Quantile regression analysis of dispersion of stock returns - evidence of herding?

Jani Saastamoinen
QUANTILE REGRESSION ANALYSIS OF DISPERSION OF STOCK RETURNS - EVIDENCE OF HERDING?

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Abstract

Numerous studies attempt to detect herding in stock markets by measuring dispersion of stock returns. In this literature, herding is defined as a decrease of dispersion of stock returns, or increase of dispersion at a less-than-proportional rate with the market return. There has been a special interest to look for the evidence of herding in the extreme tails of stock returns distribution. As a departure from the standard methodology that employs OLS and dummy variable models, we use quantile regression in our estimation. Our empirical data is from the large-capital companies in the Helsinki Stock Exchange. We find that dispersion increases in a less-than-proportional rate with the market return in the lower tail of stock return distribution. This might be the evidence of herding, but this is not the conclusive proof of herding. We also find that the rate of increase is nonlinearly increasing in the upper tail of stock return distribution. This implies that stock return dispersion increases more than CAPM suggests in the rising markets.

Keywords: behavioral finance, empirical finance, quantile regression, herd behavior.

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1. INTRODUCTION

A general belief is that herd behavior is prevalent in stock markets. However, very little evidence of herd behavior among investors exists. An increasing body of literature has been devoted to detect herding in stock markets by measuring dispersion of stock returns. In this literature, decreasing dispersion of stock returns or increase of dispersion at a less-than-proportional rate with the market return is interpreted as the evidence of herding (Chang et al. 2000, p. 1655).

The concept of herd behavior is simple. A rational agent maximizes utility (profit) conditional on a private information set. She can infer the private information of other agents by observing how they behave in the similar situation. Agent herds when she suppresses her own information in favor of the information she has learned from the others. This can lead to clustering of human behavior which has been observed in many fields of social sciences. For instance, the phenomena as diverse as fashion or revolutions can be explained by herd behavior (Bikchandani et. al 1992). In financial markets, herding could mean that investors buy or sell securities regardless of their underlying fundamentals, because some signals launch herd behavior. Herd behavior contradicts with rational asset pricing which accentuates the importance of equity fundamentals on stock pricing. Given their information, however, herding is not irrational per se because investors can profit from it.

In this paper, we study dispersion of stock returns in the Helsinki Stock Exchange (OMXH). Some characteristics of OMXH suggest that herding could take place there. Despite rapid growth in trading volumes and market capitalization during the past decade, OMXH cannot be characterized as being a particularly efficient market. Apart from Nokia and a handful of other large corporations, the publicly traded companies in OMXH are small in terms of market capitalization and number. Furthermore, trading suffers from low liquidity because a remote stock exchange does not garner as much attention from international investors or securities analysts as the major international stock markets. For these reasons, there could be room for informational asymmetries that trigger herd behavior in the stock exchange. However, detecting herding with the methods that are commonly used in the literature does not necessarily prove that investors herd. Herd behavior is one possible interpretation for the phenomenon, but the explanation could be, for example, correlated adjustment to new information (Bikchandani and Sharma 2001, p. 280).

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1 The merger between the stock exchange operators HEX (Finland) and OM Group (Sweden) spawned a new company OMX Group in 2003. OMXH will be used in reference to the Helsinki Stock Exchange.
We use daily returns from the large capital stocks listed in OMXH from July 2002 until May 2007. The conditional Capital Asset Pricing Model (CAPM) is used for rational asset pricing. This paper can be viewed as a continuation to the literature that attempts to disclose the evidence of herd behavior in financial markets by examining stock returns. Our study differs from the previous research by the choice of methodology. Instead of ordinary least squares (OLS) and dummy variable models that are prevalent in the literature, we build on Chang et al. (2000) and use quantile regression (QR) in our empirical analysis. We argue that QR is a valid alternative to the estimation of herding models such as Huang and Chirstie (1995) and Chang et al. (2000). Our findings include that dispersion increases in a less-than-proportional rate with the market return in the lower tail of stock return distribution, which might constitute the evidence of herding as defined in the literature. On the other hand, we find that the rate of increase is nonlinearly increasing in the upper tail of return distribution. The predictions of CAPM seem to hold in the middle of return distribution.

The paper proceeds in the following order. In the second section, we review the previous research. In the third section, we present the model that we use to measure dispersion of stock returns and conduct the econometric analysis. In the final section, we conclude and compare our results to the previous research.

