile refers to the case that $q_\alpha(y_{t+1}|X_t, \mathcal{G}_t) \neq q_\alpha(y_{t+1}|\mathcal{G}_t)$. If X_t does not Granger-cause y_{t+1} in distribution, $q_\alpha(y_{t+1}|X_t, \mathcal{G}_t) = q_\alpha(y_{t+1}|\mathcal{G}_t)$ since $g_{t+1}(y|X_t, \mathcal{G}_t) = g_{t+1}(y|\mathcal{G}_t)$. Therefore, non-Granger-causality in distribution implies non-Granger-causality in conditional quantile. GC in distribution does not necessarily imply GC in each quantile, while significant GC in any conditional quantile implies significant GC in distribution. For some quantiles, X_t may Granger-cause y_{t+1}, while for other quantiles it may not. Granger (2003, p. 700) notes that some quantiles may differ from other quantiles in time series behavior (such as long memory and stationarity). For example, different parts of the distribution can have different time series properties; one tail could be stationary and the other tail may have a unit root.

While the quantile forecast $q_\alpha(y_{t+1}|X_t, \mathcal{G}_t)$ can be derived from inverting the density forecast, in this paper we use a linear quantile regression. An out-of-sample test for GCQ is based on two nested linear models. The first model does not account for money-income GC in α-quantile (referred as Model 1 or "NGCQ") and the second does (referred as Model 2 or "GCQ"):

$$\text{Model 1} \quad : \quad y_{t+1} = q_\alpha(y_{t+1}|\mathcal{G}_t) + e_{1,t+1} = V_t'\theta_1(\alpha) + e_{1,t+1}, \tag{24}$$

$$\text{Model 2} \quad : \quad y_{t+1} = q_\alpha(y_{t+1}|X_t, \mathcal{G}_t) + e_{2,t+1} = W_t'\theta_2(\alpha) + e_{2,t+1}, \tag{25}$$

where $V_t \in \mathcal{G}_t$ and $W_t = (X_t' \ V_t')$ are vectors of regressors and V_t includes a constant term. The parameters $\theta_i(\alpha)$ are estimated by minimizing the "check" function discussed in Koenker and Bassett (1978) using the rolling sample of the most recent R observations at time t ($t = R, \ldots, T-1$) :

$$\begin{aligned}
\hat{\theta}_{1,t}(\alpha) &= \arg\min_{\theta_1(\alpha)} \sum_{s=t-R+1}^{t} \rho_\alpha(y_s - V_{s-1}'\theta_1(\alpha)), \\
\hat{\theta}_{2,t}(\alpha) &= \arg\min_{\theta_2(\alpha)} \sum_{s=t-R+1}^{t} \rho_\alpha(y_s - W_{s-1}'\theta_2(\alpha)),
\end{aligned}$$

where $\rho_\alpha(e) \equiv [\alpha - \mathbf{1}(e < 0)]e$. Denote $\hat{q}^1_{\alpha,t+1}(\hat{\theta}_{1,t}(\alpha))$, $\hat{q}^2_{\alpha,t+1}(\hat{\theta}_{2,t}(\alpha))$ for the α-quantile forecasts of y_{t+1} from Model 1 and Model 2 respectively, and let $\hat{e}_{i,t+1}(\hat{\theta}_{i,t}(\alpha)) = y_{t+1} - \hat{q}^i_{\alpha,t+1}(\hat{\theta}_{i,t}(\alpha))$.

A test for Granger-causality is to compare the check-loss functions of forecasts conditional on two information sets, $\mathcal{G}_t$ and $\mathcal{F}_t$. We again use the conditional predictive ability test of GW (2005). Let $L_{t+1}(y_{t+1}, \hat{y}_{i,t+1}) = \rho_\alpha(\hat{e}_{i,t+1}(\hat{\theta}_{i,t}(\alpha)))$ be the check-loss function. The null hypothesis of NGCQ is therefore

$$H_0 : E[\rho_\alpha(\hat{e}_{1,t+1}(\hat{\theta}_{1,t}(\alpha))) - \rho_\alpha(\hat{e}_{2,t+1}(\hat{\theta}_{2,t}(\alpha)))|\mathcal{F}_t] = 0, \qquad t = R, \ldots, T-1. \tag{26}$$

Under the H_0 the loss differential $\Delta L_{t+1} \equiv \rho_\alpha(\hat{e}_{1,t+1}(\hat{\theta}_{1,t}(\alpha))) - \rho_\alpha(\hat{e}_{2,t+1}(\hat{\theta}_{2,t}(\alpha)))$ is an MDS, which implies $E(h_t \Delta L_{t+1}) = 0$ for any h_t that is $\mathcal{F}_t$-measurable. Denoting $Z_{t+1} = h_t \Delta L_{t+1}$, the GW (2005) statistic is of the same form as in (6) with $\bar{Z}_{R,P}' = \frac{1}{P}\sum_{t=R}^{T-1} h_t \Delta L_{t+1}$ and $\hat{\Omega}_P = \frac{1}{P}\sum_{t=R}^{T-1} Z_{t+1} Z_{t+1}'$. Under some regularity conditions, $GW_{R,P} \to^d \chi^2_q$ as $P \to \infty$ under H_0. We choose the same test function $h_t = X_t = (x_t, \ldots, x_{t+1-q})'$ as before with $q = 12$. When the null hypothesis of the equal conditional predictive ability is rejected, the forecast model selection rule is the same as in (7) in Section 2.1.

In Section 3 for the empirical analysis, we choose $X_t = (x_t, \ldots, x_{t+1-q})'$ and $Y_t = (y_t, \ldots, y_{t+1-q})'$ with $q = 12$, and let $\mathcal{G}_t = \sigma(V_t)$ be the σ-field generated by $V_t = (Y_t', I_t, B_t)'$ where I_t denotes the 3 month T-bill interest rate and B_t denotes the business cycle coincident index. See Table 1, Panel A.

3 Empirical Analysis

In the literature, empirical studies of Granger-causality in mean commonly apply VAR models with exogenous variables. Different exogenous variables, such as treasury bill rates, federal funds rates, commercial paper rates and business cycle indicators are used. Industry production or disposable personal income is used as the proxy for income, while M2 or M1 is used as the proxy for money stock. The estimation relies on a recursive method or a rolling window method. Results for Granger-causality test vary greatly in the literature with different choice of variables and sample periods. We examine the money-income causality in mean with four data sets using an out-of-sample test.

We use monthly data of real personal income, industrial production index, M1 money stock, M2 money stock, 3-month T-bill rate and the Stock and Watson experimental coincident index in the empirical study. The sample period is from 1959:04 to 2001:12 (513 observations). The source of the Stock and Watson experimental coincident index is the website of James Stock, while source for all other data is the Federal Reserve Economic Database (FRED) of Federal Reserve Bank of St. Luis.

We construct four data sets with different money and income variables. Data Sets 1 and 2 use real personal income as income, and use M2 and M1 for money respectively. Data Sets 3 and 4 use industrial production as income, and also use M2 and M1 for money respectively. The description of those data sets is listed in Panel A of Table 1. Noting that output, money and interest rate series are all non-stationary processes, we take the log-difference of output and money series and first difference of interest rate series. Business cycle index (the Stock and Watson experimental coincident index) is a stationary process itself. Denote y_t as the output growth rate at time t, m_t as the money growth rate at time t, I_t as change of interest rate and B_t as the business cycle indicator at time t.

For all out-of-sample tests and quantile forecasting, in each subsample we set $T = 360$ (30 years), with $R = 240$ (20 years) and $P = 120$ (10 years). Forecasting horizon is 1, and a recursive method is used in each subsample. We also shift the subsample by one year each time. There are 12 subsamples used. We also construct Subsample 13 to 16 with whole sample ($T = 500$), but with a different combination of R and P. A description of those subsamples is listed in Panel B of Table 1.

3.1 Money-Income Granger-causality in Mean

In the forecasting setting, as discussed in Section 2, an out-of-sample Granger-causality test is more appropriate. Therefore, we estimate two nested models. Model 1 is the model without money-income Granger-causality in mean, while Model 2 is the model with money-income Granger-causality in mean:

$$\text{Model 1} \quad : \quad y_t = \beta_0 + \sum_{l=1}^{12} \beta_{y,l} y_{t-l} + \beta_I I_{t-1} + \beta_B B_{t-1} + \varepsilon_{1,t}, \tag{27}$$

$$\text{Model 2} \quad : \quad y_t = \beta_0 + \sum_{l=1}^{12} \beta_{y,l} y_{t-l} + \sum_{l=1}^{12} \beta_{m,l} m_{t-l} + \beta_I I_{t-1} + \beta_B B_{t-1} + \varepsilon_{2,t}. \tag{28}$$

The unconditional out-of-sample mean quadratic losses of these two models for all 16 subsamples and 4 data sets are reported in Table 2, Panel A. In Data Set 1, 2 and 4, the unconditional mean squared forecast error (MSFE) of Model 2 is generally less than that of Model 1, while in Data Set 3 the MSFE of Model 1 are smaller.

The p-values of $GW_{R,P}$ and I_P statistics are listed in Panel B of Table 2. The p-values of $GW_{R,P}$ indicate that the null hypothesis of the equal conditional predictive ability can not be rejected for all subsamples and for all four data sets.

Comparing Data Sets 1,2 to Data Sets 3, 4, GCM remains insignificant whether real personal income or industrial production is used. Similarly GCM is not significant with M1 or M2. The results of the different sample periods (Subsample 1 to 12) are very robust, which show that with the shift of the sample window, money-income causality in mean remains insignificant across all the data sets. With the increase of ratio of P/R form Subsamples 13 to 16, GCM still remains insignificant.

In a forecasting model, using so many lagged money variables in Model 2 may cause the "over-fit" of the model and damage the forecasting performance. Therefore, in order to reduce the number of parameters in the large model, we also check the robustness of our GCM results by using a weighed moving average of $(x_t, \ldots, x_{t+1-q})$ for estimation and forecasting, e.g., $\sum_{l=1}^{q} w_l x_{t+1-l}$ with weights w_l such that $\sum_{l=1}^{q} w_l = 1$. We use three such different weight functions, namely a linear declining weight, a equal weight ($w_l = q^{-1}$), and a beta polynomial function which creates flexible nonlinear declining weights as introduced in Ghysels *et al.* (2006). We use these weighted moving average (a scalar) in place of the q-vector X_t in estimation, forecasting, and testing. It is found that Model 2 (GCM) is still no better than Model 1 (NGCM) in terms of predictive ability. Hence, we find that out-of-sample GCM is not significant. Adding the information on lagged money growth rate is not very useful to improve the conditional mean forecasting of U.S. output growth over the various sample periods and different choices of the variables.

3.2 Money-Income Granger-Causality in Distribution

We conduct an out-of-sample nonparametric test based on Hong and Li (2005) for money-income Granger-causality in distribution as discussed in Section 2. Given a specific l, a nonparametric copula function is estimated for the paired PITs values $\{\hat{u}_{t+1}^{(l)}, \hat{v}_{t+1}\}_{t=R}^{T-1}$. For the boundary-modified kernel in (19), we use a quartic kernel $k(u) = \frac{15}{16}(1-u^2)^2\mathbf{1}(|u| \leq 1)$. For simplicity, bandwidths for u and v are assumed to be the same. Following Hong and Li (2005), we set $h = \hat{\sigma}_u P^{-1/6}$, where $\hat{\sigma}_u$ is the standard error of $\hat{u}_{t+1}^{(l)}$.

In Table 3, we report test statistics $\hat{Q}_P(l)$ $(l = 1, \ldots, q)$ and W_P for different data sets and different sample periods with $q = 12$. The results indicate significant Granger-causality in distribution for all data sets and most sub-samples. Although we do not find significant GCM in all subsamples, we find strong GCD in most subsamples in the four data sets. From Subsamples 1 to 12, however, we find that GCD between different lags of money and output changes over time. The results also indicate that the money-income GCD varies with sub-samples.

