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Impact of idiosyncratic volatility on stock returns: A cross-sectional study

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ABSTRACT

This paper proposes a new approach to estimate the idiosyncratic volatility premium. In contrast to the popular two-pass regression method, this approach relies on a novel GMM-type estimation procedure that uses only a single cross-section of return observations to obtain consistent estimates. Also, it enables a comparison of idiosyncratic volatility premia estimated using stock returns with different holding periods. The approach is empirically illustrated by applying it to daily, weekly, monthly, quarterly, and annual US stock return data over the course of 2000–2011. The results suggest that the idiosyncratic volatility premium tends to be positive on daily return data, but negative on monthly, quarterly, and annual data. They also indicate the presence of a January effect.

1. Introduction

The finance literature is presently witnessing a debate on idiosyncratic volatility premium. The models of Levy (1978), Merton (1987), Malkiel and Xu (2006), and Epstein and Schneider (2008) predict a positive premium in the capital market equilibrium. However, research based on Kahneman and Tversky's (1979) prospect theory indicates that the premium can be negative (e.g., see Bhootra and Hur, 2011); an additional explanation for why the premium can be negative has been suggested by Peterson and Smedema (2011).[1]

Empirical evidence on the idiosyncratic volatility premium is contradictory. Ang et al. (2006, 2009), Jiang et al. (2009), Guo and Savickas (2010), and Chabi-Yo (2011) document a negative premium. In contrast, Fu (2009) and Huang et al. (2010) find the premium to be positive. While the existing empirical studies typically apply a version of Fama and MacBeth's (1973) two-pass approach, the divergence in their results can stem from how, exactly, they compute idiosyncratic volatilities of individual stocks in the first pass.[2] For example, Ang et al. employ a realized idiosyncratic volatility measure by using daily stock returns from a previous month. In contrast, Fu uses an expected conditional idiosyncratic volatility measure by estimating an EGARCH model on a time-series of monthly returns (Fu requires having at least 30 observations in the time-series). Peterson and Smedema (2011) indicate that these alternative measures of idiosyncratic volatility can be associated with different effects on returns. Thus, the divergence in the sign of the idiosyncratic volatility premium (estimated in the second pass of the two-pass approach) may have arisen because some researchers use short-term, high-frequency data, whereas other researchers use long-term, low-frequency data—when computing stock-specific idiosyncratic volatilities in the first pass. Hence, specific details of the econometric methodology can play an important role in obtaining empirical conclusions about the idiosyncratic volatility premium (on this point, see also Fink et al., 2012).

The contribution of this paper to the literature is twofold. First, we outline a novel Generalized Method of Moments (GMM)-type econometric procedure that allows us to obtain consistent estimates of parameters of a financial market model (see more

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[1] There is also no consensus in the literature on the issues of the forecasting power and the time-series behavior of idiosyncratic volatility. Goyal and Santa-Clara (2003) document a positive relationship between equal-weighted average stock variance and future market return. However, Bali et al. (2005) show that this predictive relationship does not hold for value-weighted variance. Also, Campbell et al. (2001) report a steady increase in idiosyncratic stock volatility since 1962. However, Brandt et al. (2010) argue that this increase is only an episodic phenomenon. In this paper, we do not investigate the forecasting power and the time-series behavior of idiosyncratic volatility. We focus exclusively on the issue of the idiosyncratic volatility premium.

[2] These computed stock-specific idiosyncratic volatilities are subsequently used to estimate the idiosyncratic volatility premium in the second pass.

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on it below), using only *a single cross-section* of return data. Notably, unlike in the previous studies, having a long historical time-series of returns is not required. This approach could be particularly helpful when a researcher needs to characterize a stock market using only the most current, rather than historical, information. In addition, we empirically illustrate the proposed methodology by estimating the idiosyncratic volatility premium embedded into the US stock returns over the course of 2000–2011. We offer a detailed analysis of the premium using daily, weekly, monthly, quarterly, and annual stock return intervals. This empirical analysis is the second contribution of the paper to the literature.

A parametric financial market model underlying the return data is an important component of the proposed estimation approach. We consider a continuous-time model comprising a well-diversified market portfolio index and a cross-section of individual stocks. The index follows a geometric Brownian motion and is affected by a source of market risk. Individual stocks also follow a geometric Brownian motion and depend on this same source of market risk (i.e., it is a common risk shared by all stocks). In addition, they are affected by stock-specific idiosyncratic risks. We do not take a stance on whether idiosyncratic volatility should command a premium in the capital market equilibrium, but rather we allow for a *potential* effect of a stock's idiosyncratic volatility on the stock's drift term and estimate this effect, if any, from the data.