2. LITERATURE REVIEW

The standard economic theory is based on the assumption that economic agents are rational. Rational agents maximize utility conditional on their information set. This assumption is also behind rational asset pricing models such as the Capital Asset Pricing Model (CAPM). A market is efficient when market prices reflect correctly all information that is available to market incumbents. Consequently, prices adjust to their fundamental values as investors receive new information on market fundamentals. This implies that there should be no erroneously priced securities in the market. Given that the access to the market information is (more or less) uniform, correlated movements in stock prices might be a rational response from the investors that share a similar information set to the new information, not the evidence of herding (Bikchandani and Sharma 2001, p. 280). Obviously some informational asymmetries persist. For example, company insiders are better informed on a firm’s financial condition than other investors.

It is not uncommon that market commentators explain stock price movements as a consequence of investor herd behavior. For example, influential investors or seasoned managers are reported to be
responsible for the appreciation of stock prices in the companies that they buy or are hired to manage (Hirshleifer and Teoh 2003, pp. 47-48). This endorsement effect is a type of informational herding. In informational herding, agents suppress their own information in favor of the information they infer from the behavior of other agents. Herding need not be irrational. It can be perfectly rational behavior because other investors may have better information on the investment decision (Bikchandani and Sharma 2001, p. 280). In its most general form, Devenow and Welch (1996) define herding as “behavior patterns that are correlated across individuals.” It can also be considered a form of social learning, although the amount of learning is small in a herd (Chamley 2004, p. 66).

Intuitively, herd behavior could be common in stock markets. Assume that there are two types of investors: professionals and non-professionals. Professionals are market analysts, professional traders and portfolio managers for institutional investors or mutual funds. Non-professionals are investors that invest their savings in securities for future consumption or with speculative motives. Both types could herd. For example, professional portfolio managers tend to follow the market consensus in their asset allocation to avoid underperforming their peers (Scharfstein and Stein 1990). This type of herding stems from the agent-principal problem (Devenow and Welch 1996, pp. 607-608). Moreover, equity analysts may herd by taking cues from each others’ recommendations which could mean that the market consensus is in fact biased (Trueman 1994, Welch 2000; Bernhardt et al. 2006 for a dissenting view). Non-professionals could herd because they are less informed on market conditions, such as macroeconomic trends, or how to value securities (Shiller 1984). Therefore, it is plausible that they base their investment decisions on the information that they, at least partially, deduce from other investors.

Although rational asset pricing requires new information for a change in the value of an asset, it is theoretically possible that asset prices fluctuate without new information (Romer 1993). Froot et al. (1992) show that under specific circumstances, investors may herd on the same information. Moreover, Avery and Zemsky (1998) introduce a model of short-lived herding by market participants. The “irrational exuberance” around the initial public offerings (IPOs) of technology companies in the late-90s could be an example of herd behavior described in Welch (1992). Bikchandani et al. (1998) note that despite rationality and independent payoffs, the decisions that agents make converge rapidly, but they are idiosyncratic and fragile. For this reason, financial

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2 One can hardly find a more fitting phrase than “irrational exuberance” to describe herding in stock markets. See Robert Shiller’s definition and origins of the term in http://irrationalexuberance.com/definition.htm.
frenzies and panics could be triggered by simple observational learning mechanisms. According to Devenow and Welch (1996), three observed regularities in financial markets could result from herding. First, mergers and IPOs display waves. Second, the market consensus seems to be low and not based on private information. Third, influential market participants admit that other investors influence their investment decisions.

Various factors could lead to herding in financial markets. Hwang and Salmon (2004) discuss the possibility that macroeconomic signals lead investors to believe that the market is “easy to forecast”. The market returns to the CAPM equilibrium, when an unexpected shock alters the investors’ information set. Gleason et al. (2004) believe that investors also seek comfort from public opinion during the periods of market stress. In this case, herding could be a cost efficient way to obtain information on the direction that the market is heading. Wermers (1999) offers some support to this view by showing that the stocks that are bought by herds outperform other equities. He also finds that small-capital stocks and growth-oriented mutual funds tend to herd more. This could result from informational costs that may arise on the uncertainty over the growth prospects of an individual firm or industrial sector. As regards the informational asymmetry and uncertainty, especially stock markets in emerging economies have been suspect to display herd behavior. According to Bikchandani and Sharma (2001), this is due to informational asymmetries, liquidity constraints and institutional factors such as government intervention and poor accounting legislation.