3.3 Money-Income Granger-Causality in Quantile

As discussed in Section 2, significant GCD does not imply GCQ in each conditional quantile. Therefore, in our empirical study, we choose $\alpha = 0.05, 0.1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95$. We check the GCQ in these different quantiles of the conditional distribution of output growth.

We use the check loss function to compare the unconditional and conditional predictive ability of the GCQ and the NGCQ models.[6] The unconditional mean forecast check loss values for the GCQ and the NGCQ models at the above quantiles are reported in Table 4. The unconditional mean forecast loss ratios of GCQ to NGCQ model are depicted in Figures 1 and 2. The ratio less than 1 indicates the money-income Granger-causality in quantile. To compare the conditional check loss values the p-values of $GW_{R,P}$ and I_P statistics are reported in Table 5.

In terms of check losses and loss ratios, the GCQ model performs better than the NGCQ model in almost all subsamples of four data sets in the tails . In the central region, however, the GCQ model has lower check losses than the NGCQ model only in a few subsamples. We find the same pattern in the rolling subsamples (Subsample 1 to 12). This implies that GCQ is stable across the

[6] Besides the standard check loss, as a robust check, we also use the loss functions of the tick-exponential family introduced in Komunjer (2005). The results using these generalized check functions were essentially the same as those reported here with the standard check loss function and therefore not reported for space.

data sets. In the whole data subsamples (Subsample 13 to 16), we find more significant GCQ with the increase of P.

According to the p-values of $GW_{R,P}$ and I_P for the conditional predictive ability test, the GCQ model is significantly better to the NGCQ model in the tails of Data Set 1, 3 and 4, but not in Data Set 2. After accounting for money-income Granger-causality, quantile forecasting of output is improved at tails. The Granger-causality in quantile seems to be more significant between money and industrial production (Data Set 3 and 4) than that between money and personal income (Data Set 1 and 2). Comparing results of Data Set 1 and 2, we find M2 more significantly Granger-causes real personal income than M1 does. Causality between M2 and industrial production and that between M1 and industrial production are comparable to each other. Money does not improve forecasting of the output growth in conditional mean and the conditional quantiles close to median. However, in tails, money does significantly improve the forecasting of output tail quantiles.

4 Conclusions

The relationship between money and income is a much-studied but controversial topic in the literature. This paper follows a VAR framework and applies an out-of-sample test for money-income Granger-causality. We find that money-income Granger-causality in mean is not significant for all data sets and all subsample periods.

We test the money-income Granger-causality in distribution by a nonparametric copula. We find more significant Granger-causality in distribution in all data sets. We define Granger-causality in quantile and compare two quantile forecasts with or without money-income Granger-causality in quantile. Empirical results show the potential of improving quantile forecasting of output growth rate by incorporating information on money-income causality in quantile, especially in the tails. Causality between money and industrial production seems to more significant than that between money and real personal income, while M2 has stronger causality in quantiles to real personal income than M1 does. However, money is not very useful for forecasting near the center quantiles of the conditional distribution of output growth.

These empirical findings in this paper have never seen in the money-income literature. The new results on GCQ have an important implication on monetary policy, showing that the effectiveness of monetary policy has been underestimated by merely testing Granger-causality in mean. Money does Granger-cause income more strongly than it has been known and therefore the information on money growth can (and should) be more utilized in implementing monetary policy.

5 Appendix: Copula

As in Granger (2003, p. 694) and Patton (2006), we define the conditional copula as follows.

Sklar's Theorem for Conditional Copula: *Let $H_{t+1}(x,y)$ be a bivariate conditional distribution function with conditional margin distributions $F_{t+1}(x)$ and $G_{t+1}(y)$. Then there exists a conditional copula function C such that for all x, y*

$$H_{t+1}(x,y) = C_{t+1}(F_{t+1}(x), G_{t+1}(y)), \tag{29}$$

where $F_t(x) = \Pr[X \leq x|\mathcal{F}_t], G_t(y) = \Pr[Y \leq y|\mathcal{F}_t]$.

There are two important corollaries to this theorem:

Representation of Conditional Copula functions: *The bivariate conditional copula function can be obtained from the bivariate conditional joint distribution function $H_t(x,y)$ by the following:*

$$C_{t+1}(u,v) = H_{t+1}(F_{t+1}^{-1}(u), G_{t+1}^{-1}(v)) \tag{30}$$

where $u = F_{t+1}(x)$ and $v = G_{t+1}(y)$.

Decomposition of Bivariate Density: *Let $h_{t+1}(x,y) = \frac{\partial^2 H_{t+1}(x,y)}{\partial x \partial y}$, $f_{t+1}(x) = \frac{\partial F_{t+1}(x)}{\partial x}$, and $g_{t+1}(y) = \frac{\partial G_{t+1}(y)}{\partial y}$. Then*

$$h_{t+1}(x,y) = f_{t+1}(x) \times g_{t+1}(y) \times c_{t+1}(F_{t+1}(x), G_{t+1}(y)), \tag{31}$$

where $c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ is the conditional copula density function.

A copula function is called the independent copula if $C_{t+1}(u,v) = uv$ and $c_{t+1}(u,v) = 1$.

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Table 1. Description of Data Sets and Samples

Panel A. Description of Data Sets

	Income *Y*	Money *x*	Interest Rate *I*	Business Cycle Index *B*	Observations
Data Set 1	Real Personal Income	M2	3-Month T-bill Rate	Coincident Index	513
Data Set 2	Real Personal Income	M1	3-Month T-bill Rate	Coincident Index	513
Data Set 3	Industrial Production Index	M2	3-Month T-bill Rate	Coincident Index	513
Data Set 4	Industrial Production Index	M1	3-Month T-bill Rate	Coincident Index	513

Note: (1) To make these series stationary, we take log-difference of income and money variables, and take first difference of interest rate.

(2) The business cycle index series are taken from James Stock's web page, http://ksghome.harvard.edu/~.JStock.Academic.Ksg/xri/0201/xindex.asc, while the other data are obtained from the Federal Reserve Economic Database (FRED) of Federal Reserve Bank of St. Luis.

(3) All data are monthly data, with sample period of 1959:04 to 2001:12.

Panel B. Description of Subsamples in Out-of-sample Tests

	Starting Month	Ending Month	*T*	*R*	*P*
Subsample 1	1959:05	1990:04	360	240	120
Subsample 2	1960:05	1991:04	360	240	120
Subsample 3	1961:05	1992:04	360	240	120
Subsample 4	1962:05	1993:04	360	240	120
Subsample 5	1963:05	1994:04	360	240	120
Subsample 6	1964:05	1995:04	360	240	120
Subsample 7	1965:05	1996:04	360	240	120
Subsample 8	1966:05	1997:04	360	240	120
Subsample 9	1967:05	1998:04	360	240	120
Subsample 10	1968:05	1999:04	360	240	120
Subsample 11	1969:05	2000:04	360	240	120
Subsample 12	1970:05	2001:04	360	240	120
Subsample 13	1960:05	2001:12	500	380	120
Subsample 14	1960:05	2001:12	500	320	180
Subsample 15	1960:05	2001:12	500	260	240
Subsample 16	1960:05	2001:12	500	200	300

Note: (1) Subsample 1 to 12 have a fixed window of 30 years, with 20 years as in-sample period and 10 years as out-of-sample period. Subsamples are moving forward by a year each time.

(2) Subsample 13 to 16 are the samples that contain all observations but with different combination of *R* and *P*. Due to the 12 lags used in the model and log-difference of money and income, there are 500 observations.

Table 2. Out-of-Sample Test for Granger-causality in Mean

Panel A. Comparing Unconditional Predictive Ability (Squared error loss)

	Data Set 1		Data Set 2		Data Set 3		Data Set 4	
Loss	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Subsample 1	0.0738	0.0717	0.0738	0.0705	0.0417	0.0424	0.0417	0.0427
Subsample 2	0.0778	0.0744	0.0778	0.0750	0.0415	0.0419	0.0415	0.0418
Subsample 3	0.0779	0.0745	0.0779	0.0741	0.0386	0.0392	0.0386	0.0381
Subsample 4	0.0927	0.0884	0.0927	0.0902	0.0378	0.0377	0.0378	0.0365
Subsample 5	0.0651	0.0641	0.0651	0.0662	0.0418	0.0420	0.0418	0.0401
Subsample 6	0.0823	0.0780	0.0823	0.0784	0.0460	0.0468	0.0460	0.0455
Subsample 7	0.0837	0.0805	0.0837	0.0802	0.0447	0.0449	0.0447	0.0443
Subsample 8	0.0820	0.0776	0.0820	0.0775	0.0435	0.0436	0.0435	0.0417
Subsample 9	0.0812	0.0760	0.0812	0.0762	0.0448	0.0450	0.0448	0.0434
Subsample 10	0.0818	0.0768	0.0818	0.0770	0.0509	0.0516	0.0509	0.0498
Subsample 11	0.0839	0.0785	0.0839	0.0788	0.0484	0.0485	0.0484	0.0472
Subsample 12	0.1124	0.1036	0.1124	0.1031	0.0452	0.0455	0.0452	0.0438
Subsample 13	0.1252	0.1162	0.1252	0.1155	0.0406	0.0405	0.0406	0.0395
Subsample 14	0.0926	0.0881	0.0926	0.0874	0.0418	0.0419	0.0418	0.0409
Subsample 15	0.1014	0.0956	0.1014	0.0949	0.0414	0.0420	0.0414	0.0410
Subsample 16	0.0993	0.0937	0.0993	0.0920	0.0416	0.0420	0.0416	0.0413

Notes: Quadratic loss values for two models are reported. "Model 1" refers to the model without Granger-causality in mean, while "Model 2" refers to the model with Granger-causality in mean. The loss value of Model 2 is shaded when it is smaller than that of Model 1.

Panel B. Test for Conditional Predictive Ability

	Data Set 1		Data Set 2		Data Set 3		Data Set 4	
	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}
Subsample 1	0.3955	0.5667	0.6308	0.3833	0.6314	0.6167	0.3383	0.4333
Subsample 2	0.5427	0.5583	0.2509	0.4083	0.4873	0.5417	0.3636	0.4083
Subsample 3	0.2569	0.5667	0.3610	0.3667	0.4353	0.5333	0.8697	0.4417
Subsample 4	0.5396	0.5250	0.6276	0.4583	0.5154	0.5000	0.4129	0.4083
Subsample 5	0.7671	0.5250	0.6449	0.5000	0.5722	0.5250	0.2756	0.4333
Subsample 6	0.5588	0.4750	0.5760	0.4583	0.6943	0.5417	0.2167	0.5167
Subsample 7	0.6292	0.5083	0.4428	0.5083	0.7674	0.5500	0.3960	0.5167
Subsample 8	0.6817	0.4583	0.4991	0.5083	0.8779	0.5583	0.3921	0.5083
Subsample 9	0.5851	0.4333	0.5627	0.5167	0.7594	0.5667	0.4280	0.4750
Subsample 10	0.5015	0.4083	0.5034	0.4750	0.7118	0.6083	0.3141	0.4750
Subsample 11	0.5988	0.3833	0.5423	0.4417	0.7641	0.5250	0.6201	0.4750
Subsample 12	0.4113	0.3250	0.3970	0.4500	0.6066	0.5500	0.6814	0.4583
Subsample 13	0.6436	0.4167	0.3064	0.4167	0.8561	0.4833	0.6548	0.4250
Subsample 14	0.5155	0.4500	0.5330	0.4500	0.8597	0.5778	0.3590	0.4333
Subsample 15	0.3409	0.4583	0.3249	0.3875	0.7694	0.5833	0.5249	0.4083
Subsample 16	0.2876	0.4233	0.1256	0.3467	0.8342	0.5900	0.3855	0.4600

Notes: P_{GW} refers to the asymptotic p-value of the nR^2 version of the Wald statistics of Giacomini and White (2005). We choose a linear test function which contains 12 lags of money growth rate. The asymptotic p-values of the Giacomini and White statistics are obtained from a chi-square distribution with 12 degrees of freedom. I_{GW} refers to the I_P statistic in Giacomini and White (2005). See Section 2.1. At 10% level, if $P_{GW} < 0.10$ and $I_{GW} < 0.5$, we may prefer Model 2 (GCM) over the Model 1 (NGCM); if $P_{GW} < 0.10$ and $I_{GW} > 0.5$, we may prefer Model 1 to Model 2. None of the cases satisfies ($P_{GW} < 0.10$ and $I_{GW} < 0.5$) or ($P_{GW} < 0.10$ and $I_{GW} > 0.5$). In fact all p-values are very large.

