Systematic Mispricing

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Abstract

We provide statistical estimates of individual security mispricing which is defined as the departure of the market price from the prediction of a fundamental asset pricing model. We show that there is a return premium associated with systematic mispricing risk which is the dependence of the individual security mispricing on a market wide mispricing factor. The risk or characteristic-adjusted return spread between high and low mispricing risk decile portfolios is 50-70 *bp* per month depending on the specification of the market mispricing factor. When portfolios are formed on estimates of both systematic mispricing risk and the liquidity betas of Amihud (2002), Pastor-Stambaugh (2003) or Liu (2006) there is evidence of a significant risk-adjusted return spread associated with systematic mispricing risk, but no longer any evidence of a systematic liquidity risk premium. When portfolios are formed using estimates of the mispricing return bias of Brennan and Wang (2007) and systematic mispricing risk, both characteristics are shown to contribute to the return premium.

1 Introduction

The basic one-period mean-variance theory of asset pricing expresses security risk premia in terms of the covariation of their returns with the return on aggregate wealth. Subsequent extension to an intertemporal setting by Merton (1973) allows for asset prices to covary with state variables that describe the investment opportunity set, and for risk premia to depend on these covariations. The state variables include the interest rate, as originally described by Merton, and the slope of the capital market line, as well as variables that describe the future evolution of these descriptors of the short run investment opportunity set.[1]

More recently, two new types of state variable that fall outside the classical paradigm of rational asset pricing in frictionless markets, have been introduced into empirical asset pricing models, and have been found to be associated with significant return premia. The first type reflects developments in 'behavioral' finance and is generally described as investor 'sentiment'. The second type of state variable is associated with the state of market liquidity which is now recognized as a potentially important determinant of asset prices. In this paper we consider a third state variable which we label as the 'aggregate mispricing factor', and show that it is associated with a significant return premium which appears to subsume the systematic liquidity risk premium reported in previous studies.

We define security mispricing as departures of the market price of the security from the predictions of a given asset pricing model that follow a stationary distribution. It can also be viewed as the fluctuations of the market price about an estimate of the 'fundamental value'. Mispricing is thus an asset pricing model dependent concept, and in our empirical analysis we assume that the relevant asset pricing model is the Fama-French 3-factor model simply because this has become the canonical model for empirical asset pricing. Mispricing may be merely random and idiosyncratic, or it may result from fluctuations in market wide state variables, such as investor sentiment and market illiquidity, both of which are shown to be associated with security prices that are not subsumed in the Fama-French asset pricing model. The impact of idiosyncratic mispricing errors on expected stock returns have been

[1] See Brennan, Wang and Xia (2004) and Nielsen and Vassalou (2006).

documented by by Brennan and Wang (2007) as statistically significant and economically important, due to the 'mispricing return bias' effect arising from Jensen's inequality. This paper, on the other hand, focuses on whether individual security mispricing varies in a systematic way and therefore commands a risk premium.

For each stock, we first estimate time-series of mispricing by applying a Kalman filter to the residuals from the Fama-French 3-factor model. This measure of mispricing is a measure only of *relative* mispricing since it presumes that the Fama-french portfolios themselves are correctly priced. As a result, the cross-sectional average of our (relative) mispricing estimates is always close to zero, so that in itself it is not an ideal measure of *aggregate* mispricing risk. However, we conjecture that the cross-sectional average of (relative) mispricing is correlated with a state variable that corresponds to aggregate mispricing, so that return covariance with this average (relative) mispricing will proxy for covariance with the true underlying aggregate mispricing factor. As an alternative approach, we proxy for the aggregate mispricing factor by the cross-sectional dispersion of individual security mispricing and measure systematic mispricing risk by the covariance of return with innovations in mispricing dispersion. For both of the proxies for the aggregate mispricing factor, we test whether the sensitivity of security mispricing to the aggregate mispricing factor is associated with return differentials after adjusting for risk using the CAPM, Fama-French and momentum augmented multi-factor models.

We find strong evidence of a return premium associated with systematic mispricing risk. Specifically, the difference in risk adjusted return between portfolios with high and low systematic mispricing risk is 0.51 to 0.72% per month, depending on the proxy for the aggregate mispricing factor. For robustness, we also adjust returns using size and book-to-market matched portfolios and find similar results. Moreover, we find that our measures of systematic mispricing risk offer incremental explanatory power for risk-adjusted returns relative to the liquidity risk variables captured by Pastor and Stambaugh(2003), Acharya and Pedersen(2005) and Liu(2006). On the other hand, there is only weak evidence that these measures of systematic liquidity risk have incremental explanatory power for returns after adjusting for the role of systematic mispricing risk. Finally, since our measures of systematic mispricing risk are likely to be correlated with the mispricing return bias of

Brennan and Wang (2007), we examine whether our measures of systematic mispricing risk have explanatory power for returns after accounting for the mispricing return bias and we find that they do.