Recently, there has been much interest to find the empirical evidence of herding in stock markets with econometric methods. The pioneering study in this field is Christie and Huang (1995) (referred to as CH henceforth). They present a methodology that is based on the cross-sectional standard deviation (CSSD) to detect herding during periods of market stress. CSSD is defined as

$$CSSD_i = \sqrt{\frac{\sum_{j=1}^{n}(r_{ij} - \bar{r}_i)^2}{n-1}},$$

(1)

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3 Market stress is defined as a period of large stock price movements which usually corresponds with extreme market returns. 1% and 5% tails of stock returns distribution are commonly used thresholds for market stress in the literature.
where \( r_{i,t} \) is the return from a security \( i \) and \( \bar{r}_t \) is the average return from \( n \) securities. CH also present a model that is based on the cross-sectional absolute deviation (CSAD) to alleviate problems with outliers. The measure for CSAD is

\[
CSAD_t = \frac{1}{n} \sum_{i=1}^{n} |r_{i,t} - \bar{r}_t|.
\]  

(2)

CH estimate a market stress model

\[
CSSD_t = \alpha + \gamma_1 D^U_t + \gamma_2 D^L_t + \varepsilon_t .
\]  

(3)

The dummy variables \( D^U_t, D^L_t \) take the value of unity, if stock returns lie in the upper (U) or lower (L) tail of stock returns distribution, and zero otherwise. If stock returns approach the market rate of return, their returns become more correlated, which is interpreted as the evidence of herding\(^4\). With this method, however, CH fail to detect the evidence of herding in the major US stock exchanges.

Chang et al. (2000) (referred to as CCK henceforth) propose an alternative method to detect herding. They write an expected CSAD in period \( t \) as

\[
ECSAD_t = \frac{1}{n} \sum_{i=1}^{n} [\beta_i - \beta_m] E[r_m - r_i].
\]  

(4)

where \( \beta_i, \beta_m \) are the time-invariant beta coefficients for a security \( i \) and the market respectively and \( r_m \) is the market rate of return. If \( \bar{r}_t = r_m \), equations (2) and (4) are equivalent. CCK show that equity return dispersion is a \textit{linear} and increasing function of the market return, because

\[
\frac{\partial ECSAD_t}{\partial E[r_m]} = \frac{1}{n} \sum_{i=1}^{n} |\beta_i - \beta_m| > 0
\]

\[
\frac{\partial^2 ECSAD_t}{\partial E[r_m]^2} = 0.
\]  

(5)

\(^4\) We report the statistically significant findings in the literature review as herding.
CCK argue that if herding takes place, then dispersion of returns increases at a less-than proportional-rate with the market return or the rate could even be decreasing. For this reason, they estimate a nonlinear model

\[ CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t, \]  

where a negative and statistically significant \( \gamma_2 \) could indicate the presence of herd behavior. Compared to CH, CCK argue that this model requires less non-linearity in the return dispersion to detect herding, which is consistent with rational asset pricing models. They also show that both model lead to similar conclusions. CCK test their model in the stock markets of the US, Japan, Hong Kong, South-Korea and Taiwan. They find \( \gamma_2 \) is negative and statistically significant in Taiwan and South-Korea, whereas the coefficient is statistically insignificant in the US, Japan and Hong Kong.

The subsequent research has applied in most cases the methods of CH and CCK with minor modifications and conflicting results. Tan (2005) augments the method of CCK with rolling beta-coefficient estimates. She contends that this is more convenient approach in the dynamics of extreme price movements. Her evidence suggests that herding exists in the Chinese A-share markets, where domestic investors are allowed to trade. In contrast, she reports that no herding takes place in the Chinese B-share markets, where international investors trade. In a further investigation into the Chinese stock markets, Tan et al. (2008) detect herding prevalent in the both A- and B-shares market. These findings contradict with Demirer and Kutan (2006), who also examine herding in the Chinese stock markets. They find no evidence of market-wide or sectoral herding. Different lengths in data sets could explain these mutually contradictory results.

Mixed evidence of herding is present in other markets as well. Henker et al. (2006) do not detect herding in the Australian stock market. Cajueiro and Tabak (2007) inspect the Japanese stock market, where they report herding behavior only in the extreme down markets. Chiang and Zheng (2008) disclose the evidence of herding in the US, Japan, Hong Kong, Germany and the UK stock markets. Gleason et al. (2004) focus on intraday herding of sector ETFs in the US. They find no evidence of herding, but note that there is asymmetry in the increase of dispersion between the rising and falling markets. The rate of increase is lower in the falling markets, which they interpret as weak evidence of “myopic loss aversion”.