Table 3. Hong and Li (2005) Statistics for Granger-causality in Distribution

Panel A. Data Set 1

	$Q_P(1)$	$Q_P(2)$	$Q_P(3)$	$Q_P(4)$	$Q_P(5)$	$Q_P(6)$	$Q_P(7)$	$Q_P(8)$	$Q_P(9)$	$Q_P(10)$	$Q_P(11)$	$Q_P(12)$	W_P
Subsample 1	-1.164	-0.355	-0.193	-0.229	2.150	1.206	-0.204	2.222	1.055	1.140	2.424	1.157	2.658
Subsample 2	-1.753	-1.212	-0.764	-0.301	1.545	1.346	-0.234	1.866	0.655	-0.021	0.065	-0.359	0.241
Subsample 3	-2.935	-1.085	-2.476	-1.640	0.223	0.304	-1.558	0.110	-0.973	-0.983	-0.833	-1.295	-3.793
Subsample 4	-1.872	-0.579	-1.775	-0.122	1.642	2.369	-0.773	0.626	-1.083	-0.788	-1.880	-1.597	-1.683
Subsample 5	0.890	1.235	0.486	1.375	3.590	2.695	-0.651	0.519	-1.060	-0.704	-1.677	-1.401	1.529
Subsample 6	2.698	2.601	2.909	3.512	5.836	4.960	2.546	4.006	3.670	3.238	0.755	1.044	10.905
Subsample 7	4.016	4.716	6.046	6.882	9.078	7.232	5.285	5.970	4.752	3.929	3.003	3.110	18.481
Subsample 8	2.574	2.539	2.617	3.478	4.914	4.695	4.233	4.840	5.256	6.664	4.192	4.796	14.664
Subsample 9	3.576	3.185	2.984	3.442	6.540	5.483	4.270	4.413	5.569	5.853	3.627	3.055	15.011
Subsample 10	0.989	0.359	1.164	0.865	3.570	3.142	1.757	1.906	3.300	4.354	2.645	1.774	7.455
Subsample 11	0.174	-1.117	-0.544	-0.657	1.023	0.641	0.431	-0.479	1.001	2.244	1.430	-0.598	1.024
Subsample 12	-0.536	-0.901	0.926	-0.227	2.011	0.930	-0.629	-1.333	0.706	1.551	0.106	-1.677	0.268
Subsample 13	-1.021	-1.603	0.861	-0.067	1.565	0.586	-0.672	-1.078	0.570	0.893	0.153	-1.436	-0.361
Subsample 14	-1.949	-2.155	-0.796	-0.403	2.311	0.543	-0.636	0.453	1.008	0.381	-0.157	-0.952	-0.679
Subsample 15	-0.509	-0.776	0.548	1.193	3.539	2.725	-0.492	1.080	2.170	1.235	1.472	-0.666	3.325
Subsample 16	0.934	-0.159	2.836	2.348	5.388	4.182	1.121	1.973	4.238	3.190	2.699	0.022	8.306

Panel B. Data Set 2

	$Q_P(1)$	$Q_P(2)$	$Q_P(3)$	$Q_P(4)$	$Q_P(5)$	$Q_P(6)$	$Q_P(7)$	$Q_P(8)$	$Q_P(9)$	$Q_P(10)$	$Q_P(11)$	$Q_P(12)$	W_P
Subsample 1	-0.626	0.721	1.533	0.240	0.691	1.174	0.216	0.444	-0.365	2.648	3.470	1.886	3.474
Subsample 2	-0.259	-0.147	0.434	0.112	0.378	-0.277	-0.413	-0.034	-0.801	0.997	1.077	1.187	0.651
Subsample 3	0.270	0.271	1.280	0.178	0.325	0.767	0.114	0.089	-1.340	0.818	1.992	1.121	1.699
Subsample 4	1.702	2.618	2.743	0.986	0.842	2.338	1.739	0.726	-0.296	1.560	2.613	2.203	5.709
Subsample 5	0.324	0.909	1.313	-0.407	0.631	1.541	1.812	0.067	-0.111	1.712	2.158	1.376	3.269
Subsample 6	0.840	0.693	0.848	0.299	0.501	1.094	1.541	-0.046	0.116	0.929	1.660	1.185	2.789
Subsample 7	-0.560	-0.479	-1.397	-1.455	-1.003	-1.067	0.493	-0.294	-0.601	1.226	1.590	0.847	-0.779
Subsample 8	-0.270	-1.352	-1.248	-2.133	-1.155	-1.511	0.065	-1.869	-1.529	-1.133	-0.335	-0.633	-3.783
Subsample 9	0.813	0.131	0.346	-1.537	-0.908	-0.922	0.408	-0.756	-0.597	-0.183	-0.666	-0.816	-1.354
Subsample 10	1.782	0.259	0.256	0.029	0.802	-0.093	0.849	0.270	0.221	0.846	0.034	0.179	1.569
Subsample 11	2.476	1.799	2.393	1.418	2.244	0.427	1.450	1.061	1.229	1.539	0.651	0.071	4.838
Subsample 12	3.791	4.578	3.340	2.832	2.921	2.061	2.949	2.224	1.984	3.407	2.254	1.116	9.658
Subsample 13	4.966	6.319	4.890	4.689	4.864	4.351	4.352	3.218	2.594	3.200	1.454	0.695	13.161
Subsample 14	-0.766	-0.466	-1.353	-1.676	-0.884	-1.348	-1.122	-1.771	-2.595	-0.932	-0.722	-1.447	-4.354
Subsample 15	0.977	2.046	0.747	0.623	1.101	1.080	0.992	0.738	-1.424	1.353	1.550	0.119	2.859
Subsample 16	2.919	4.084	1.919	2.774	3.192	2.569	2.763	2.585	0.936	3.634	3.602	1.337	9.328

Panel C. Data Set 3

	$Q_P(1)$	$Q_P(2)$	$Q_P(3)$	$Q_P(4)$	$Q_P(5)$	$Q_P(6)$	$Q_P(7)$	$Q_P(8)$	$Q_P(9)$	$Q_P(10)$	$Q_P(11)$	$Q_P(12)$	W_P
Subsample 1	-0.615	0.016	0.146	0.928	-0.115	0.168	-0.151	0.326	2.457	-0.071	1.421	2.722	2.088
Subsample 2	-0.300	-0.815	0.019	1.556	0.475	0.261	0.801	0.475	1.795	-0.868	0.222	1.316	1.425
Subsample 3	-0.060	-0.967	-0.555	1.109	0.137	-0.209	1.186	-0.415	0.356	-1.425	-0.517	0.362	-0.288
Subsample 4	0.014	-0.536	-0.359	1.680	0.984	-1.029	2.589	-1.096	-1.084	-1.383	-1.583	-0.990	-0.806
Subsample 5	2.386	1.871	1.918	2.767	2.283	-0.206	2.836	-0.456	-0.509	-0.544	-0.938	-0.098	3.265
Subsample 6	5.011	3.332	4.553	4.846	4.428	2.777	5.834	3.137	2.581	2.407	2.474	1.736	12.447
Subsample 7	6.930	6.254	7.004	7.478	7.165	5.471	8.036	5.632	4.028	4.295	4.189	3.525	20.209
Subsample 8	3.827	3.372	3.387	1.905	2.774	2.882	5.560	2.936	3.152	4.378	4.365	3.206	12.051
Subsample 9	2.280	2.517	2.700	2.307	3.241	2.444	4.931	2.811	3.201	3.455	3.263	1.826	10.097
Subsample 10	-0.104	0.173	0.674	0.465	0.751	0.610	4.171	1.762	2.069	1.711	2.810	1.370	4.752
Subsample 11	-0.913	-0.488	0.451	-0.486	-0.845	-0.022	2.940	-0.120	-0.038	-0.019	0.462	-1.177	-0.073
Subsample 12	-0.607	-0.053	1.151	-0.569	-0.888	0.111	3.074	1.057	-0.799	-1.001	-0.544	-1.068	-0.039
Subsample 13	-1.405	-0.420	0.336	-1.792	-1.984	-0.551	1.892	-0.218	-0.714	-1.051	-1.105	-1.855	-2.559
Subsample 14	-1.442	-0.785	-0.192	-1.350	-1.317	-1.215	0.822	-0.899	-0.981	-1.895	-0.923	-1.736	-3.439
Subsample 15	0.246	1.173	1.756	1.320	0.184	0.472	2.490	0.552	1.379	-0.947	0.133	-0.636	2.344
Subsample 16	1.280	3.100	2.357	1.237	0.257	1.908	4.866	2.181	2.295	-0.182	1.413	-0.018	5.974

Panel D. Data Set 4

	$Q_P(1)$	$Q_P(2)$	$Q_P(3)$	$Q_P(4)$	$Q_P(5)$	$Q_P(6)$	$Q_P(7)$	$Q_P(8)$	$Q_P(9)$	$Q_P(10)$	$Q_P(11)$	$Q_P(12)$	W_P
Subsample 1	-1.119	-0.602	0.120	1.060	0.214	0.450	2.082	1.653	0.335	0.331	2.063	2.448	2.608
Subsample 2	-1.115	-0.902	-0.074	0.064	-0.367	-0.175	1.451	0.760	0.738	-0.411	2.154	2.960	1.467
Subsample 3	-0.561	-0.065	0.352	0.990	0.864	-0.107	1.218	1.396	0.066	-0.341	1.256	1.520	1.901
Subsample 4	-0.769	0.080	0.668	0.636	1.222	0.018	1.120	1.023	0.175	-0.067	0.465	0.824	1.557
Subsample 5	-0.536	0.101	0.277	0.599	1.114	-0.087	1.990	1.728	0.319	0.361	1.049	1.063	2.303
Subsample 6	-0.027	0.393	0.699	1.620	1.823	0.299	1.881	0.709	-0.082	0.335	0.939	1.063	2.786
Subsample 7	-1.776	-0.610	-0.342	-0.113	0.079	0.163	0.651	-0.499	-0.536	0.530	0.964	0.814	-0.195
Subsample 8	-1.990	-1.006	-0.855	-0.610	-0.992	-1.358	-0.886	-1.827	-2.647	-1.487	-0.756	-0.484	-4.300
Subsample 9	-0.502	-0.045	0.883	0.102	-0.326	-0.414	-0.108	-1.599	-1.475	-0.800	-0.985	-1.025	-1.816
Subsample 10	1.337	1.417	0.869	1.182	1.140	0.600	0.789	-0.639	0.279	1.175	0.262	0.964	2.707
Subsample 11	2.623	2.696	1.990	3.156	1.929	1.471	1.420	0.046	1.301	2.397	1.588	2.965	6.808
Subsample 12	3.591	4.635	3.488	5.044	3.510	2.387	2.021	1.413	2.933	4.781	3.947	4.621	12.231
Subsample 13	3.700	5.968	4.239	5.951	3.888	3.603	2.776	1.696	1.864	3.690	2.936	4.388	12.903
Subsample 14	-1.802	-0.420	-0.943	0.036	-1.665	-1.146	-1.540	-2.198	-1.991	-1.360	-0.682	0.166	-3.910
Subsample 15	-0.469	1.639	0.581	1.826	0.052	-0.764	0.347	0.469	-0.398	0.331	1.220	3.715	2.468
Subsample 16	1.570	3.996	2.187	5.170	2.128	2.021	1.834	0.875	1.990	2.435	3.387	6.474	9.834

Notes: $Q_P(l)$ and W_P are asymptotically N(0,1) as P goes to infinity. They are one-sided test with the upper tailed 5% N(0,1) critical value of 1.645. Shaded are the statistics significant at 5% level.