The estimation approach is empirically illustrated using US stock price data from the Center for Research in Security Prices (CRSP) over the 2000–2011 time period. We estimate the financial market model separately on every return interval in the dataset, and then aggregate the results according to the return data frequency: daily, weekly, monthly, quarterly, and annual. We find that estimates of the idiosyncratic volatility premium computed on daily return data tend to be positive and statistically significant. In comparison, estimates of the premium on weekly return data are, on average, negative but not statistically significant. In turn, premia estimated from monthly, quarterly, and annual return data tend to be negative and statistically significant. Estimates of the idiosyncratic volatility premium for the same time period—but computed at different frequencies—are positively associated. In addition, the calculated values of the idiosyncratic volatility component of the conditional expected return suggest that the impact of the idiosyncratic volatility on the expected return can be economically significant. The results of robustness checks indicate the presence of a January effect. In particular, idiosyncratic volatility premia computed using daily, weekly, and monthly return data over the month of January tend to be higher (and positive, on average) than corresponding estimates from non-January data. Also, in the cases of daily and weekly data, the per annum average estimates of the premium tend to be similar across different calendar years during 2000–2011.

As noted earlier, the existing empirical studies of the idiosyncratic volatility premium typically employ a version of the conventional two-pass regression method of Fama and MacBeth (1973).[3] Despite its intuitive appeal, the two-pass method has several well-known econometric limitations. For example, it delivers consistent estimates only when the time-series length (rather than the number of stocks) grows infinitely large (Shanken, 1992). Also, since the regressors in the second pass (e.g., individual stock-specific idiosyncratic volatilities) are measured with error, the estimator is subject to an errors-in-variables problem (Miller and Scholes, 1972), which may induce an attenuation bias in the estimates (Kim, 1995). The statistical properties of the second-pass estimator are complex. As such, it is not uncommon for these complexities to be ignored in practice, resulting in biased inference (Shanken, 1992; Jagannathan and Wang, 1998). Moreover, accounting for the time-varying nature of stock betas (Fama and French, 1997; Lewellen and Nagel, 2006; Ang and Chen, 2007) and idiosyncratic volatilities (Fu, 2009) is challenging and requires the imposition of additional assumptions, which further complicate statistical inference.

One of the goals of the estimation approach proposed in this paper is to address these econometric limitations. In particular, the approach delivers consistent estimates as the number of stocks (rather than the time-series data length) grows infinitely large. Thus, it is not affected by the available time-series length of the stock return data. Also, since it does not involve estimating individual stock-specific betas and idiosyncratic volatilities, it is not subject to the errors-in-variables problem arising in the two-pass regression method, and it does not require the imposition of strong assumptions about their time-series behavior. Instead, the approach relies on a parametric model describing a financial market setting, and on a distributional assumption regarding a cross-section of the betas and idiosyncratic volatilities (we model them as random coefficients). While the need to make the distributional assumption might be seen as a potential limitation, practitioners can explore several alternative assumptions to check the robustness of the estimates to a misspecification. Overall, we believe our approach will be an attractive alternative to the two-pass regression method, especially when researchers need to characterize a stock market using only the most current, rather than historical, information.

The remainder of this paper proceeds as follows. Section 2 specifies the financial market model. Section 3 outlines the econometric approach. Section 4 describes the data used in the empirical analysis. Section 5 discusses the results. Section 6 concludes. Selected analytical formulas are derived in the appendix.

2. Financial market model

We first specify a financial market model and discuss how it relates to the classical financial framework. We then derive expressions for gross returns and specify distributional assumptions that help implement a GMM-type econometric procedure outlined in Section 3.

2.1. Model setup

Financial investors trade in many risky assets in continuous time. One of the assets is a well-diversified stock portfolio bearing only market risk. In what follows, this asset is referred to as "the market index." Its price at time t is denoted by M_t. All other risky assets are individual stocks bearing the market risk and stock-specific idiosyncratic risks. We index the stocks by i, with $i = 1, 2, \ldots$, and denote the price of a stock i at time t by S_t^i. In addition to the market index and the stocks, there is a default-free bond that pays interest at a risk-free rate r.

The price dynamics of the market index follows a geometric Brownian motion and is described by a stochastic differential equation:

$$dM_t/M_t = \mu_m dt + \sigma_m dW_t, \tag{1}$$

with a drift

$$\mu_m = r + \delta\sigma_m, \tag{2}$$

where W_t is a standard Brownian motion indicating a source of the market risk, $\sigma_m > 0$ is the market volatility, and δ is the market risk premium. As explained in Section 3, the estimation procedure will not allow us to identify δ, because this parameter is differenced out when stock returns are conditioned on the market index return.

[3] Black et al. (1972), among others, contributed to the development of the two-pass methodology.