As a departure from the methodology of CH and CCK, Hwang and Salmon (2004) develop a model of “beta herding” that tests the herding hypothesis against the CAPM equilibrium. They argue that their measure for herding is an improvement over CH and CCK, because it conditions herding on fundamentals. As the proof, they report the evidence of herding in the US and South Korean stock markets during “regular” market conditions. Interestingly, their results indicate that periods of market stress cause stock valuations to return back to fundamental valuations as predicted by the CAPM equilibrium. Thus, concentrating the detection efforts to periods of the extreme price movements may be misplaced because they report adverse herding taking place in the stressed markets. Hwang & Salmon (2006) present a nonparametric version of the beta herding measure. Using this measure, they report similar findings in the US, UK and South Korean stock markets as in Hwang and Salmon (2004).

While these results are interesting, the major shortcoming in these models is that they cannot verify explicitly that a causal relation between investors’ herd behavior and the observed decreases or nonlinearities in equity returns dispersions exists. Herding in CH’s market stress model could also result from changes in the time-series volatility or independent adjustment to fundamentals (Hwang and Salmon 2004, p. 588). Devenow and Welch (1996) note that correlated arrival of information to independently acting investors could be mistaken for herding. CCK point out that an alternative to the herding hypothesis could be the presence of a non-linear market model. Hirshleifer and Teoh (2003) argue that herd behavior could result from a combination of preference, reputational and informational effects, direct payoff interactions and imperfect rationality. As a result, decreasing dispersion or nonlinearities in returns cannot be considered the conclusive evidence of herd behavior.

3. ECONOMETRIC ANALYSIS

3.1 Data and Methodology

Our data consists of daily closing price quotes for the large-capital companies in the OMXH. In addition to the stock price data, we use daily closing prices for the general OMXH stock price index (OMXHPI) to approximate the returns from an equal-weighted market portfolio. Daily quotes of the one-month Euribor interest rate are used as a proxy for the risk-free asset. A short-term interest rate is used to eliminate temporal risks that arise from the long-term bond market investments. The unit root tests indicate that each variable has a stationary time-series (see table A1 in Appendix).
Altogether, the data consists of 32 companies with approximately 250 price quotes per company in a year during the observation period from June 28th 2002 until May 31st 2007. This amounts to roughly 1200 observations during the entire observation period. The beginning of the observation period is generally considered the time when the bear market, which began along the burst of the stock market bubble in 2000, bottomed out and the bull market began. As a result, the data is characterized by the change in the general market sentiment. This could be due to some new information or macro-economic shock that changed the expectations on stock returns. For example, the major central banks kept interest rates at the historically low levels at the time. This could be a fertile economic climate for herd formation (Hwang and Salmon 2004, p.590).

In spirit of the sector analysis of Demirer and Kutan (2006), we are interested in the group of stocks, namely the large-capital stocks (large-cap). These are the most actively traded companies in OMXH. By definition, a firm is a large-cap when its market capitalization exceeds 1 billion (1 000 000 000) euros\(^5\). We concentrate on them because they are more liquid than small-capital (small-cap) or mid-capital companies (mid-cap) and have accurate daily trading data available. Some small-caps, for instance, are not traded for weeks. In addition, the large-caps have more diverse ownership base, and they garner more interest from foreign and domestic securities analysts. For these reasons, herding is less likely among the large-caps than among the mid-caps or small-caps. For simplicity, we consider a company to be a large-cap from the beginning of the year during which its annual financial results indicate that its market capitalization exceeds 1 billion euros. There are also two cases where divestment has significantly altered the company’s market value. In these cases, the values for analysis have been calculated for the parent company and its spin-off from the date of the divestment.

We use CAPM to model rational asset pricing. CAPM incorporates information on returns from a risk-free asset and a market portfolio to give a measure of systematic risk for an individual stock. CAPM states that the return for a stock \(i\) in period is

\[
r_{i,t} = r_{f,t} + \beta_i E_i [(r_{m,t} - r_{f,t})],
\]

\[(7)\]
where $\beta_i$ is the beta-coefficient which measures an equity $i$’s sensitivity to the movements of the market$^6$. In general, $\beta_i$ is calculated by using daily, weekly or monthly data on returns ranging from 26 weeks to several years. Since the frequency or time span of the data that is used in calculations is not standard, the value of $\beta_i$ for the same stock shows variation depending on the calculation method. We use daily returns $r_{ij}$ from July 1$^{st}$ 2002 to May 31$^{st}$ 2007 in the estimates for $\hat{\beta}_i$.$^7$ The returns from the market portfolio $r_{m,t}$ are approximated by OMXHPI data from the same period. Returns from the one-month Euribor interest rate serve as a proxy for the risk-free rate of return $r_{f,t}$.