Table 4. Out-of-Sample Test for Granger-causality in Quantiles
Comparing Unconditional Predictive Ability (Check loss)

Panel A. Data Set 1

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ
1	0.0342	0.0264	0.0537	0.0551	0.0603	0.0617	0.0705	0.0710	0.0741	0.0729	0.0751	0.0723	0.0731	0.0722	0.0718	0.0711	0.0647	0.0654	0.0471	0.0483	0.0343	0.0292
2	0.0399	0.0277	0.0538	0.0535	0.0613	0.0641	0.0721	0.0715	0.0766	0.0743	0.0789	0.0745	0.0756	0.0738	0.0734	0.0733	0.0651	0.0690	0.0483	0.0491	0.0345	0.0301
3	0.0413	0.0272	0.0541	0.0528	0.0627	0.0652	0.0718	0.0712	0.0787	0.0741	0.0820	0.0749	0.0791	0.0749	0.0761	0.0706	0.0649	0.0652	0.0457	0.0449	0.0321	0.0290
4	0.0361	0.0259	0.0586	0.0573	0.0719	0.0720	0.0828	0.0851	0.0932	0.0930	0.0952	0.0920	0.0928	0.0899	0.0868	0.0832	0.0731	0.0713	0.0498	0.0463	0.0311	0.0296
5	0.0244	0.0224	0.0419	0.0427	0.0553	0.0565	0.0678	0.0694	0.0802	0.0780	0.0806	0.0790	0.0792	0.0752	0.0739	0.0693	0.0647	0.0594	0.0430	0.0367	0.0236	0.0232
6	0.0327	0.0300	0.0418	0.0415	0.0594	0.0566	0.0716	0.0738	0.0826	0.0793	0.0829	0.0833	0.0829	0.0782	0.0790	0.0710	0.0650	0.0615	0.0463	0.0390	0.0285	0.0223
7	0.0332	0.0311	0.0412	0.0445	0.0580	0.0567	0.0714	0.0743	0.0801	0.0819	0.0823	0.0826	0.0817	0.0804	0.0797	0.0766	0.0679	0.0643	0.0468	0.0423	0.0284	0.0238
8	0.0305	0.0277	0.0406	0.0394	0.0580	0.0573	0.0701	0.0733	0.0782	0.0829	0.0804	0.0821	0.0790	0.0800	0.0784	0.0752	0.0665	0.0655	0.0466	0.0420	0.0277	0.0218
9	0.0277	0.0289	0.0423	0.0378	0.0606	0.0594	0.0730	0.0738	0.0763	0.0820	0.0800	0.0842	0.0830	0.0836	0.0796	0.0781	0.0626	0.0617	0.0396	0.0362	0.0255	0.0183
10	0.0280	0.0274	0.0425	0.0379	0.0602	0.0572	0.0730	0.0764	0.0802	0.0838	0.0814	0.0846	0.0814	0.0826	0.0797	0.0792	0.0664	0.0653	0.0415	0.0392	0.0260	0.0173
11	0.0294	0.0291	0.0443	0.0395	0.0641	0.0592	0.0755	0.0776	0.0816	0.0875	0.0838	0.0867	0.0844	0.0855	0.0817	0.0809	0.0670	0.0662	0.0426	0.0406	0.0257	0.0168
12	0.0419	0.0339	0.0602	0.0537	0.0772	0.0701	0.0868	0.0891	0.0937	0.0986	0.0988	0.1006	0.0999	0.1010	0.0936	0.0950	0.0792	0.0762	0.0521	0.0478	0.0336	0.0259
13	0.0409	0.0346	0.0664	0.0639	0.0865	0.0869	0.0987	0.1010	0.1053	0.1093	0.1093	0.1099	0.1051	0.1077	0.1027	0.0993	0.0840	0.0838	0.0588	0.0483	0.0335	0.0256
14	0.0346	0.0324	0.0525	0.0503	0.0692	0.0705	0.0800	0.0821	0.0858	0.0896	0.0894	0.0898	0.0860	0.0879	0.0834	0.0824	0.0699	0.0707	0.0490	0.0450	0.0306	0.0241
15	0.0379	0.0320	0.0604	0.0593	0.0743	0.0748	0.0855	0.0865	0.0912	0.0922	0.0943	0.0922	0.0909	0.0908	0.0889	0.0859	0.0749	0.0757	0.0535	0.0503	0.0346	0.0280
16	0.0378	0.0326	0.0589	0.0572	0.0720	0.0728	0.0829	0.0845	0.0879	0.0904	0.0906	0.0895	0.0874	0.0880	0.0856	0.0836	0.0715	0.0728	0.0513	0.0470	0.0313	0.0255

Note: (1) The numbers in the first column is referring to the 16 subsamples. See Table 1, Panel B.
(2) "NGCQ" refers to Model 1, the quantile forecasting model without money-income Granger-causality in quantile, i.e, not including the lagged money growth rate as independent variables.
(3) "GCQ" refers to Model 2, the quantile forecasting model with money-income Granger-causality in quantile, i.e, including the lagged money growth rate as independent variables.
(4) A check loss function proposed by Koenker and Bassett (1978) is used to evaluate the out-of-sample performance of the two quantile forecasting models. The out-of-sample average of the loss values are reported in this table. The loss value of Model 2 is shaded when it is smaller than that of Model 1.

Panel B. Data Set 2

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ
1	0.0342	0.0245	0.0537	0.0429	0.0603	0.0626	0.0705	0.0679	0.0741	0.0712	0.0751	0.0735	0.0731	0.0749	0.0718	0.0746	0.0647	0.0670	0.0471	0.0465	0.0343	0.0278
2	0.0399	0.0249	0.0538	0.0447	0.0613	0.0648	0.0721	0.0702	0.0766	0.0730	0.0789	0.0747	0.0756	0.0775	0.0734	0.0753	0.0651	0.0686	0.0483	0.0468	0.0345	0.0270
3	0.0413	0.0229	0.0541	0.0439	0.0627	0.0608	0.0718	0.0690	0.0787	0.0737	0.0820	0.0764	0.0791	0.0786	0.0761	0.0756	0.0649	0.0624	0.0457	0.0415	0.0321	0.0254
4	0.0361	0.0211	0.0586	0.0496	0.0719	0.0686	0.0828	0.0834	0.0932	0.0908	0.0952	0.0952	0.0928	0.0941	0.0868	0.0857	0.0731	0.0684	0.0498	0.0423	0.0311	0.0257
5	0.0244	0.0217	0.0419	0.0401	0.0553	0.0549	0.0678	0.0724	0.0802	0.0775	0.0806	0.0817	0.0792	0.0786	0.0739	0.0691	0.0647	0.0570	0.0430	0.0351	0.0236	0.0203
6	0.0327	0.0249	0.0418	0.0409	0.0594	0.0548	0.0716	0.0724	0.0826	0.0817	0.0829	0.0845	0.0829	0.0806	0.0790	0.0709	0.0650	0.0587	0.0463	0.0346	0.0285	0.0182
7	0.0332	0.0256	0.0412	0.0421	0.0580	0.0558	0.0714	0.0717	0.0801	0.0787	0.0823	0.0842	0.0817	0.0814	0.0797	0.0748	0.0679	0.0641	0.0468	0.0363	0.0284	0.0196
8	0.0305	0.0268	0.0406	0.0390	0.0580	0.0548	0.0701	0.0725	0.0782	0.0799	0.0804	0.0830	0.0790	0.0780	0.0784	0.0741	0.0665	0.0644	0.0466	0.0361	0.0277	0.0170
9	0.0277	0.0286	0.0423	0.0384	0.0606	0.0574	0.0730	0.0713	0.0763	0.0825	0.0800	0.0854	0.0830	0.0810	0.0796	0.0748	0.0626	0.0587	0.0396	0.0360	0.0255	0.0183
10	0.0280	0.0279	0.0425	0.0383	0.0602	0.0592	0.0730	0.0753	0.0802	0.0849	0.0814	0.0853	0.0814	0.0831	0.0797	0.0747	0.0664	0.0644	0.0415	0.0380	0.0260	0.0180
11	0.0294	0.0297	0.0443	0.0413	0.0641	0.0620	0.0755	0.0787	0.0816	0.0860	0.0838	0.0893	0.0844	0.0856	0.0817	0.0774	0.0670	0.0640	0.0426	0.0381	0.0257	0.0185
12	0.0419	0.0334	0.0602	0.0501	0.0772	0.0732	0.0868	0.0913	0.0937	0.0995	0.0988	0.1047	0.0999	0.0997	0.0936	0.0918	0.0792	0.0754	0.0521	0.0455	0.0336	0.0268
13	0.0409	0.0319	0.0664	0.0605	0.0865	0.0862	0.0987	0.1016	0.1053	0.1119	0.1093	0.1110	0.1051	0.1082	0.1027	0.1029	0.0840	0.0899	0.0588	0.0498	0.0335	0.0292
14	0.0346	0.0272	0.0525	0.0483	0.0692	0.0686	0.0800	0.0809	0.0858	0.0889	0.0894	0.0892	0.0860	0.0884	0.0834	0.0835	0.0699	0.0717	0.0490	0.0440	0.0306	0.0243
15	0.0379	0.0278	0.0604	0.0527	0.0743	0.0750	0.0855	0.0857	0.0912	0.0925	0.0943	0.0935	0.0909	0.0933	0.0889	0.0890	0.0749	0.0775	0.0535	0.0489	0.0346	0.0287
16	0.0378	0.0297	0.0589	0.0522	0.0720	0.0731	0.0829	0.0829	0.0879	0.0900	0.0906	0.0900	0.0874	0.0889	0.0856	0.0846	0.0715	0.0742	0.0513	0.0459	0.0313	0.0263

Panel C. Data Set 3

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ
1	0.0200	0.0163	0.0335	0.0328	0.0528	0.0520	0.0674	0.0685	0.0755	0.0767	0.0823	0.0800	0.0800	0.0764	0.0704	0.0681	0.0572	0.0577	0.0344	0.0345	0.0199	0.0183
2	0.0197	0.0155	0.0338	0.0306	0.0569	0.0550	0.0693	0.0718	0.0778	0.0779	0.0807	0.0811	0.0780	0.0764	0.0677	0.0664	0.0535	0.0543	0.0332	0.0342	0.0196	0.0174
3	0.0191	0.0147	0.0315	0.0279	0.0518	0.0513	0.0653	0.0657	0.0744	0.0727	0.0780	0.0750	0.0738	0.0764	0.0664	0.0674	0.0519	0.0517	0.0337	0.0334	0.0195	0.0181
4	0.0181	0.0149	0.0316	0.0278	0.0515	0.0506	0.0637	0.0607	0.0751	0.0708	0.0747	0.0731	0.0726	0.0722	0.0656	0.0625	0.0505	0.0500	0.0335	0.0356	0.0212	0.0191
5	0.0198	0.0145	0.0362	0.0299	0.0575	0.0527	0.0701	0.0681	0.0798	0.0735	0.0787	0.0773	0.0746	0.0772	0.0668	0.0660	0.0516	0.0485	0.0329	0.0352	0.0204	0.0192
6	0.0223	0.0157	0.0379	0.0313	0.0580	0.0607	0.0737	0.0744	0.0828	0.0825	0.0837	0.0859	0.0804	0.0822	0.0707	0.0713	0.0553	0.0541	0.0356	0.0346	0.0214	0.0192
7	0.0213	0.0166	0.0387	0.0315	0.0592	0.0583	0.0748	0.0728	0.0811	0.0808	0.0806	0.0803	0.0783	0.0800	0.0683	0.0684	0.0539	0.0536	0.0365	0.0333	0.0208	0.0192
8	0.0206	0.0165	0.0398	0.0310	0.0584	0.0564	0.0734	0.0728	0.0784	0.0784	0.0785	0.0801	0.0758	0.0786	0.0695	0.0687	0.0561	0.0536	0.0344	0.0331	0.0221	0.0201
9	0.0208	0.0167	0.0392	0.0317	0.0590	0.0578	0.0741	0.0738	0.0812	0.0795	0.0807	0.0814	0.0772	0.0789	0.0703	0.0708	0.0574	0.0543	0.0366	0.0344	0.0232	0.0207
10	0.0207	0.0168	0.0417	0.0337	0.0659	0.0619	0.0776	0.0774	0.0859	0.0841	0.0855	0.0870	0.0824	0.0833	0.0751	0.0743	0.0623	0.0601	0.0406	0.0373	0.0231	0.0231
11	0.0195	0.0169	0.0420	0.0332	0.0646	0.0615	0.0809	0.0771	0.0881	0.0874	0.0878	0.0879	0.0828	0.0824	0.0744	0.0737	0.0609	0.0580	0.0392	0.0324	0.0195	0.0185
12	0.0195	0.0167	0.0421	0.0323	0.0618	0.0578	0.0769	0.0731	0.0821	0.0855	0.0835	0.0827	0.0799	0.0792	0.0724	0.0702	0.0578	0.0556	0.0399	0.0324	0.0197	0.0187
13	0.0206	0.0172	0.0414	0.0331	0.0607	0.0553	0.0722	0.0708	0.0770	0.0789	0.0813	0.0792	0.0745	0.0723	0.0663	0.0645	0.0552	0.0535	0.0350	0.0297	0.0188	0.0163
14	0.0195	0.0164	0.0382	0.0318	0.0592	0.0553	0.0719	0.0703	0.0782	0.0799	0.0815	0.0810	0.0757	0.0761	0.0671	0.0663	0.0538	0.0531	0.0339	0.0312	0.0197	0.0176
15	0.0200	0.0162	0.0367	0.0312	0.0568	0.0543	0.0705	0.0701	0.0776	0.0796	0.0827	0.0813	0.0773	0.0758	0.0684	0.0667	0.0556	0.0560	0.0346	0.0325	0.0193	0.0175
16	0.0195	0.0161	0.0377	0.0321	0.0582	0.0550	0.0714	0.0702	0.0774	0.0793	0.0820	0.0810	0.0771	0.0759	0.0683	0.0676	0.0557	0.0557	0.0347	0.0317	0.0192	0.0173