The remainder of the paper is organized as follows. Section 2 discusses related literature. In Section 3 we show how a stationary mispricing process with a systematic component is related to expected returns. Section 4 presents our empirical results and Section 5 concludes.

2 Related Literature

This paper is related to the existing literature which links security returns to variables that do no have an direct impact on the fundamental determinants of asset prices such as the conditional joint distribution of futures payoffs, time preference, and risk aversion.

One subset of this literature focuses on sentiment related variables. De Long *et al.* (1990) propose a model in which stock prices are responsive to 'noise trader sentiment', which is defined as the component of expectations about asset returns not warranted by fundamentals. They argue that if sentiment accounts for the fluctuating discounts on closed end funds in a systematic way, then it will be priced and therefore can explain why *on average* closed end funds sell at a discount. In support of this, Swaminathan (1996) shows that the closed end fund discount forecasts future returns on small firms, and Lee *et al.* (1991) show that changes in discounts on closed end funds tend to move together and with the (contemporaneous) returns on both small stocks and stocks with low institutional ownership. Lee *et al* (1991) interpret their findings as evidence that the closed end fund discount is an index of individual investor sentiment. Baker and Wurgler (2006) provide further evidence of the cross sectional effects of investor sentiment on stock prices by combining several measures of sentiment into a single index, and showing that the level of the index predicts the relative returns on stocks categorized on the basis of an *a priori* assessment of their likely sensitivity to sentiment. Kumar and Lee (2006) show that retail individual trades are systematically correlated, and the systematic trading account for return comovements for stocks that are costly to arbitrage. Evidence that institutional trading also may introduce a non-fundamental factor into security prices and returns is provided by Sias (1996), Jones and Lipson (2001), and Hughen *et al.* (2005). Glushkov (2007) reports that systematic sentiment risk earns a significant yet *negative* risk premium.

Another subset of the literature concentrates on variables capturing market liquidity condition. Chordia *et al.* (2000) were the first to demonstrate that the time-varying liquidity of the markets for individual securities has common market-wide components. Amihud (2002) further shows that the level of market illiquidity affects expected returns, that, as a result, unexpected increases in market liquidity reduce stock prices, and that the effect is greatest for small illiquid firms. This is consistent with market liquidity acting as a state variable like sentiment which moves stock market prices around their fundamental values. Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006) and Liu (2006) all present empirical evidence showing that cross-sectional differences in risk-adjusted expected stock returns are related to the sensitivity of the stock return to innovations in the state of market liquidity, each paper using a different proxy for market liquidity. Chacko (2006) and Downing *et al.* (2006) find similar results for the corporate and municipal bond markets respectively.

Security mispricing due to the slow adjustment of prices to new information about fundamentals is documented in an extensive literature starting with Ball and Brown (1968) who study slow adjustment to earnings news[2]. Brennan and Wang (2007) show that average returns on individual securities are related to what they label the 'mispricing return bias'. The bias, which is the result of Jensen's inequality, arises when market prices fluctuate about their fundamental values but are on average unbiased. In Brennan and Wang (2007) it was shown that portfolios formed on the basis of ex-ante measures of the mispricing return bias have risk adjusted return differentials of the order of more than 8% per year. Unlike Brennan and Wang (2007), this paper takes no position on whether market prices are unbiased and focuses instead on whether expected returns are related to sensitivity to a common element in security mispricing.

[2]See Bernard *et al.* (1997) for a more recent survey of the evidence.

3 A Model of Systematic Mispricing

Let P_{it}^* denote the fundamental price of asset i at time t. By the fundamental price we mean the price that reflects the discounted rational expectations of the asset payoffs. It is of course always possible to express a market price as the discounted value of the expected payoffs for some discount rate, so in distinguishing between the fundamental price and the market price we are implicitly limiting the factors that determine the discount rate. We shall not elaborate on this at this stage except to say that the discount rate depends only on the risk characteristics of underlying cash flows. Then, suppose that market prices at time t, $P_{i,t}(i = 1, \cdots, n)$ are related to the fundamental prices $P_{i,t}^*$ by:

$$P_{i,t} = P_{i,t}^* Z_{it} = P_{i,t}^* e^{z_{i,t}} \equiv P_{i,t}^* e^{\gamma_i z_{m,t} + \xi_{i,t}} \tag{1}$$

where $z_{i,t}$ is the *log* of mispricing for security i, $z_{m,t}$ is a market wide state variable, γ_i is the sensitivity of security i's mispricing to the market wide state variable. $\gamma_i z_{m,t}$ is the systematic element of mispricing, and $\xi_{i,t}$ is the idiosyncratic element.