Equation (7) implies that $\beta_i$ remains constant over time. In financial literature, the assumption that the beta-coefficient is time-invariant has met criticism (for example, see Blume (1975), Fabozzi & Francis (1978)). Hwang & Salmon (2004) argue that betas could become biased because of herding. They suggest that investors may change their beliefs about the performance of individual stocks which leads to convergence in betas. In practice, investors could expect that stock returns match the market returns. As a consequence, the stocks that outperform the market will be sold because they are expected to be over-valued, whereas the stocks that under-perform are being bought because they seem under-valued. For this reason, we follow Tan (2005) and use the rolling beta, which is denoted by $\beta_{i,t}$, to take into account variation in the beta coefficient over time. An estimate for $\hat{\beta}_{i,t}$ is calculated by using daily returns from the previous 26 weeks. The rolling beta is obtained by deleting the oldest observation and adding a new observation and then estimating $\hat{\beta}_{i,t}$.

Given rational expectations, the actual value of $E[CSAD]$ is equation (4) and an error term $\varepsilon_t \sim N(0,\sigma^2)$. Thus, $CSAD$ (with the rolling beta) becomes

$$CSAD_t = \sum_{i=1}^{n} \frac{1}{n} |\hat{\beta}_{i,t} - 1| E_t [(r_{m,t} - r_{f,t})] + \varepsilon_t$$

(8)

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$^6$ See Appendix, Equations (A1)-(A2).

$^7$ A shorter period is used, if a firm has not been listed in the stock exchange throughout the observation period.

$^8$ See Appendix, Equations (A3) – (A5).
To test whether herding as defined by CCK exist, we estimate the following equation with quantile regression (QR)

\[ CSAD_t = \alpha + \eta_1 r_{m,t} + \eta_2 r_{m,t}^2 + \varepsilon_t, \]  

(9)

Unlike CCK, we do not use absolute values for \( r_{m,t} \), because QR enables the examination of effects in different points of market return distribution. If \( \gamma_2 \) is negative and statistically significant, it indicates that investors herd around the market rate of return. In other words, dispersion of returns decreases or increases at a decreasing rate and approaches the market rate of return, which could be an indicator of herd behavior.

### 3.2 Quantile Regression Approach

While the researchers following CH have employed OLS with dummy variables, there are good reasons to opt for quantile regression (QR) in attempts to detect herding in equity markets. First, financial data usually does not pass the test of normality. QR is a semiparametric alternative to OLS. Compared to OLS, QR may be a more efficient estimation method when the distribution of errors is non-normal (Barnes & Hughes 2002, p. 5). Second, since the market stress models are prevalent in the empirical financial herding literature, QR is a versatile tool in analyzing extreme quantiles of return distribution. However, Hwang and Salmon (2004) warn that researchers may not detect herding because they observe only the extreme tails of return distribution. Moreover, they argue rightfully that the definition of market stress is subjective. QR solves these problems because it provides a method to estimate the effects on the dependent variable over the entire distribution. As the third argument, CH note that the method based on CSSD is sensitive to outliers. Since QR is robust to the presence of outliers, they will not pose a severe threat to the reliability of results (Koenker & Hallock 2001, p. 17).

QR can be used to obtain estimates for herding in the tails of market return distribution\(^9\). Therefore, we can test the impact of market stress, but do not require as high level of nonlinearity for detection as in CH (see CCK, pp. 1657-1658). By setting \( \tau = 0.05 \) or \( \tau = 0.01 \), we obtain quantile estimates for the extremely low returns. Similarly, setting \( \tau = 0.95 \) or \( \tau = 0.99 \) produces quantile estimates for the extremely high returns. The regression equation is

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\(^9\) See Quantile Regression in Appendix.
\[ CSAD_t(\tau|\chi) = \alpha + \eta_1 r_{m,t}(\tau) + \eta_2 (r_{m,t}(\tau))^2 + \epsilon_t. \] (10)

As an alternative to OLS estimates, we run median regression on equation (10). The results for median regression \((CSAD(0.5))\) are presented in Table 1. Since \(\eta_1 (0.535)\) is positive and statistically significant and \(\eta_2 (0.023)\) is positive and statistically insignificant, there is a positive and linear relationship between CSAD and \(r_{m,t}\). This indicates that on a median trading day stock pricing is rational.

