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The decomposition of jump risks in individual stock returns[☆]

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ABSTRACT

This paper proposes a GARCH-jump mixed model for individual stock returns that takes into account four types of risks: the systematic and idiosyncratic jumps and the systematic and idiosyncratic diffusive volatility. By considering a general pricing kernel with all underlying risk factors, we decompose the expected stock return into four risk premiums related to the four types of risks. Empirically, we estimate the model jointly for daily stock returns and market returns and investigate the asset pricing consequences. We find that idiosyncratic jump intensity contributes a major part of the total jump intensity and idiosyncratic jumps are key determinants of expected stock return.

1. Introduction

Jumps in stock returns of individual firms are triggered by either systematic events or idiosyncratic shocks. During events such as the oil crisis in 1973, Black Monday in 1987, the dot-com crash in 2000 and the subprime crisis from 2007 to 2009, the financial market witnessed large jumps in most traded stocks. In addition, individual stocks experience jumps due to firm-specific events, such as earnings surprises, mergers and acquisitions, etc. In a recent study, Kapadia and Zekhnini (2018) find that the entire annual average return of a typical stock accrues over the four days on which its stock price jumps, confirming that firm-specific jumps are important determinants of the mean returns of a stock.

In this paper, we provide a new modeling framework for individual stocks that allows for the estimation of time-varying systematic and idiosyncratic jump intensities and volatilities. From an asset pricing point of view, it is of both theoretical and practical importance to understand, how the systematic and idiosyncratic jump intensities can be estimated, and how they are related to the equity risk premium. This new model accommodates the joint dynamic structures of individual stock returns and the market returns, while allowing for jumps. Under such a framework, we estimate the dynamics of idiosyncratic and systematic jump intensities and volatilities for individual stocks and investigate the roles of different risks in the dynamics of equity premium.

We model the return innovation by a Generalized Autoregressive Conditional Heteroskedastic (GARCH)-jump mixture model in the spirit of Maheu et al. (2013). Different from Maheu et al. (2013) which only focuses on the market returns, we intend to investigate the dynamics of individual excess stock returns and allow the stock innovations to be affected by the market innovations.

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The market innovation has two components, which we call "market jump" and "market diffusion". The jump component follows a compound Poisson-normal distribution with autoregressive jump intensities. The diffusive component is governed by an asymmetric two-component GARCH process. The stock innovation has four components: "systematic jump", "idiosyncratic jump", "systematic diffusion" and "idiosyncratic diffusion". The systematic jump in the stock innovation is triggered by the market jump with a certain probability. The systematic diffusion component loads on the market diffusion component governed by "beta", similar to that in the Capital Asset Pricing Model (CAPM). The idiosyncratic components are directed by similar dynamic structures as in the market components, but are independent from their systematic counterparts. To estimate the model, we provide a filter that can decompose daily excess stock returns into large (jump) versus small (diffusion) components, as well as systematic and idiosyncratic counterparts in each of them.

In addition, our model allows for the decomposition of the dynamic equity premium by assuming a general pricing kernel with all underlying risk factors in the economy. The traditional CAPM suggests that the idiosyncratic risk is diversified away and not priced. However, empirical studies find that idiosyncratic risks matter not only in predicting the time series of stock market return,[3] but also in pricing in the cross-section of stock returns.[4]

In this paper, we include the idiosyncratic components of the stock innovations in the pricing kernel and test whether they are significantly priced in the dynamics of the equity premium. The specification of the pricing kernel is similar to that in Gourier (2016) and Bégin et al. (2017). The expected stock return can be consequently decomposed into four risk premiums: premiums on systematic and idiosyncratic diffusion risks and systematic and idiosyncratic jump risks.

We conduct a joint estimation strategy to identify different components in daily returns of 15 stocks from 1963 to 2015. For each stock, we estimate the model for the market return and the stock return jointly. We find that the idiosyncratic jump intensity accounts for 82.25% of the total jump intensity, and idiosyncratic variance accounts for 66.70% of the total variance on average. The contribution of idiosyncratic risks declines over time, implying that the firms are more and more affected by the systematic risks over the past 50 years. Further, all four types of risks are related to sizable premium in the expected return of individual stocks over time. The equity premium associated to idiosyncratic (jump) risks contribute to 57.18% (16.25%) of the total equity premium on average.

The closest econometrics approach to ours is Maheu et al. (2013). They estimate a GARCH-jump mixed model for the market returns with time-varying jump and diffusive risk premiums. We extend their framework to accommodate the estimation for individual stock returns by incorporating systematic and idiosyncratic counterparts in both jump and diffusive components. Our work is also related to Maheu and McCurdy (2004), who estimate the dynamics of jump and diffusive components in stock returns with constant equity premium. The difference between their model and ours is that we introduce the systematic and idiosyncratic counterparts in each component and consider their roles in the time-varying equity premium. On the technical side, we provide a procedure to filter out the four components in stock innovation. This is comparable to the one in Christoffersen et al. (2012), who estimated different specifications of dynamic jump model for the S&P 500 index.

Our paper complements the recent studies that intend to disentangle the four types of risks in equity premiums and in higher order risk premiums. Using stock return and option prices, Gourier (2016) and Bégin et al. (2017) conduct a joint estimation using both stock and option data to decompose the four risk premiums associated with systematic and idiosyncratic diffusive and jump risks. Consistent with their findings, we also find that idiosyncratic risks contribute to more than 40% of the total equity premium on average and that idiosyncratic risk mostly comes from the jump risk component. Instead of using both stocks and options, we use 50 years of daily stock returns to identify the dynamics of jump risks. Using the time series of stock returns, we are able to further investigate the evolution of the contribution of different risks over a long period, in contrast to the fact that their analysis started from 1996 due to the availability of option data. To better capture the contribution of systematic risks in equity premium over a long time frame, we allow the exposures of the stock to the market jump and diffusion risks to be time varying, related to the business cycle variable. While Gourier (2016) and Bégin et al. (2017) apply a two-step procedure that they first estimate the market parameters and then estimate the parameters for individual stocks using the estimates from the first step, we jointly estimate the model for market return and stock return to capture the common structures in diffusive volatility and jump intensity.

The remainder of the paper proceeds as follows: Section 2 presents our model setup and discusses the expected stock return under our model. Section 3 describes the estimation methodology. Section 4 provides the data and the estimation results. Section 4.4 discusses the implications on asset pricing and Section 5 concludes.

2. Model

Our model builds on Maheu and McCurdy (2004) and Maheu et al. (2013). The former suggests mixed GARCH-jump models for individual stocks, while the latter considers time-varying equity premium in the market returns. We extend their approaches by accommodating both systematic and idiosyncratic risks in individual stock returns. Section 2.1 presents the model for market return and the dynamics of volatility and jump intensity. Then we discuss the model for individual stock returns in Section 2.2. Lastly, we specify a pricing kernel and derive the expression of expected returns of individual stocks in Section 2.3.

[3] For example, Goyal and Santa-Clara (2003) and Guo and Savickas (2006).

[4] For example, Ang et al. (2006), Fu (2009), Ang et al. (2009), Huang et al. (2010) and Stambaugh et al. (2015), and Kapadia and Zekhnini (2018).