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Performance measurement with selectivity, market and volatility timing[☆]



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ABSTRACT

The performance of portfolio managers depends on market timing, volatility timing, and security selection. We develop holdings-based performance measures that adjust for risk using stochastic discount factors, display all three components in a consistent framework, and avoid strong assumptions about managers' behavior. Previous models leave out some of the components of performance, and correcting for this we deliver better measures of selectivity. Sorting stocks held by funds on selectivity produces a quintile spread in four-factor alphas greater than 2.5% per year before costs and more than 1.7% greater than found using the Daniel, Grinblatt, Titman, and Wermers (1997) measure.

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1. Introduction

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 $\operatorname{Cov}(x'_t, r_{t+1}) \equiv \Sigma_i \operatorname{Cov}(x_{it}, r_{it+1})$, the sum over the securities *i*, of the covariances between portfolio holdings, x_{it} , and the subsequent realized excess returns, r_{it+1} .¹ However, a well-specified performance measure is based on $\operatorname{Cov}(x'_t, m_{t+1})$, the sum of the superior between between between the superior between between the superior between between the superior between between the superior between the s

off by Grinblatt and Titman (1989, 1993) (GT). Earlier

holdings-based measures essentially examine

This paper develops new measures of investment performance based on portfolio holdings, contributing to the literature on holdings-based performance measures kicked

 $Cov(x'_t, m_{t+1}r_{t+1})$, the sum of the covariances between the portfolio holdings and the subsequent abnormal, or

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¹ We characterize the GT measure as an estimate of the covariance. Empirically, GT estimate $E\{|x-x_{lag}|^{T}\}$, a weight-change measure, where the lagged weight, x_{lag} , serves as a proxy for the expected weight.

risk-adjusted returns, where m_{t+1} is a stochastic discount factor (SDF) (see Ferson, 2013; Ferson and Lin, 2014).

We use popular linear SDFs in this paper, but the idea can be used with any SDF. Our approach is parsimonious. Only three parameters are needed for each mutual fund, in addition to the market-wide SDF parameters. This allows us to easily examine models with multiple benchmarks, and we consider models with up to five benchmarks. We illustrate the approach, applying it to a sample of mutual funds. Using linear SDFs, the performance measures display security selectivity, market timing and volatility timing in a consistent framework. These three aspects of performance have each been treated in the literature, but they have not been examined together in a single model.

It has been known since Grant (1977) that if managers attempt to both time markets and pick undervalued securities, then measures of selectivity are contaminated by the timing behavior. This is a version of a missing variables bias, and it is necessary to incorporate the timing behavior to accurately extract the selectivity ability. We show that volatility timing behavior, as well as market level timing behavior, affects measures of selectivity. Thus, even if the goal of a study is simply to measure selectivity ability, it is necessary to consider both market and volatility timing behaviors.²

Empirically, we compare the performance of our selectivity measure with the currently most popular holdingsbased selectivity measure, the measure of Daniel, Grinblatt, Titman, and Wermers (1997) (DGTWcs). If the terms missing from the DGTWcs measure that our model exposes are important relative to the cost in estimation error, our measures should perform better. We find that our selectivity performance measure predicts the future before-cost performance of the stocks selected better than the DGTWcs measure. We rank the funds on the measures using past data and group them into quintiles. We form portfolios of the underlying stocks held by each quintile's funds and examine the subsequent Carhart (1997) four-factor alphas for the before-cost stock portfolio returns. The high-low quintile spread using our measure is 2.6% per year on an equally weighted (EW) basis, with a *t*-ratio in excess of 4.6. The spread using DGTWcs is only 0.8% with a *t*-ratio of 1.3. The spreads are smaller on a value-weighted (VW) basis, but still significant using our measure, with a t-statistic of 2.7. The average spread returns are very similar when we exclude the smallest 20% of the funds (those with assets under management below \$43.6 million dollars), so the results are not driven by the smaller funds.

Our measures use the before-cost hypothetical returns that result from multiplying funds' reported holdings by the before-cost returns of the stocks held. This follows GT and most of the holdings-based performance literature. This literature interprets such before-cost measures as reflecting skill. The after-cost fund returns, such as reported on the Center for Research in Security Prices (CRSP) database, subtract the expense ratios and funds' actual trading costs and therefore better measure the returns left over for investors. Recently, Berk and van Binsbergen (2015) and Pastor, Stambaugh and Taylor (2015) argue that before-cost alphas should be adjusted for the scale of the fund to measure a fund's skill. We therefore present some tests in which we adjust our selectivity measures for scale. Repeating the previous exercise with the scaleadjusted measures following Berk and van Binsbergen, the four-factor quintile spread between the future returns of the stocks held by the high selectivity skill and those held by the low selectivity skill funds is 1.5% per year, with a *t*-ratio of 3.9. Using the Pastor, Stambaugh, and Taylor approach, the spread is 1.3% with a *t*-ratio of 2.0. As before, the spreads are smaller on a value-weighted basis and, in these cases they are not statistically significant.

Beyond an interest in better selectivity measures, we want to understand other aspects of funds' ability. Our decomposition features selectivity, factor level timing, and factor volatility timing performance. Previous studies document market timing behavior, at least for subsets of funds.³ Fund managers can also engage in volatility-related behavior; for example, reducing market exposure when anticipated volatility is high. Fleming, Kirby, and Ostdiek (2001), Johannes, Polson, and Stroud (2002), and Han (2006), among others, find that strategies attempting to predict volatility have an economically significant impact on the returns and risks of portfolios. A few studies present empirical evidence for volatility-related timing behavior in funds. Busse (1999) finds evidence that US equity fund returns react to market volatility. Aragon and Martin (2012) find that hedge funds can time volatility.⁴ However, most of the mutual fund performance literature focuses on selectivity performance. Our decompositions indicate that, for the average fund, both factor level and volatility timing are substantial fractions of the total performance, thus deserving of more research attention.

We contribute to this literature with a new analysis of volatility timing. Volatility timing is especially interesting relative to fund managers' incentives. It is well known that fund managers face incentives to take actions that can depart from the interests of fund investors. With respect to volatility timing, investors would prefer fund managers to reduce market exposure in anticipation of higher market volatility (e.g., Busse, 1999). However, managers' adverse incentives can induce funds to increase market exposure at high volatility times, in response to tournament effects (Brown, Harlow, and Starks, 1996) or flowperformance incentives (Sirri and Tufano, 1998; Chevalier and Ellison, 1997). We find evidence that funds are more likely to engage in adverse volatility timing behavior when facing more powerful adverse incentives. We also find evidence consistent with an interpretation in which superior ability gives a fund the cover to manage volatility for short-term compensation gains. For example, funds with

² Boguth, Carlson, Fisher, and Simutin (2011) also suggest that volatility timing can impart biases to estimates of alpha in return regressions measuring performance.

³ See, for example, Becker, Ferson, Myers, and Schill (1999), Bollen and Busse (2001), Chen, Ferson, and Peters (2010), and the references therein.

⁴ Holmes and Faff (2004) apply Busse's returns-based model in Australia, and Kim and In (2012) examine Busse's model using simulations. Cao, Chen, Liang, and Lo (2013) consider both market and volatility timing for hedge funds in a returns-based analysis.

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