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Panel D. Data Set 4

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ	NGCQ	GCQ
1	0.0200	0.0167	0.0335	0.0329	0.0528	0.0529	0.0674	0.0694	0.0755	0.0782	0.0823	0.0782	0.0800	0.0749	0.0704	0.0701	0.0572	0.0564	0.0344	0.0343	0.0199	0.0167
2	0.0197	0.0165	0.0338	0.0322	0.0569	0.0549	0.0693	0.0698	0.0778	0.0765	0.0807	0.0779	0.0780	0.0735	0.0677	0.0670	0.0535	0.0551	0.0332	0.0361	0.0196	0.0173
3	0.0191	0.0155	0.0315	0.0306	0.0518	0.0489	0.0653	0.0644	0.0744	0.0719	0.0780	0.0744	0.0738	0.0717	0.0664	0.0646	0.0519	0.0526	0.0337	0.0349	0.0195	0.0183
4	0.0181	0.0164	0.0316	0.0304	0.0515	0.0484	0.0637	0.0609	0.0751	0.0666	0.0747	0.0698	0.0726	0.0720	0.0656	0.0630	0.0505	0.0534	0.0335	0.0356	0.0212	0.0188
5	0.0198	0.0172	0.0362	0.0327	0.0575	0.0525	0.0701	0.0655	0.0798	0.0711	0.0787	0.0745	0.0746	0.0725	0.0668	0.0662	0.0516	0.0526	0.0329	0.0353	0.0204	0.0188
6	0.0223	0.0182	0.0379	0.0340	0.0580	0.0565	0.0737	0.0736	0.0828	0.0774	0.0837	0.0799	0.0804	0.0781	0.0707	0.0718	0.0553	0.0565	0.0356	0.0384	0.0214	0.0187
7	0.0213	0.0191	0.0387	0.0353	0.0592	0.0582	0.0748	0.0697	0.0811	0.0779	0.0806	0.0795	0.0783	0.0768	0.0683	0.0711	0.0539	0.0545	0.0365	0.0361	0.0208	0.0178
8	0.0206	0.0169	0.0398	0.0349	0.0584	0.0553	0.0734	0.0675	0.0784	0.0759	0.0785	0.0769	0.0758	0.0747	0.0695	0.0709	0.0561	0.0544	0.0344	0.0341	0.0221	0.0187
9	0.0208	0.0159	0.0392	0.0341	0.0590	0.0557	0.0741	0.0694	0.0812	0.0772	0.0807	0.0787	0.0772	0.0767	0.0703	0.0723	0.0574	0.0580	0.0366	0.0349	0.0232	0.0196
10	0.0207	0.0168	0.0417	0.0400	0.0659	0.0590	0.0776	0.0732	0.0859	0.0812	0.0855	0.0821	0.0824	0.0799	0.0751	0.0764	0.0623	0.0615	0.0406	0.0390	0.0231	0.0194
11	0.0195	0.0164	0.0420	0.0389	0.0646	0.0589	0.0809	0.0770	0.0881	0.0813	0.0878	0.0837	0.0828	0.0774	0.0744	0.0742	0.0609	0.0597	0.0392	0.0364	0.0195	0.0189
12	0.0195	0.0165	0.0421	0.0352	0.0618	0.0555	0.0769	0.0728	0.0821	0.0777	0.0835	0.0788	0.0799	0.0745	0.0724	0.0722	0.0578	0.0574	0.0399	0.0370	0.0197	0.0193
13	0.0206	0.0168	0.0414	0.0325	0.0607	0.0536	0.0722	0.0671	0.0770	0.0738	0.0813	0.0736	0.0745	0.0710	0.0663	0.0673	0.0552	0.0528	0.0350	0.0327	0.0188	0.0169
14	0.0195	0.0163	0.0382	0.0325	0.0592	0.0547	0.0719	0.0687	0.0782	0.0771	0.0815	0.0760	0.0757	0.0730	0.0671	0.0679	0.0538	0.0531	0.0339	0.0329	0.0197	0.0175
15	0.0200	0.0165	0.0367	0.0320	0.0568	0.0531	0.0705	0.0676	0.0776	0.0769	0.0827	0.0766	0.0773	0.0736	0.0684	0.0690	0.0556	0.0542	0.0346	0.0338	0.0193	0.0170
16	0.0195	0.0162	0.0377	0.0321	0.0582	0.0534	0.0714	0.0685	0.0774	0.0767	0.0820	0.0768	0.0771	0.0739	0.0683	0.0692	0.0557	0.0548	0.0347	0.0336	0.0192	0.0173

Table 5. Out-of-Sample Test for Granger-causality in Quantiles
Test for Conditional Predictive Ability

Panel A. Data Set 1

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}
1	0.2818	0.5083	0.5807	0.5167	0.1110	0.5917	0.3490	0.6250	0.8786	0.7500	0.5353	0.6083	0.3963	0.6417	0.1906	0.7083	0.0004	0.5667	0.0137	0.6833	**0.0001**	**0.3333**
2	**0.0117**	**0.4500**	0.7422	*0.4667*	0.0471	0.6083	0.3107	0.5167	0.8232	0.6167	0.9025	*0.4833*	0.8333	0.5417	0.4207	0.6500	0.0002	0.6750	0.0085	0.6417	**0.0015**	**0.4000**
3	**0.0093**	**0.4167**	0.9786	*0.4417*	0.3736	0.6750	0.5723	0.5583	0.9165	0.5417	0.7042	*0.4083*	0.2305	*0.4167*	0.2389	*0.4583*	0.1774	0.6167	0.0220	0.5667	**0.0464**	**0.3583**
4	**0.0030**	**0.4667**	0.9390	*0.4667*	0.7655	0.5583	0.7137	0.6250	0.8008	0.7417	0.5908	0.6417	0.4173	0.5000	0.2084	0.5083	**0.0739**	**0.4667**	0.0192	0.5000	**0.0691**	**0.4583**
5	**0.0023**	**0.4000**	0.8785	0.5667	0.7851	0.5583	0.4333	0.6083	0.8219	0.6500	0.4146	0.6000	0.2930	*0.4417*	**0.0937**	**0.4500**	**0.0759**	**0.3500**	0.2597	*0.3917*	0.0133	0.5417
6	0.1779	*0.3500*	0.4385	*0.4917*	0.5595	*0.4083*	0.5189	0.5333	0.7671	0.5250	0.7387	0.6333	0.4010	*0.4333*	0.2000	*0.4083*	0.6170	*0.3750*	**0.0859**	**0.3917**	**0.0496**	**0.4083**
7	0.4243	*0.3417*	0.0984	0.6000	0.6746	*0.4417*	0.5268	0.5917	0.5550	0.5583	0.6462	0.5333	0.5811	*0.4750*	0.2645	*0.4583*	0.6681	*0.3417*	0.1077	*0.4167*	**0.0797**	**0.4417**
8	**0.0090**	**0.2833**	**0.0540**	**0.4583**	0.4654	*0.4750*	0.3460	0.5917	0.3853	0.6250	0.7581	0.5750	0.6841	*0.4750*	0.3531	*0.4500*	0.6698	0.5167	0.4106	*0.3750*	0.3230	*0.3333*
9	0.1369	0.5083	**0.0245**	**0.1250**	0.4969	*0.4500*	0.6165	0.5333	0.0344	0.6667	0.0833	0.6417	0.5256	0.5417	0.4596	*0.4917*	0.2128	*0.4583*	0.3320	*0.4167*	**0.0782**	**0.3583**
10	**0.0308**	**0.4333**	**0.0463**	**0.1583**	0.4546	*0.4000*	0.2683	0.5583	0.0689	0.5583	0.5733	0.6083	0.8052	0.5750	0.5605	*0.4833*	0.5908	*0.4250*	0.1066	*0.3833*	**0.0577**	**0.2917**
11	**0.0264**	**0.4000**	**0.0482**	**0.2417**	0.6302	*0.3000*	0.3969	*0.4917*	0.1790	0.6750	0.7448	0.5917	0.6209	0.5667	0.4993	*0.4500*	0.5628	*0.3667*	0.2056	*0.3417*	**0.0101**	**0.2500**
12	**0.0276**	**0.4167**	0.1218	*0.1917*	0.5791	*0.3000*	0.2310	0.5083	0.1766	0.6667	0.5141	*0.4917*	0.7996	*0.4917*	0.4245	*0.4833*	0.2632	*0.3000*	**0.0051**	**0.2667**	**0.0140**	**0.2417**
13	0.1685	*0.4583*	**0.0846**	**0.4167**	0.2196	*0.3833*	0.1963	0.5500	0.1008	0.6000	0.7883	0.6750	0.4584	0.6167	0.2115	*0.4417*	0.2124	*0.4250*	0.2393	*0.2833*	**0.0408**	**0.2500**
14	0.1136	0.5056	0.2827	*0.4056*	0.3981	0.5000	0.2287	0.6111	0.1810	0.6778	0.7713	0.6944	0.5418	0.6000	0.3520	*0.4944*	0.2462	*0.4944*	0.2197	*0.3889*	**0.0011**	**0.1889**
15	**0.0852**	**0.4958**	0.3348	*0.4333*	0.5132	*0.4958*	0.3477	0.5917	0.3066	0.6375	0.6190	0.6333	0.4214	0.5833	0.2017	*0.4833*	0.0854	0.5458	**0.0676**	**0.3917**	**0.0000**	**0.2375**
16	**0.0105**	**0.4567**	**0.0902**	**0.3967**	0.1426	0.5100	0.1308	0.6100	0.0696	0.6600	0.3022	0.5867	0.2714	0.6133	0.1773	*0.4867*	0.0378	0.5267	**0.0237**	**0.3300**	**0.0000**	**0.2433**

Notes: (1) The numbers in the first column is referring to the 16 subsamples. See Table 1, Panel B.

(2) P_{GW} refers to the asymptotic p-value of the nR^2 version of the Wald statistics of Giacomini and White (2005). We choose a linear test function which contains 12 lags of money growth rate. The asymptotic p-values of the Giacomini and White statistics are obtained from a chi-square distribution with 12 degrees of freedom.