Then, neglecting dividend payments,[3] we have:

$$\begin{aligned} 1 + R_{i,t} &= \frac{P_{i,t+1}}{P_{i,t}} = \frac{P_{i,t+1}^*}{P_{i,t}^*} \frac{e^{\gamma_i z_{m,t+1} + \xi_{i,t+1}}}{e^{\gamma_i z_{m,t} + \xi_{i,t}}} \\ &= (1 + R_{i,t}^*) e^{\gamma_i \Delta z_{m,t} + \Delta \xi_{i,t}} \\ &\approx (1 + R_{it}^*) \left(1 + \gamma_i \Delta z_{m,t} + \Delta \xi_{i,t} + \frac{1}{2} [(\gamma_i \Delta z_{m,t})^2 + (\Delta \xi_{i,t})^2] + \gamma_i \Delta z_{m,t} \Delta \xi_{i,t} \right) \end{aligned} \tag{2}$$

where $R_{i,t}^*$ is the rate of return based on the fundamental price, $\Delta z_{m,t} \equiv z_{m,t+1} - z_{m,t}$ and $\Delta \xi_{i,t} \equiv \xi_{i,t+1} - \xi_{i,t}$. Taking expectations in (2) under the assumption of joint normality and $E[\Delta \xi_{i,t} \Delta z_{m,t}] = 0$:

$$\begin{aligned} E[R_{i,t}] &\approx E[R_{i,t}^*] + E[R_{i,t}^*] E \left(\gamma_i \Delta z_{m,t} + \Delta \xi_{i,t} + \frac{1}{2} \left[(\gamma_i \Delta z_{m,t})^2 + (\Delta \xi_{i,t})^2 \right] \right) \\ &+ E \left((\gamma_i \Delta z_{m,t} + \Delta \xi_{i,t}) + \frac{1}{2} \left[(\gamma_i \Delta z_{m,t})^2 + (\Delta \xi_{i,t})^2 \right] \right) + cov \left(R_{i,t}^*, \gamma_i \Delta z_{m,t} + \Delta \xi_{i,t} \right) \end{aligned} \tag{3}$$

[3] For a detailed analysis of the role of dividends see Brennan and Wang (2007).

Neglecting the second term in (3) which is a product of expected returns and expected changes in the state variables, the expected market return is related to the fundamental return by[4]:

$$E[R_{i,t}] \approx E[R^*_{i,t}] + \gamma_i E[\Delta z_{m,t}] + \frac{1}{2}\gamma_i^2 E[(\Delta z_{m,t})^2] + \gamma_i cov\left(R^*_{i,t}, \Delta z_{m,t}\right) + E[\Delta\xi_{i,t}] + \frac{1}{2}E[(\Delta\xi_{i,t})^2] + cov\left(R^*_{i,t}, \Delta\xi_{i,t}\right) \quad (4)$$

It is natural to assume that z_m follows a time-homogeneous process. The process is also assumed to be stationary so that $E[\Delta z_m] = 0$, for otherwise the ratio of the market price to fundamentals would be explosive. Then the expected return associated with the mispricing for stock i, $\Xi_{i,t}$, is given by:

$$\Xi_{i,t} = \frac{1}{2}\gamma_i^2 E[(\Delta z_m)^2] + \gamma_i \rho_{i,\Delta z_m}\sigma_i\sigma_{\Delta z_m} + E[\Delta\xi_{i,t}] + \frac{1}{2}E[(\Delta\xi_{i,t})^2] + cov\left(R^*_{i,t}, \Delta\xi_{i,t}\right). \quad (5)$$

$\rho_{i,\Delta z_m}$ is the correlation between the *fundamental* return and the innovation in the state variable, $z_{m,t}$, and γ_i measures the sensitivity of the *mispricing* to the state variable. $E[\Delta\xi_{i,t}]$ is the expected change in idiosyncratic mispricing. We shall refer to $\Xi_{i,t}$ as the *mispricing return premium.* It is the component of expected return which does not depend on fundamentals but on the pricing process itself. If $E[\Delta\xi_{i,t}] = 0$, then the mispricing premium reduces to the mispricing return bias described by Brennan and Wang (2007). However, unlike z_m, ξ_i is quite likely to follow a time-dependent process. For example, it is possible that young firms have highly volatile mispricing so that $E[(\Delta\xi_i)^2]$ is large, and that this is offset by a negative drift in mispricing, $E[\Delta\xi_i] < 0$; and that as they mature, both the volatility and drift of mispricing tend to zero. Thus, it is not possible to place *a priori* restrictions on $E[\Delta\xi_i]$, or on $\Xi_{i,t}$.

