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Monetary environments and stock returns revisited: A quantile regression approach

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HIGHLIGHTS

- We investigate the relationship between stock returns and monetary environments.
- We use quantile regression to investigate the relationship at the different quantiles.
- We find that monetary policy is effective only when the returns are high.
- The response of the stock markets to monetary policy is found to be asymmetric.

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ABSTRACT

We investigate the impact of monetary conditions on stock market returns at different points on the return distributions. Our results reveal no association between stock returns and monetary environments at the lower quantiles. At the upper quantiles, however, we find that expansive monetary conditions lead to significantly larger stock returns. The relationship between returns and monetary conditions at the upper quantiles is also found to be asymmetric, exhibiting a monotonic increase in responsiveness at successive quantiles.

1. Introduction

There is little doubt that actions by monetary authorities have a significant impact on asset prices. Expansionary monetary policy, for example, causes interest rates to fall, encouraging a rebalancing from risk-free investments to more risky assets such as stocks. Greater demand for stocks then brings about an increase in prices. Waud (1970) and Thorbecke (1997), among many others, offer an alternative explanation. Since stock prices equal the expected present values of future net cash flows, monetary easing increases future cash flows, decreases the discount rates, or both, causing prices to rise. For these reasons, financial market participants closely monitor and anticipate how central banks react to economic shocks.

A number of studies exploring the relationship between stock returns and monetary environments suggest that stock returns rise (fall) following monetary easing (tightening). An early work by Waud (1970) shows that discount rate changes and stock returns are negatively related. Subsequent works by Jensen and Johnson (1995), Jensen et al. (1996), Thorbecke (1997) and Conover et al. (1999) all agree that stock returns are significantly higher under expansive monetary environments than are returns under restrictive policy periods. More recently, Ehrmann and Fratzscher (2004) find that an unexpected tightening of 50 basis points is estimated to decrease the US equity returns by about 3% on the day of the monetary policy announcement. Furthermore, using a VAR approach, Bernanke and Kuttner (2005) report a 1-day gain of roughly 1% in the CRSP value-weighted index following a hypothetical unanticipated 25-basis-point easing.

Motivated by previous studies, we revisit the subject by employing quantile regression to examine how monetary policy conditions affect the different quantiles of stock returns. Our results show no association between stock returns and monetary environments at the lower quantiles of the stock return distributions.

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At the upper quantiles, however, the relationship is found to be statistically significant and asymmetric. The results from the tests of equality of slope parameters, proposed by Koenker and Bassett (1982), confirm that the slope parameters at the upper quantiles are not equal to the slope parameters at the lower quantiles.

The rest of the paper is organised as follows: in the next section, we describe the data. Section 3 briefly explains the methodology. The estimation results are discussed in Section 4. And finally, Section 5 concludes the paper.

2. Data

Our dataset consists of monthly time series of the effective federal funds rate and returns on four US stock market indices: the Dow Jones Industrial Average (DJIA), the Morgan Stanley Country Index for the US (MSCI), the NASDAQ composite (NASDAQ) and the S&P 500 composite (S&P500). All the series were downloaded from Datastream. For each of the stock market indices, the first observations are: January 1964 (DJIA), January 1970 (MSCI), February 1971 (NASDAQ) and January 1964 (S&P500). The last observations for all the series in the dataset are July 2013. We calculate returns on the stock markets as percentage changes in the respective indices.

To determine whether the monetary environment is expansive or restrictive, we focus on the most recent change in the effective federal funds rate. Unless the interest rate is changed in the opposite direction, the monetary environment classification remains the same. For example, the monetary environment is classified as expansive in the period immediately following an interest rate decrease, after which the classification remains unchanged even there is a further cut in the interest rate in the subsequent period. Similarly, an episode of restrictive monetary environment begins when the interest rate first increases and ends when the direction of the interest rate change is reversed. This approach is adopted by Jensen and Johnson (1995), Jensen et al. (1996) and Conover et al. (1999). Furthermore, consistent with Waud (1970), Jensen et al. (1996) and Conover et al. (1999), observations that include the first month of monetary policy reversal are discarded from the data.