(3) I_{GW} refers to the I_P statistic in Giacomini and White (2005). See Section 2.4. The cases with $I_{GW} < 0.5$ are in italic font.

(4) At 10% level, if $P_{GW} < 0.10$ and $I_{GW} < 0.5$, we prefer Model 2 (GCQ) over Model 1 (NGCQ). These cases are reported in bold font. If $P_{GW} < 0.10$ and $I_{GW} > 0.5$, we prefer Model 1 to Model 2.

Panel B. Data Set 2

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}
1	0.2807	*0.3667*	0.1231	*0.3750*	0.4618	0.6250	0.2078	*0.4667*	0.8602	*0.3917*	0.8072	0.5250	0.9176	0.6000	0.1888	0.5667	0.4006	0.6583	0.2339	*0.3667*	0.7987	0.5583
2	0.1806	*0.3000*	**0.0917**	**0.3583**	0.1331	0.6500	0.8506	0.5417	0.6823	*0.4667*	0.8186	*0.4833*	0.2067	0.6083	0.3493	0.6083	0.5402	0.6500	0.7581	0.5333	0.4597	0.5667
3	0.3696	*0.3417*	0.1491	*0.3833*	0.3980	*0.4750*	0.1047	0.5583	0.4155	*0.4333*	0.7648	*0.4250*	0.0801	0.5333	0.2544	0.5250	0.4612	0.5250	0.2908	0.5167	0.1073	*0.4667*
4	0.3098	*0.3833*	0.8066	*0.3917*	0.2213	0.5000	0.5586	0.5500	0.7943	*0.4417*	0.5041	0.5417	0.4057	0.5000	0.7743	0.5833	0.9892	*0.4750*	0.4418	*0.4917*	0.2694	*0.4000*
5	0.1841	0.5750	0.7400	0.5500	0.2389	0.5750	0.4050	0.5417	0.9000	*0.4417*	0.5773	0.5417	0.5708	*0.4750*	0.6092	0.5000	0.8365	*0.4667*	0.2673	*0.4917*	0.2902	0.5250
6	0.3506	*0.4500*	0.5748	0.5000	0.7058	0.5917	0.4254	0.5417	0.8269	*0.4917*	0.3867	0.5667	0.9264	*0.4667*	0.8446	0.5583	0.6801	*0.4917*	0.7764	*0.4417*	0.2083	*0.4000*
7	0.1188	*0.4917*	0.1424	*0.4500*	0.5984	0.5750	0.1807	0.6167	0.3759	0.5583	0.4557	0.5917	0.9468	0.5000	0.7618	0.5083	0.7373	*0.4917*	0.9127	*0.4667*	**0.0778**	**0.4667**
8	0.3962	*0.4000*	0.1220	0.5250	0.7881	0.5167	0.2918	0.5583	0.5949	0.5750	0.3366	0.5750	0.8092	*0.4667*	0.8322	*0.4833*	0.6634	*0.4833*	0.7598	*0.4583*	0.1876	*0.4000*
9	0.1687	*0.3917*	0.1529	*0.4167*	0.9013	*0.4583*	0.4243	0.5083	0.6083	0.5750	0.5560	0.6000	0.6200	*0.4083*	0.7952	*0.4667*	0.7985	*0.4417*	0.8676	*0.4583*	0.2678	*0.3667*
10	0.2158	*0.4083*	0.1697	*0.4250*	0.8797	0.5500	0.5663	0.5917	0.3183	0.5833	0.2243	0.5750	0.6142	*0.4500*	0.7359	*0.4000*	0.7464	*0.4333*	0.7461	*0.4583*	0.3208	*0.3750*
11	0.1161	*0.4167*	0.3558	*0.4250*	0.9078	0.5083	0.4310	0.6000	0.5188	0.5583	0.4967	0.6167	0.7559	*0.4833*	0.6883	*0.4167*	0.7432	*0.3917*	0.6174	*0.4667*	0.2842	*0.3667*
12	0.4149	*0.3083*	0.2064	*0.3750*	0.6057	*0.4500*	0.3425	0.6167	0.3115	0.6083	0.8020	0.6833	0.6114	0.5167	0.7200	*0.4417*	0.8789	0.5000	0.3480	*0.4417*	0.1240	*0.4333*
13	0.4703	*0.2667*	0.1809	*0.3500*	0.4873	0.5000	0.1789	0.5833	0.3375	0.7083	0.6073	0.5250	0.3707	0.6167	0.6284	*0.4500*	0.7196	0.6250	0.5094	*0.4333*	0.2045	*0.4500*
14	0.4873	*0.3333*	0.7352	*0.3444*	0.5495	0.5333	0.1617	0.6056	0.2251	0.6500	0.6093	0.5611	0.5650	0.6111	0.8186	*0.4667*	0.8099	0.5778	0.7512	*0.4667*	0.2650	0.5167
15	0.1730	*0.3083*	0.4755	*0.2917*	0.2644	0.5792	0.0625	0.5167	0.2018	0.5708	0.5094	0.5375	0.5353	0.6583	0.8686	*0.4958*	0.7485	0.6833	0.6875	*0.4250*	0.1122	0.5000
16	**0.0591**	**0.3400**	0.1244	*0.2933*	0.1716	0.5700	0.0520	0.5100	0.0596	0.5867	0.4000	0.5133	0.3424	0.5500	0.6366	*0.4367*	0.5880	0.6167	0.5468	*0.4233*	0.0294	0.5167

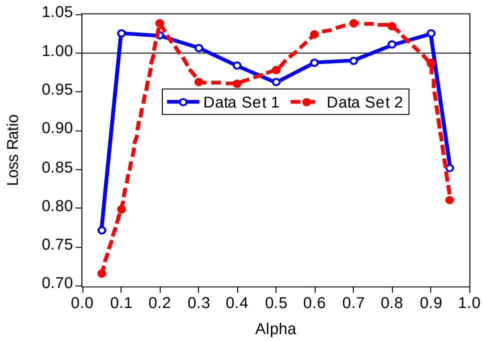
Panel C. Data Set 3

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}
1	**0.0342**	**0.3000**	0.7361	0.5333	**0.0454**	**0.4667**	0.3457	0.5750	0.7504	0.5667	0.7219	*0.4500*	0.5045	*0.4833*	0.3287	*0.4333*	0.9278	*0.4250*	0.1215	0.5083	**0.0022**	**0.4417**
2	**0.0002**	**0.3417**	0.1628	*0.3417*	0.2214	*0.4833*	0.5189	0.6500	0.6532	*0.4917*	0.5541	0.6083	0.6286	0.5250	0.7982	*0.4167*	0.4725	0.5333	0.0689	0.5583	**0.0020**	**0.4333**
3	**0.0028**	**0.3250**	**0.0606**	**0.4250**	0.4015	*0.4833*	0.4234	0.5333	0.5310	*0.4500*	0.6211	*0.3917*	0.2468	0.6083	0.8133	*0.4833*	0.2971	*0.4583*	0.0719	0.5083	**0.0016**	**0.4333**
4	**0.0335**	**0.4083**	**0.1007**	**0.4083**	0.1330	*0.4583*	0.6568	*0.3333*	0.3921	*0.3917*	0.3471	0.5083	0.3360	0.5250	0.6631	*0.2583*	**0.0740**	**0.3750**	0.0083	0.5333	**0.0360**	**0.4000**
5	**0.0783**	**0.2167**	**0.0280**	**0.2583**	0.1675	*0.2833*	0.8474	*0.3583*	0.5685	*0.3083*	0.6190	0.5000	0.1731	0.6333	0.6806	*0.3667*	**0.0511**	**0.2750**	0.0147	0.5917	**0.0088**	**0.4333**
6	0.1249	*0.2750*	**0.1017**	**0.2417**	0.7646	0.6750	0.8068	*0.4750*	0.5166	0.5083	0.2172	0.6000	0.0282	0.5667	0.3202	0.5000	**0.0340**	**0.3667**	**0.0020**	**0.4250**	**0.0085**	**0.4167**
7	0.1356	*0.2083*	**0.0620**	**0.1750**	0.3267	*0.4250*	0.5371	*0.4000*	0.3812	*0.4667*	0.4027	0.5167	0.1652	0.5833	0.4593	0.5250	**0.0195**	**0.4750**	**0.0157**	**0.4000**	**0.0318**	**0.3833**
8	**0.0539**	**0.2083**	**0.1045**	**0.1417**	0.6332	*0.4167*	0.5413	*0.4167*	0.5070	*0.4583*	0.4126	0.6083	0.3790	0.5750	0.3531	*0.4917*	0.4377	*0.3917*	**0.0129**	**0.4417**	**0.0031**	**0.3333**
9	**0.0134**	**0.2500**	**0.0170**	**0.2500**	0.8869	*0.4250*	0.3226	*0.4667*	0.7960	*0.4417*	0.2367	0.5333	0.5232	0.5583	0.3490	0.5083	0.1172	*0.4083*	**0.0270**	**0.4333**	**0.0044**	**0.3167**
10	**0.0049**	**0.2333**	**0.0296**	**0.1583**	0.6305	*0.3417*	0.7290	0.5250	0.5032	*0.4333*	0.4176	0.5833	0.6161	*0.4833*	0.6840	*0.4583*	0.1679	*0.4083*	**0.0216**	**0.3833**	**0.0014**	**0.4500**
11	**0.0023**	**0.2750**	**0.0202**	**0.1417**	0.5731	*0.3750*	0.3595	*0.3750*	0.8133	*0.4583*	0.1803	*0.4667*	0.2682	*0.4333*	0.5943	0.5000	0.5793	*0.3917*	**0.0075**	**0.2667**	0.2386	*0.4000*
12	**0.0019**	**0.3000**	**0.0164**	**0.1333**	0.3927	*0.3417*	0.1993	*0.4167*	0.5847	0.6833	0.1255	*0.4750*	0.4161	*0.4500*	0.7979	*0.4417*	0.4001	*0.3333*	**0.0037**	**0.2417**	**0.1045**	**0.3833**
13	**0.0048**	**0.3167**	**0.0881**	**0.2167**	0.1320	*0.3250*	0.7178	*0.4833*	0.2517	0.5417	0.4681	*0.4500*	0.2813	*0.4000*	0.6677	*0.4333*	0.1654	*0.4333*	**0.0580**	**0.1833**	**0.0075**	**0.4333**
14	**0.0019**	**0.2556**	0.1205	*0.2056*	0.2170	*0.3333*	0.9851	*0.4500*	0.7164	0.6556	0.4882	0.5222	0.3393	0.5722	0.6736	*0.4778*	0.3259	*0.4889*	**0.0875**	**0.2722**	**0.0001**	**0.4111**
15	**0.0014**	**0.2042**	0.1190	*0.1917*	**0.0914**	**0.3917**	0.8946	0.5208	0.7946	0.6583	0.3457	*0.4833*	0.2288	*0.4833*	0.8215	*0.4292*	0.2571	0.5125	**0.0545**	**0.3167**	**0.0000**	**0.4375**
16	**0.0002**	**0.2167**	**0.0226**	**0.1933**	0.1229	*0.3200*	0.8991	*0.4567*	0.4114	0.6500	0.4170	0.5067	0.1150	0.5400	0.5778	0.5200	**0.0722**	**0.4800**	**0.0036**	**0.2533**	**0.0000**	**0.4333**