Next, we examine market stress by inspecting extreme quantiles of return distribution as an alternative to the market stress models. The results are reported also in Table 1. As CH, we use the arbitrary 1% and 5% thresholds for market stress. Setting \(\tau = 0.01\) corresponds to the 1% lower tail of stock return distribution (extremely low returns) and \(\tau = 0.05\) corresponds to the 5% lower tail. Regression yields positive and statistically significant \(\eta_1 (0.521)\) and negative and statistically significant \(\eta_2 (-10.805)\) for \(CSAD(0.01)\). For the 5% threshold, which corresponds to \(CSAD(0.05)\), we obtain \(\eta_1 (0.513)\) and \(\eta_2 (-8.590)\), which are both statistically significant with comparable magnitude. These results indicate that there is a decreasing rate in the increase of dispersion because the nonlinear term is negative and statistically significant. As a result, the linear relation between increase in dispersion and the market returns disappears during stock sell-offs, which contradicts with the predictions of CAPM.

Extremely high returns are located in the upper tail of return distribution. Setting \(\tau = 0.95\) and \(\tau = 0.99\) correspond to the 5% and 1% of the extremely high returns, respectively. The results can be found in Table 1. For \(CSAD(0.99)\), both \(\eta_1 (0.525)\) and \(\eta_2 (7.783)\) are positive and statistically significant. The same conclusion applies to \(CSAD(0.95)\), for which the coefficients \(\eta_1 (0.515)\) and \(\eta_2 (7.180)\) are positive and statistically significant. This implies that dispersion increases with an increasing rate in the upper tail of stock returns distribution. This indicates that investors place more emphasis on the equity fundamentals than CAPM suggests, when the market posts extremely high returns. Consequently, investors do not herd.
Table 1 Results for median regression and quantile regression for the market stress model.

<table>
<thead>
<tr>
<th>CSAD(τ)</th>
<th>α</th>
<th>η₁</th>
<th>η₂</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSAD(0.5)</td>
<td>-0.000</td>
<td>0.535</td>
<td>0.023</td>
<td>0.794</td>
</tr>
<tr>
<td></td>
<td>(-1.79*)</td>
<td></td>
<td>(0.13)</td>
<td></td>
</tr>
<tr>
<td>CSAD(0.95)</td>
<td>0.001</td>
<td>0.515</td>
<td>7.180</td>
<td>0.818</td>
</tr>
<tr>
<td></td>
<td>(5.75***)</td>
<td></td>
<td>(3.62***)</td>
<td></td>
</tr>
<tr>
<td>CSAD(0.05)</td>
<td>-0.001</td>
<td>0.513</td>
<td>-8.590</td>
<td>0.838</td>
</tr>
<tr>
<td></td>
<td>(-4.90***)</td>
<td></td>
<td>(3.53***)</td>
<td></td>
</tr>
<tr>
<td>CSAD(0.99)</td>
<td>0.002</td>
<td>0.525</td>
<td>7.783</td>
<td>0.872</td>
</tr>
<tr>
<td></td>
<td>(6.84***)</td>
<td></td>
<td>(4.51***)</td>
<td></td>
</tr>
<tr>
<td>CSAD(0.01)</td>
<td>-0.001</td>
<td>0.521</td>
<td>-10.805</td>
<td>0.897</td>
</tr>
<tr>
<td></td>
<td>(-5.94***)</td>
<td></td>
<td>(4.50***)</td>
<td></td>
</tr>
</tbody>
</table>

The results for quantile regression on $CSAD_{\tau}(\tau | x) = \alpha + \eta_1 r_{m,t}(\tau) + \eta_2 [r_{m,t}(\tau)]^2 + \epsilon$, with varying values for $\tau$. T-statistics are reported in parentheses. * indicates a 10% significance level; ** indicates a 5% significance level; *** indicates a 1% significance level.

Examining quantile process provides a more robust view on the effects at different quantiles. A visual representation of the estimates with the 95% confidence interval is presented in Figure 1 and the exact coefficients are reported in table A2 in Appendix. Using different values of $\tau$, $\eta_1$ remains positive and statistically significant. This shows that the relation between $r_{m,t}$ and CSAD remains positive all over distribution. More interesting is the graph for $r_{m,t}^2$. It clearly shows how the rate of increase of dispersion is decreasing in the lower tail, flat in the middle as rational asset pricing suggests, and increasing in the upper tail of distribution. In fact, $\eta_2$ remains negative and statistically significant up to the first quartile (25%). After this, it is statistically insignificant when $\tau \in (0.25,0.70)$ with the sign switching from negative to positive at the median. Finally, the coefficient becomes positive and statistically significant in the upper tail of distribution. These results indicate that equity return dispersion increases at a decreasing rate in the bearish market, which defies rational asset pricing. This might constitute the evidence of herding, but the conclusion cannot be validated with this data. Equity return dispersion behaves as predicted when returns are within the “normal” range. When the market turns bullish, the rate of equity return dispersion increases nonlinearly. This implies that investors could place more emphasis on equity fundamentals when the market is rising notably.
Figure 1. Quantile Process.
4. DISCUSSION

The main contribution of this paper is the application of quantile regression to the analysis of dispersion of stock returns. QR is a suitable tool to analyze dispersion of returns in the extreme tails of stock returns distribution. We use methodology of Chang et al. (2000) to detect a decrease or less-than-proportionate increase in dispersion of stock returns. Our empirical analysis focuses on the large-capital companies in OMXH. We find that dispersion does not decrease on an average trading day. In this respect, asset pricing is rational and investors do not herd.