3. Methodology

In this section, we briefly explain the quantile regression method. Consider the following conditional quantile function:

$$q_\tau\left(R_t|M_t\right) = \alpha_\tau + \beta_\tau M_t \quad (1)$$

where $\tau \in (0, 1)$, R_t is the monthly stock return and M_t is the dummy variable equal to one if the monetary environment is expansive and zero if the monetary environment is restrictive. It is worth noting that Eq. (1) is also adopted by Conover et al. (1999) but is estimated using OLS in their paper. The estimates of α_τ and β_τ in Eq. (1) are defined as the solutions to:

$$\min_{\alpha_\tau,\beta_\tau} \sum_{t=1}^{T} \rho_\tau\left(R_t - \alpha_\tau - \beta_\tau M_t\right) \quad (2)$$

where $\rho_\tau(z)$ is the check function given by $\rho_\tau(z) = z\left(\tau - \mathbf{1}_{[z\leq 0]}\right)$, where $\mathbf{1}_{[z\leq 0]}$ is the indicator function taking only two values: 1 if $z \leq 0$ and 0 otherwise. As explained in Koenker and Hallock (2001), the function $\rho_\tau(z)$ imposes different weights on positive and negative residuals depending on the value of τ; when $\tau = 0.5$, this is the median estimator.

4. Results and discussions

We first describe the distributions of the stock returns. The mean monthly returns (standard deviations) for the four stock indices are: 0.630 (4.226) for DJIA, 0.635 (4.486) for MSCI, 0.894 (6.141) for NASDAQ and 0.616 (4.344) for S&P500. Except for MSCI, the mean monthly returns for the other three stock indices are in line with the value of 0.640 reported in Conover et al. (1999). The third and fourth moments show that the distributions are negatively skewed and leptokurtic. The Jarque–Bera statistics confirm that none of the indices follow the normal distribution. Moreover, at the median the returns are all positive with values lying between 1.012 and 1.288; the returns at the 40th quantile and below are all negative.

Table 1
Quantile regression model specification test results.

τ	DJIA	MSCI	NASDAQ	S&P500
0.05	−0.974	−0.981	−0.819	−1.014
	(0.850)	(0.732)	(0.511)	(0.822)
0.1	−0.970	−0.977	−0.879	−1.001
	(0.471)	(0.649)	(0.361)	(0.862)
0.2	−0.962	−0.991	−0.878	−0.098
	(0.516)	(0.769)	(0.584)	(0.792)
0.3	−0.971	−0.985	−0.896	−0.984
	(0.764)	(0.441)	(0.749)	(0.885)
0.4	−0.960	−0.967	−0.875	−0.984
	(0.729)	(0.261)	(0.203)	(0.965)
0.5	−0.957	−0.981	−0.891	−0.976
	(0.657)	(0.922)	(0.807)	(0.962)
0.6	−0.968	−0.987	−0.891	−0.986
	(0.381)	(0.391)	(0.624)	(0.486)
0.7	−0.952	−0.968	−0.862	−0.977
	(0.281)	(0.974)	(0.494)	(0.566)
0.8	−0.968	−0.987	−0.890	−0.986
	(0.411)	(0.556)	(0.842)	(0.637)
0.9	−0.974	−0.996	−0.890	−0.969
	(0.912)	(0.682)	(0.509)	(0.614)
0.95	−0.976	−1.000	−0.933	−0.983
	(0.895)	(0.697)	(0.870)	(0.426)

The *p*-values are shown in parentheses.

Next, we perform a nonparametric heteroskedasticity-consistent model specification test, discussed in Racine (2006), on our baseline model in Eq. (1). As pointed out by Kim and White (2003), when the conditional quantile regression model is misspecified, confidence intervals and hypothesis tests based on the conventional covariance matrix are invalid. The nonparametric test of Racine (2006) is an extension of Zheng (1998)'s test and is appropriate for a model containing both discrete and continuous variables. We test the model in Eq. (1) at $\tau = 0.05, 0.1, 0.2, \ldots, 0.9, 0.95$, following Racine (2006)'s recommendation for testing for the correct specification for each quantile at which the model is estimated. We present the test statistics along with the bootstrapped standard errors in Table 1. According to the results, we cannot reject the null hypotheses of correct specification at the 10% significance level, indicating that Eq. (1) is correctly specified at all the quantiles under investigation.[1]

Setting $\tau = 0.05, 0.1, 0.2, \ldots, 0.9, 0.95$, we proceed to estimate Eq. (1) using quantile regression. Since our conditional quantile model is found to be correctly specified, we calculate the standard errors for the quantile regression estimators using the standard method described in Koenker and Bassett (1978). For the purpose of comparison, the model is also estimated using the ordinary least square (OLS) method. The estimation results are shown in Table 2.

[1] As a check for robustness, we also calculated the standard errors, assuming the normal distributions for the test statistics. The results obtained under the assumption of the normal distribution also fail to reject the null hypotheses of correct specification at the 10% significance level at all the quantiles.