Economic Modelling 64 (2017) 97–104

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/econmod

Disagreement and the risk-return relation

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ARTICLE INFO

JEL classification:
G1

Keywords:
Disagreement
Risk-return relation
Time-varying effect
Crowded trades
Volatility

ABSTRACT

Disagreement is an important behavioral factor in financial market, and this paper investigates the impact of disagreement on the risk-return relation. We construct disagreement of crowded trades (DCT) index to measure disagreement, and discover that DCT has a significant impact on the risk-return relation. Furthermore, DCT change has a time-varying effect on the risk-return relation. When DCT change is negative, the risk-return relation is significant and negative; when DCT change is positive, the risk-return relation is significantly positive. When we use different conditional variance models and different market portfolios, such results are still robust. Moreover, our empirical results have important practical implications for asset allocation decisions.

1. Introduction

The risk-return relation has been one of the most important and extensively investigated issues in the financial economics literature (e.g., Christensen et al., 2015; Nyberg, 2012; Sévi, 2013; Yang and Jia, 2016; Yu and Yuan, 2011). Theories of traditional finance generally predict a positive risk-return relation (e.g., Merton, 1973, 1980). However, researchers find the conflicting empirical evidence on the risk-return relation. In dozens of empirical investigations, some researchers discover a positive risk-return relation (e.g., Campbell and Hentschel, 1992; French et al., 1987; Kanas, 2012; Lundblad, 2007; Nyberg, 2012), some researchers show a negative risk-return relation (e.g., Brandt and Kang, 2004; Campbell, 1987; Nelson, 1991; Whitelaw, 1994), and some researchers present that both a positive and a negative relation subsist (e.g., Glosten et al., 1993; Harvey, 2001; Turner et al., 1989). Prior studies have detected that the results of the risk-return relation rely heavily on the conditional variance models selected (e.g., Ghysels et al., 2005; Harvey, 2001; Lundblad, 2007; Yu and Yuan, 2011). Nevertheless, from the standpoint of investor sentiment, Yu and Yuan (2011) show that their results are robust across different volatility models. Specifically, the investor sentiment is an important behavioral factor (Harvey et al., 2016) in stock market. Therefore, it is meaningful to study the risk-return relation from the standpoint of other behavioral factors.

Investors have differing estimates of the returns from investing in a risky security, which is defined as the disagreement (Miller, 1977). The disagreement is an important behavioral factor in financial market, and it has a considerable effect on the returns and the volatility. On the one hand, researchers state that the disagreement plays a vital role in the stock returns. Much of the extant work implies that the disagreement causes the returns to increase (e.g., Basak, 2005; Carlin et al., 2014; Chen et al., 2010; David, 2008; Varian, 1985). David (2008) posits that a positive risk premium should be associated with the disagreement. Carlin et al. (2014) use the data of prepayment speed forecasts (PSA) to measure the disagreement, and show that the increased disagreement is associated with the higher expected returns. In contrast, an extensive literature finds that the disagreement should lead to a negative risk premium (e.g., Chen et al., 2002; Diether et al., 2002; Miller, 1977; Park, 2005; Yu, 2011). Miller (1977) thinks that short-sale constraints cause the disagreement to have a positive (negative) impact on the stock prices (the stock returns). Using the Institutional Brokers' Estimate System database on analyst forecast, Yu (2011) supports the conclusions of Miller (1977). On the other hand, researchers find a positive relation between the disagreement and the price volatility (e.g., Baker et al., 2016; Banerjee and Kremer, 2010; Carlin et al., 2014; Shalen, 1993; Zapatero, 1998). Zapatero (1998) describes that the additional information inducing heterogeneous beliefs produces the higher volatility of interest rates. Carlin et al. (2014) use the PSA data, and document the positive effect of disagreement on the return volatility. Based on these findings, we discover that the disagreement can affect both the returns and the volatility. Motivated by these results, in this paper, we intend to investigate whether the disagreement has an impact on the risk-return relation.

To study the effect of disagreement on the risk-return relation, we start by constructing the disagreement index. In previous empirical studies, researchers use the survey data to construct the indexes for disagreement, for example, the analyst forecasts of the long-term growth rate of earnings-per-share (e.g., Kim et al., 2014; Moeller

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http://dx.doi.org/10.1016/j.econmod.2017.03.021
Received 28 February 2017; Received in revised form 23 March 2017; Accepted 26 March 2017
Available online 30 March 2017

et al., 2007; Yu, 2011). Different from these indexes, in this paper, we use the trading data to construct the disagreement index: The disagreement of crowded trades (DCT) index. In order to construct the DCT index, we first calculate the buyer-initiated crowded trades and the seller-initiated crowded trades. The buyer-initiated crowded trades (the seller-initiated crowded trades) is calculated as the total market buyer-initiated volume (the total market seller-initiated volume) divided by the shares outstanding of market, and it represents the degree of buyer-initiated investors' crowded trades (the degree of seller-initiated investors' crowded trades). Specifically, we use the algorithm of Lee and Ready (1991) to measure the total market buyer-initiated volume (the total market seller-initiated volume). Next, we define the DCT index as the buyer-initiated crowded trades minus the seller-initiated crowded trades, and the DCT index measures the disagreement between buyer-initiated investors and seller-initiated investors.