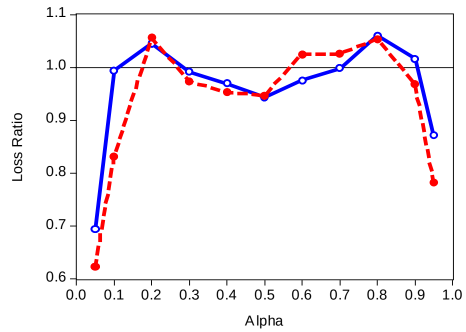
Panel D. Data Set 4

Sub-sample	α=0.05		α=0.10		α=0.20		α=0.30		α=0.40		α=0.50		α=0.60		α=0.70		α=0.80		α=0.90		α=0.95	
	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}	P_{GW}	I_{GW}
1	**0.0081**	**0.4833**	**0.0084**	**0.4583**	0.1951	*0.4083*	0.1332	*0.4250*	0.7680	*0.4667*	0.2510	*0.3750*	0.5779	*0.3583*	0.9801	0.5000	0.3654	*0.3833*	**0.0014**	**0.4333**	**0.0021**	**0.3917**
2	**0.0037**	**0.4417**	**0.0056**	**0.4000**	0.3283	*0.4500*	0.2313	*0.3750*	0.1783	*0.4000*	0.8149	*0.4000*	0.7112	*0.3333*	0.7611	*0.4917*	0.6745	0.5000	**0.0202**	**0.4917**	**0.0080**	**0.3917**
3	**0.0019**	**0.5000**	**0.0078**	**0.4083**	0.7356	*0.4000*	0.6402	*0.4417*	0.9155	*0.4083*	0.9113	*0.4083*	0.9358	*0.4167*	0.7816	*0.4167*	0.3524	0.5500	0.2679	*0.4083*	**0.0119**	**0.4417**
4	**0.0004**	**0.4500**	**0.0085**	**0.4500**	0.1666	*0.4417*	0.6785	*0.4250*	0.4025	*0.3917*	0.7741	*0.4083*	0.6752	*0.4417*	0.5652	*0.4917*	0.1638	0.5583	**0.0742**	**0.4500**	**0.0051**	**0.4083**
5	**0.0111**	**0.4083**	0.1882	*0.3583*	0.6711	*0.3833*	0.5476	*0.3583*	0.6543	*0.3583*	0.6180	*0.3833*	0.4914	*0.4667*	0.7021	*0.4750*	0.5980	0.5167	0.1346	0.5000	**0.0196**	**0.4917**
6	**0.0067**	**0.3750**	0.2514	*0.3917*	0.3594	*0.4750*	0.8207	*0.4417*	0.7712	*0.4417*	0.3885	*0.4833*	0.5146	0.5333	0.6875	0.5667	0.7047	0.5250	0.3628	*0.4750*	0.5757	*0.3833*
7	**0.0230**	**0.4000**	0.3645	*0.3917*	0.4066	*0.3917*	0.4869	*0.3917*	0.6833	*0.4500*	0.2507	0.5250	0.1488	0.5583	0.4163	0.5417	0.3176	0.5500	**0.0945**	**0.4583**	0.4612	*0.4500*
8	**0.0930**	**0.3333**	0.5361	*0.3167*	0.3967	*0.4250*	0.2520	*0.3833*	0.7235	*0.4667*	0.2463	0.5333	0.2189	0.5917	0.5478	0.5833	0.2662	0.5583	0.1818	*0.4417*	0.2824	*0.3917*
9	**0.0243**	**0.2583**	0.5334	*0.3333*	0.2645	*0.3667*	0.3288	*0.3917*	0.5132	*0.4417*	0.4936	0.5250	0.6028	0.5500	0.5393	0.6167	0.2938	0.6333	**0.0622**	**0.3083**	0.1289	*0.2917*
10	**0.0114**	**0.2667**	0.4668	*0.3583*	0.4884	*0.3000*	0.5001	*0.3333*	0.7305	*0.3833*	0.6840	*0.4750*	0.2987	0.5000	0.5580	0.6000	0.2553	0.5583	0.3269	*0.3000*	**0.0518**	**0.3500**
11	**0.0378**	**0.2583**	**0.0922**	**0.3000**	0.1814	*0.3833*	0.4745	*0.3500*	0.6067	*0.3250*	0.5999	*0.3917*	0.4640	*0.4000*	0.9251	0.5667	0.4268	0.5750	0.3540	*0.2750*	0.2558	*0.3417*
12	**0.0345**	**0.3750**	**0.0233**	**0.2333**	**0.0278**	**0.3417**	**0.0975**	**0.3250**	0.3869	*0.3833*	0.7960	*0.3500*	0.7283	*0.3917*	0.8043	0.5500	0.0977	0.5500	0.0518	*0.3333*	0.2169	*0.3750*
13	**0.0167**	**0.3583**	**0.1028**	**0.1667**	**0.0111**	**0.3167**	**0.0708**	**0.3500**	0.1258	*0.3833*	0.2977	*0.3083*	0.8779	*0.4333*	0.4378	0.6000	0.2789	0.5083	0.4551	*0.3250*	**0.0061**	**0.4250**
14	**0.0005**	**0.3833**	**0.0597**	**0.2833**	**0.0260**	**0.3556**	0.1560	*0.3667*	0.3499	*0.3833*	0.4375	*0.3500*	0.6112	*0.4500*	0.4692	0.5389	0.5680	*0.4444*	0.3593	*0.3833*	**0.0009**	**0.4056**
15	**0.0000**	**0.3833**	**0.0111**	**0.2792**	**0.0074**	**0.3833**	**0.0891**	**0.3583**	0.2700	*0.3708*	0.2732	*0.3250*	0.6790	*0.4000*	0.5759	0.5167	0.4683	*0.4125*	0.1597	*0.3833*	**0.0000**	**0.3417**
16	**0.0000**	**0.3967**	**0.0039**	**0.2600**	**0.0002**	**0.3567**	**0.0330**	**0.3900**	0.2101	*0.4033*	0.2876	*0.3567*	0.5747	*0.4767*	0.2579	0.5900	0.2720	*0.4400*	**0.0658**	**0.3533**	**0.0000**	**0.3900**

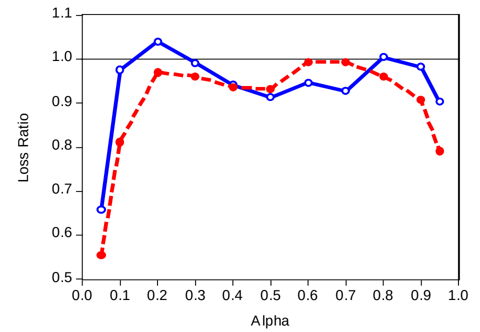
Figure 1. Loss Ratio for Data Set 1 and Data Set 2