Testing market stress with QR yields different results. We find that the coefficient for the nonlinear term, which that measures the rate of increase, is negative and significant in the lower tail (5% or 1%) of stock returns distribution. This contradicts with CAPM. On the other hand, the coefficient is positive and statistically significant in the upper tail (95% and 99%). This indicates a nonlinear increase in dispersion. These results compare especially well with Cajueiro and Tabak (2007) who also find decreasing dispersion in the bottom tail of stock returns distribution. The results from quantile process indicate statistically significant negative coefficient up to the first quartile (25%) of stock returns distribution. After this, the coefficient remains negative but statistically insignificant almost up to the median. A possible explanation for this could be that stock sell-offs disturb the information set of investors, who then cut their losses or consolidate earnings by selling when other investors sell too. One cause for this finding could be the observation period, which coincides with an economic expansion and a bull market. As the stock market is effectively forecasting future earnings, the fear that the business cycle is turning into a downward trend might spark sell-offs. Overall, this might constitute the evidence of herding. However, this is just speculation because there is no control device that would implicate herding as the causal factor.

As a future direction for research, it would be worthwhile to include all stocks listed in OMXH in the analysis. It is possible that the deviations from CAPM in the increase of dispersion might be more prominent among the smaller companies because informational asymmetries could be starker than among the larger companies (Gleason et al. 2004, p. 692). Moreover, including trading volumes into the analysis might give different results as well as increasing the length of the dataset. Thus, our results should be interpreted cautiously – even if one accepts the premise that these methods disclose herd behavior - as their robustness remains to be tested. In a broader perspective, QR should be applied in other stock markets as well to improve the view that the market stress and non-linear herding models have provided in the previous research.
REFERENCES


**APPENDIX**

**Measure for Stock Return Dispersion**

The rate of return $r_i$ is calculated from stock prices (or stock indices) with

$$r_i = \frac{p_t - p_{t-1}}{p_{t-1}}, \quad \text{(A1)}$$

where $p_t$ indicates the value (price) of a security in period $t$.

The basic formula to calculate $\beta_i$ is

$$\hat{\beta}_i = \frac{\text{cov}(r_{i,t}, r_{m,t})}{\text{var}(r_{m,t})}. \quad \text{(A2)}$$

The method to measure herding is essentially the same as in Chang (2000) and Tan (2005). First, we calculate the absolute value of deviation of excess return (AVD) for each stock $i$ in period $t$. This is

$$AVD_{i,t} = |\hat{\beta}_{i,t} - \beta_{m,t}| E_{i}[(r_{m,t} - r_{f,t})]. \quad \text{(A3)}$$

Since we know that $\beta_{f,m} = 1$ always, equation (A3) can be expressed as

$$AVD_{i,t} = |\hat{\beta}_{i,t}| E_{i}[(r_{m,t} - r_{f,t})]. \quad \text{(A4)}$$

---

Next, we need a measure for the expected cross-sectional average deviation (CSAD) for \( n \) stocks. We obtain this from

\[
E[CSAD_t] = \frac{1}{n} \sum_{i=1}^{n} AVD_{i,t} = \frac{1}{n} \sum_{i=1}^{n} \left| \hat{\beta}_{i,t} - \mu_i \right| = \mu_i [ (r_{m,t} - r_{f,t}) ] .
\]  

(A5)

**Quantile Regression**

A simple way to understand QR is to draw an analogue from least squares regression (Koenker 2005). OLS solves the minimization problem

\[
\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 .
\]  

(A6)

In a similar manner, \( Q_\tau (\tau | x) = x^T \beta \) specifies the \( \tau \)th conditional function, and \( \hat{\beta}(\tau) \) solves the minimization problem

\[
\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta) .
\]  

(A7)

An estimator \( \hat{\beta}(\tau) \) can be found by solving

\[
\hat{\beta}_\tau = \arg \min_{\beta} \left( \sum_{i:y_i > x_i^T \beta} \tau | y_i - x_i^T \beta | + \sum_{i:y_i < x_i^T \beta} (1-\tau) | y_i - x_i^T \beta | \right).
\]  

(A8)

Thus, QR minimizes a weighted sum of the absolute errors. Choosing a value \( \tau \in (0,1) \) gives the appropriate weights for the minimization problem. Setting \( \tau = 0.5 \) yields median regression as a special case of QR. By asymptotic normality, coefficients can be compared to the critical values of t-statistics.