Using the DCT index showed above, we investigate whether the DCT affects the risk-return relation. We find the significant impact of DCT change on the risk-return relation. Moreover, there is a time-varying effect of DCT change on the risk-return relation: The risk-return relation is significantly negative when the DCT change is negative, while the risk-return relation is significantly positive when the DCT change is positive. Our analysis has the following striking features. On the one hand, we innovatively study the risk-return relation from the standpoint of disagreement. On the other hand, our results are robust across different conditional variance models, and our empirical results are also robust across different market portfolios with different values of stock capitalization.

In brief, we make several contributions to this literature. Firstly, this paper uses the disagreement of crowded trades (DCT) index to measure the disagreement, and this paper is the first to construct the disagreement index by using the trading data (the total market buyer-initiated volume, the total market seller-initiated volume and the shares outstanding data). Secondly, we discover that the DCT plays a vital role in the risk-return relation. Thirdly, we find that there is a time-varying effect of DCT change on the risk-return relation. Besides, when we use different conditional variance models and different market portfolios with different values of stock capitalization, our results are still robust. In practice, our empirical results should play important roles in asset allocation decisions. For instance, asset management firms should consider decreasing their holdings on high-risk stocks during the periods of negative DCT change, since the risk in these periods is poorly compensated; and asset management firms should consider increasing their holdings on high-risk stocks in the periods of positive DCT change, since the risk during these periods is compensated well.

The rest of this literature is organized as follows. Section 2 describes four conditional variance models and the DCT index, and provides the summary statistics of all variables. Section 3 considers the main empirical results. Section 4 gives additional robustness tests to verify the sensitivity of our results. Section 5 concludes.

2. Data

2.1. Conditional variance models

There exist the conflicting conclusions of the risk-return relation. Some researchers consider that such results are sensitive to the selection of conditional variance models (e.g., Ghysels et al., 2005; Harvey, 2001; Lundblad, 2007; Yu and Yuan, 2011). Accordingly, in this subsection, we show four conditional variance models which are used in the rest of this paper: The moving average model, the exponentially weighted moving average model, the GARCH(1,1) model and the EGARCH(1,1) model.

2.1.1. Moving average model

A natural measurement of the conditional variance is to use the moving average model (e.g., Brock et al., 1992). This model uses the realized variance from time $t-19$ to time t as the conditional variance for the returns at time $t+1$:

$$Var_t(R_{t+1}) = \sum_{d=0}^{20-1} \frac{(r_{t-d} - \bar{r})^2}{20-1}. \tag{1}$$

Here $Var_t(R_{t+1})$ is the conditional variance for the market portfolio; r_{t-d} is the daily return for the market portfolio at time $t-d$; and $\bar{r}$ is the daily average return for the market portfolio from time $t-19$ to time t.

2.1.2. Exponentially weighted moving average model

Morgan (1996) proposes the exponentially weighted moving average model. Compared with the moving average model, the exponentially weighted moving average model has longer historical data and weighting system. The conditional variance calculated by the exponentially weighted moving average model is:

$$Var_t(R_{t+1}) = \lambda Var_{t-1}^2(R_t) + (1-\lambda) r_t^2. \tag{2}$$

Here $Var_t(R_{t+1})$ is the conditional variance for the market portfolio; r_t is the daily return for the market portfolio at time t; and λ is the decay factor estimated by minimizing the error of estimation of estimate value for variance (herein, $\lambda = 0.94$).

2.1.3. GARCH(1,1) model

The GARCH model is proposed by Bollerslev (1986), and is extensively used in measuring the conditional variance (e.g., Lin and Fei, 2013). The GARCH(1,1) model is the third volatility model, and the conditional variance calculated by the GARCH(1,1) model is:

$$R_{t+1} = \mu + \varepsilon_{t+1}, \tag{3}$$

and

$$Var_t(R_{t+1}) = \alpha_1 + \alpha_2 \varepsilon_t^2 + \alpha_3 Var_{t-1}(R_t). \tag{4}$$

Here R_{t+1} is the daily excess return for the market portfolio; $Var_t(R_{t+1})$ is the conditional variance for the market portfolio; and ε_{t+1} is the residual.

2.1.4. EGARCH(1,1) model

Due to the asymmetric property of volatility, Nelson (1991) suggests to use the EGARCH model to estimate the conditional variance. EGARCH(1,1) models the conditional variance as:

$$R_{t+1} = \mu + \varepsilon_{t+1}, \tag{5}$$

and

$$\ln Var_t(R_{t+1}) = \beta_1 + \beta_2 \ln Var_{t-1}(R_t) + \beta_3 \frac{\varepsilon_t}{\sqrt{Var_{t-1}(R_t)}} + \beta_4 \left| \frac{\varepsilon_t}{\sqrt{Var_{t-1}(R_t)}} \right|. \tag{6}$$

Here R_{t+1} is the daily excess return for the market portfolio; $Var_t(R_{t+1})$ is the conditional variance for the market portfolio; and ε_{t+1} is the residual.

2.2. Disagreement of crowded trades index

Miller (1977) thinks that there is the disagreement in financial market when investors have differing estimates of the expected returns from investing in a risky asset. In prior empirical analyses, researchers provide many proxies for disagreement, and these proxies are based on the survey data, such as the prepayments speed forecasts (e.g., Carlin et al., 2014) and the analyst forecasts of the long-term growth rate of earnings-per-share (e.g., Kim et al., 2014; Moeller et al., 2007; Yu, 2011). However, in this paper, we use the trading data to construct the proxy for disagreement: The disagreement of crowded trades (DCT)