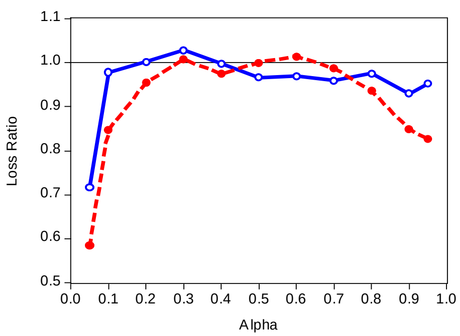
(a) Subsample 1



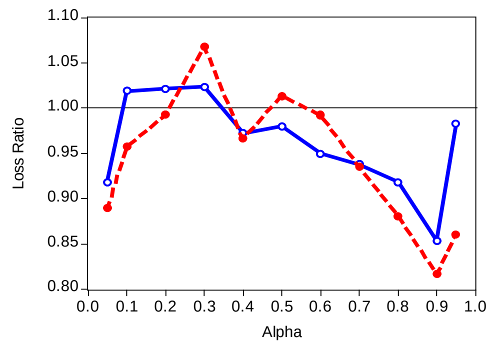
(b) Subsample 2



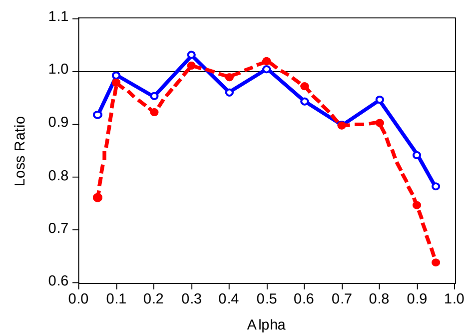
(c) Subsample 3



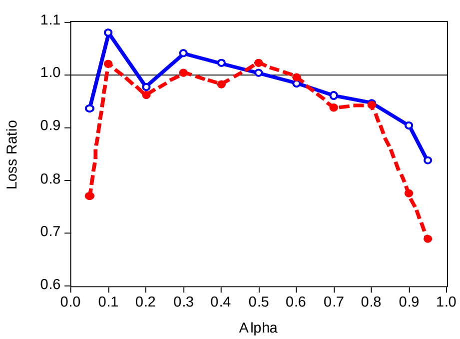
(d) Subsample 4



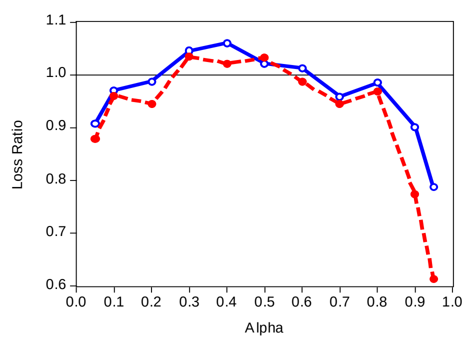
(e) Subsample 5



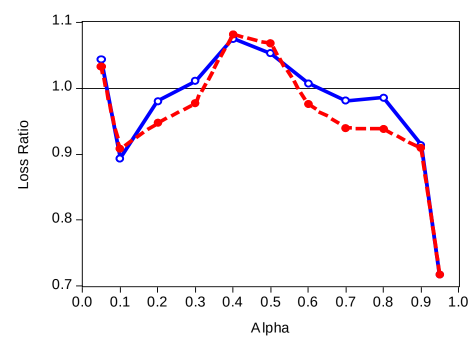
(f) Subsample 6



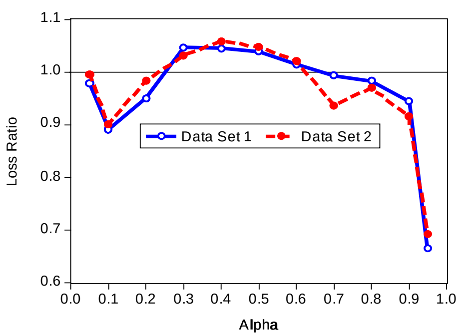
(g) Subsample 7



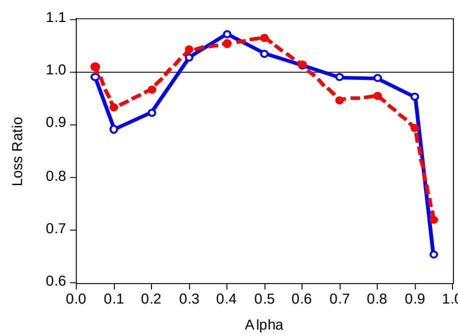
(h) Subsample 8



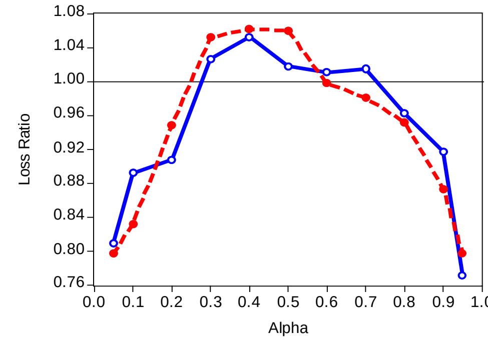
(i) Subsample 9



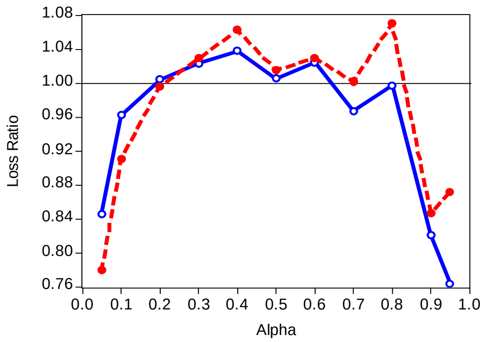
(j) Subsample 10



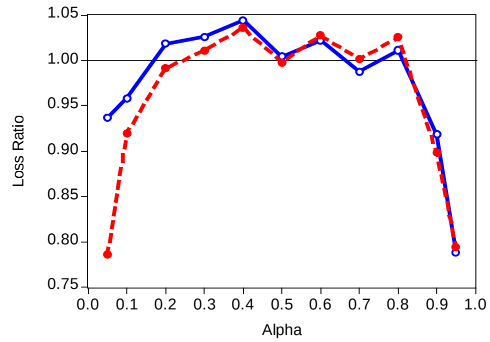
(k) Subsample 11



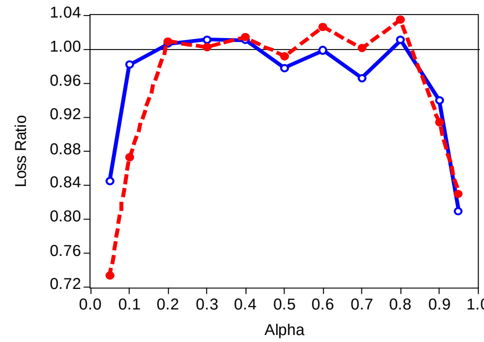
(l) Subsample 12



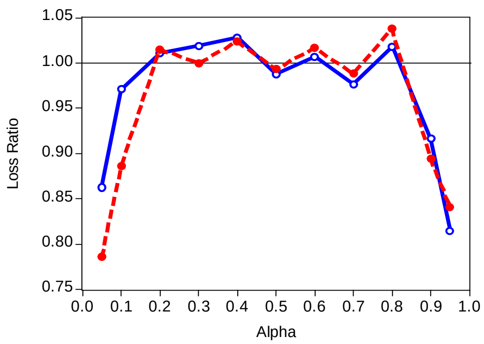
(m) Subsample 13



(n) Subsample 14



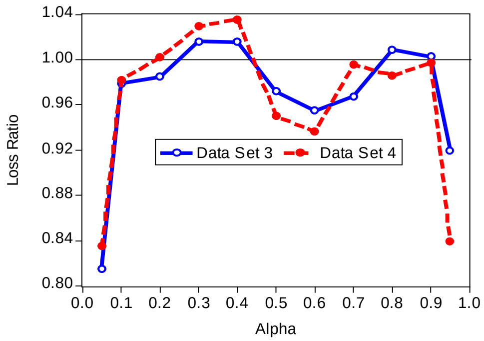
(o) Subsample 15



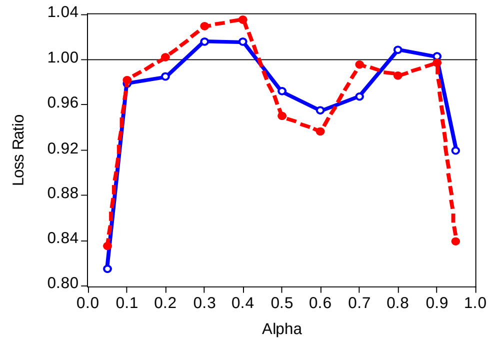
(p) Subsample 16

Note: Plotted are the ratios of the check loss of GCQ model (Model 2) to that of NGCQ model (Model 1) for different values of α. The ratio smaller than 1 indicates money-income Granger-causality in quantile. "GCQ" denotes Granger-causality in quantile and "NGCQ" denotes non-Granger-causality in quantile. Two lines denote the loss ratio for Data Set 1 (solid line, real personal income and M2) and Data Set 2 (dashed line, real personal income and M1).

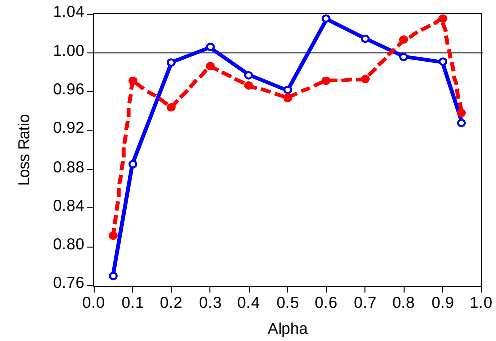
Figure 2. Loss Ratio for Data Set 3 and Data Set 4



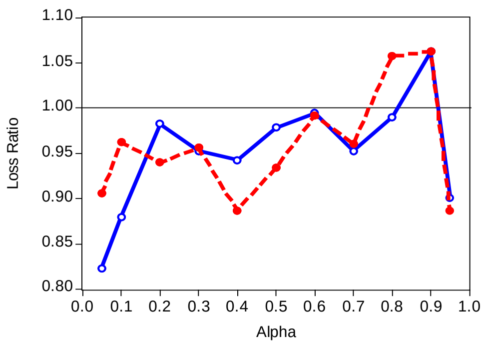
(a) Subsample 1



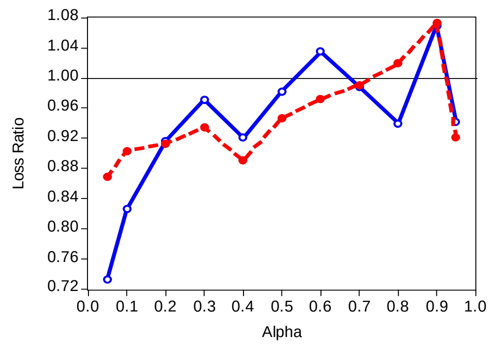
(b) Subsample 2



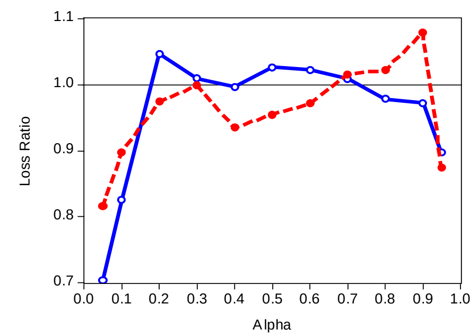
(c) Subsample 3



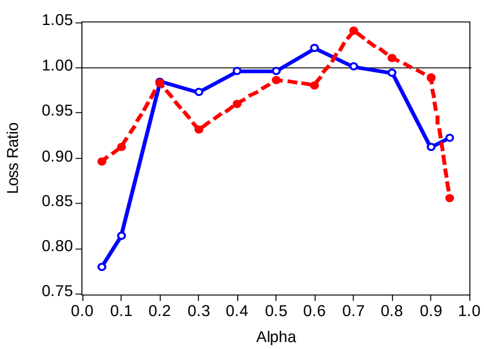
(d) Subsample 4



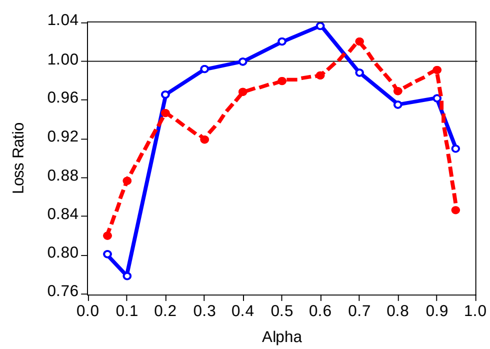
(e) Subsample 5



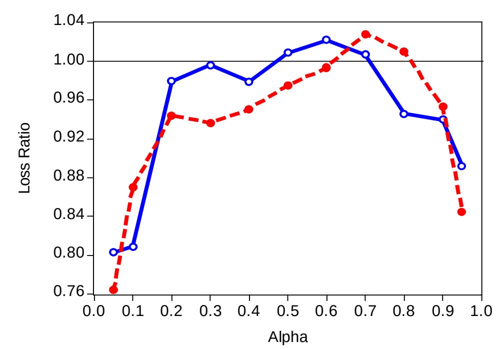
(f) Subsample 6



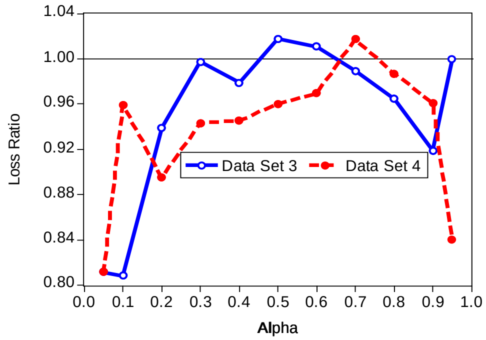
(g) Subsample 7



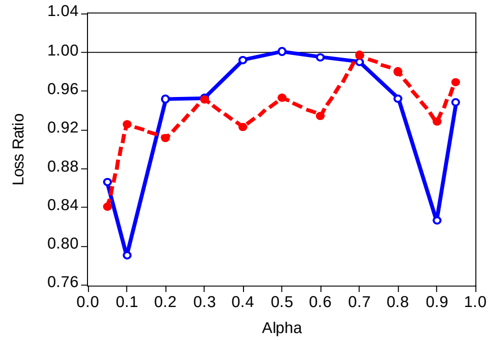
(h) Subsample 8



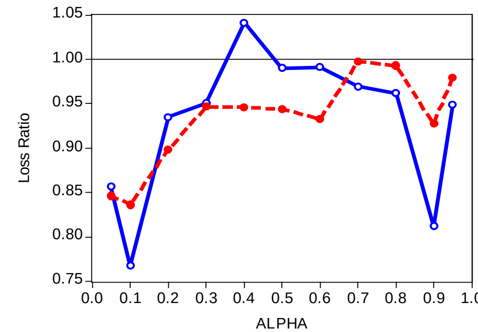
(i) Subsample 9



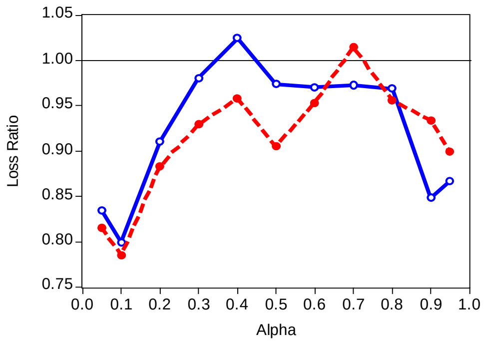
(j) Subsample 10



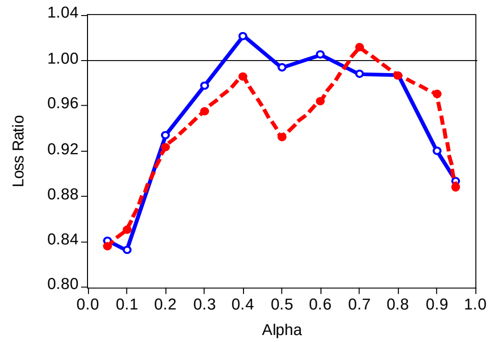
(k) Subsample 11



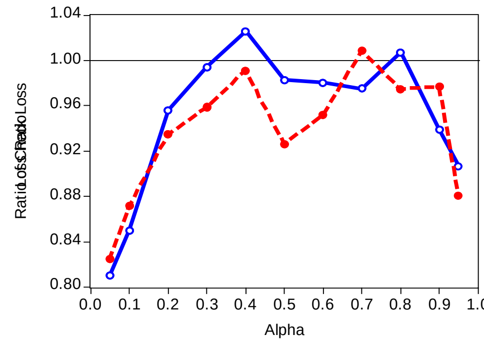
(l) Subsample 12



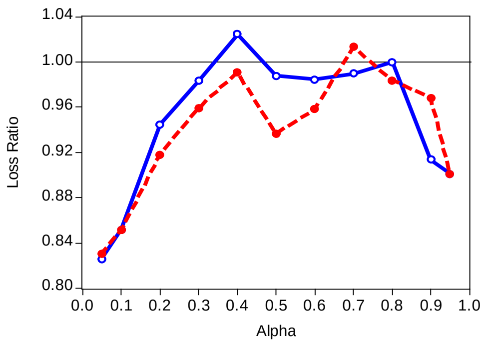
(m) Subsample 13



(n) Subsample 14



(o) Subsample 15



(p) Subsample 16

Note: Plotted are the ratios of the check loss of GCQ model (Model 2) to that of NGCQ model (Model 1) for different values of α. The ratio smaller than 1 indicates money-income Granger-causality in quantile. "GCQ" denotes Granger-causality in quantile and "NGCQ" denotes non-Granger-causality in quantile. Two lines denote the loss ratio for Data Set 3 (solid line, industrial production and M2) and Data Set 4 (dashed line, industrial production and M1).