**Table A1: Advanced Dickey-Fuller Test for Unit Root.**

<table>
<thead>
<tr>
<th>Test</th>
<th>CSAD</th>
<th>( r_m )</th>
<th>( r_m^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF</td>
<td>-14.86*</td>
<td>-15.22*</td>
<td>-12.72*</td>
</tr>
</tbody>
</table>

The Advanced Dickey-Fuller test for each time series. * indicates a 1% significance level for rejecting a unit root.
Table A2: Quantile Process Coefficients.

<table>
<thead>
<tr>
<th>QUANTILE</th>
<th>$\alpha$</th>
<th>$\eta_1$</th>
<th>$\eta_2$</th>
</tr>
</thead>
<tbody>
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<td>-0.001209</td>
<td>0.513173</td>
<td>-8.589747</td>
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<tr>
<td></td>
<td>(-4.90***)</td>
<td>(74.26***)</td>
<td>(-3.53***)</td>
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<td>0.100</td>
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<td>0.498159</td>
<td>-6.295085</td>
</tr>
<tr>
<td></td>
<td>(-9.07***)</td>
<td>(50.00***)</td>
<td>(-7.08***)</td>
</tr>
<tr>
<td>0.150</td>
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<td>0.513989</td>
<td>-4.800845</td>
</tr>
<tr>
<td></td>
<td>(-9.12***)</td>
<td>(27.32***)</td>
<td>(-3.97***)</td>
</tr>
<tr>
<td>0.200</td>
<td>-0.000568</td>
<td>0.494383</td>
<td>-2.899906</td>
</tr>
<tr>
<td></td>
<td>(-5.86***)</td>
<td>(52.80***)</td>
<td>(-2.39** )</td>
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<tr>
<td>0.250</td>
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<td>-1.737380</td>
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<tr>
<td></td>
<td>(-8.25***)</td>
<td>(45.08***)</td>
<td>(-11.22***)</td>
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<tr>
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<td>0.533878</td>
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</tr>
<tr>
<td></td>
<td>(-5.03***)</td>
<td>(58.11***)</td>
<td>(-1.18)</td>
</tr>
<tr>
<td>0.350</td>
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<tr>
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<td>(-5.84***)</td>
<td>(83.40***)</td>
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<tr>
<td>0.400</td>
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<tr>
<td></td>
<td>(-5.21***)</td>
<td>(121.36***)</td>
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<tr>
<td>0.450</td>
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<tr>
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<td></td>
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<td>(140.25***)</td>
<td>(0.89)</td>
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<tr>
<td>0.650</td>
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<td>0.409111</td>
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<td></td>
<td>(3.30***)</td>
<td>(125.58***)</td>
<td>(1.17)</td>
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<tr>
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<td>0.603955</td>
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<tr>
<td></td>
<td>(5.36***)</td>
<td>(153.63***)</td>
<td>(2.07**)</td>
</tr>
<tr>
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<td>0.000255</td>
<td>0.539819</td>
<td>0.766309</td>
</tr>
<tr>
<td></td>
<td>(5.22***)</td>
<td>(116.35***)</td>
<td>(1.66*)</td>
</tr>
<tr>
<td>0.800</td>
<td>0.000434</td>
<td>0.528863</td>
<td>1.412366</td>
</tr>
<tr>
<td></td>
<td>(5.29***)</td>
<td>(37.16***)</td>
<td>(1.27)</td>
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<tr>
<td>0.850</td>
<td>0.000748</td>
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<td>(17.16***)</td>
<td>(4.80***)</td>
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<tr>
<td></td>
<td>(8.01***)</td>
<td>(52.97***)</td>
<td>(4.62***)</td>
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<tr>
<td></td>
<td>(5.75***)</td>
<td>(72.34***)</td>
<td>(3.62***)</td>
</tr>
</tbody>
</table>

The results for quantile regression on \( \text{CSAD}_i(\tau \mid x) = \alpha + \eta_1 r_{m,i}(\tau) + \eta_2 [r_{m,i}(\tau)]^2 + \epsilon_i \) with varying \( \tau \). T-statistics are reported in parentheses. * indicates a 10% significance level; ** indicates a 5% significance level; *** indicates a 1% significance level.