In order to identify mispricing, we shall assume in our empirical analysis that innovations in mispricing are independent of the fundamental returns, so that $cov(R^*_i, \Delta z_m) = cov(R^*_i, \Delta\xi_i) = 0$. Then, we note from equation (5) $\Xi_{i,t}$ is an increasing function of $|\gamma_i|$. Motivated by this observation, we shall test whether the mispricing return premium, $\Xi_{i,t}$, is related to systematic mispricing risk, γ_i.

[4]Brennan and Wang (2007) refer to the difference between the expected market return and the fundamental return as the mispricing return bias.

4 Empirical Analysis

In this section, we develop estimates of security mispricing and present evidence of a systematic component, which we characterize in terms of the mean and cross-sectional dispersion of mispricing. We then show that risk adjusted returns are related to our proxies for systematic mispricing risk. Our empirical analysis is based on the assumption that mispricing is independent of fundamentals.

First, individual security mispricing, $z_{i,t}$, is estimated each month using a Kalman filter under the assumption that z_i follows a simple AR1 process as in Brennan and Wang (2007). The AR1 assumption is restrictive, and does not allow for positive short term autocorrelation in returns: as a result, the estimation algorithm does not converge for a significant number of stocks.[5] Average mispricing in month t, $\bar{z}_t$, is simply the arithmetic average of the individual security mispricings, $z_{i,t}$, for that month. The cross-sectional dispersion of mispricing, $\sigma_t(z)$, is calculated for each month. To allow for the changing number and composition of the securities in the sample,[6] $\sigma_t(z)$ was scaled by dividing by the moving average of the past 60 months. We denote the scaled dispersion by $\sigma_t^*(z)$. The two proxies that we use for the aggregate mispricing variable, $z_{m,t}$, are then $\bar{z}_t$ and $\sigma_t^*(z)$.

Following Fama and MacBeth (1973), individual securities are assigned to 10 portfolios each year on the basis of estimates of systematic mispricing risk obtained by regressing changes in estimated security mispricing on the aggregate mispricing variable. These portfolios are used to test whether expected returns are related to systematic mispricing risk.

4.1 Data

The primary data that we use are the monthly returns on all stocks registered on the NYSE, AMEX and NASDAQ from January 1962 to December 2004, which are taken from CRSP.

[5]We also developed an estimate of the bias based on an AR2 process for the mispricing. See Khil and Lee (2002). The empirical results for this model are qualitatively similar to those for the AR1 process. However, they are less significant, which is probably due to the difficulty of identifying the parameters of the more complex model.

[6]There is a significant increase in the number of stocks from 1966, since many stocks, for the first time, became eligible for Kalman filter estimations with sufficiently long return history. Large jump in number of stocks also occurs for 1986, for a similar reason for NASDAQ stocks.

We include only common shares, and exclude preferred stocks, ADR's, REIT's, etc. To alleviate the potential influence of 'stale prices', we include only observations with positive trading volume and with valid month-end closing prices. We also filter out penny stocks. We use as risk factors monthly returns on the 3 Fama-French factors, and the momentum factor of Carhart (1997); these, together with 1-month Tbill returns, are taken from Ken French's website.[7] We use data on book values from COMPUSTAT, and on prices, market capitalization and share turnover from CRSP. Various measures of market liquidity were taken from WRDS or supplied by the original authors.

4.2 AR1 Estimates of Mispricing

As seen in Section 3, mispricing is defined by the relation between the market price of a security, P_{it}, and its fundamental price, P^*_{it}. The fundamental price in turn depends on the model that is used for generating the discount rate to convert rational expectations of payoffs into current prices. We assume that returns under this fundamental asset pricing model can be described by an ex-post version of the Fama-French (1993) 3-factor model (FF3):

$$R^*_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + c_i SMB_t + d_i HML_t + \epsilon_{i,t} \tag{6}$$

where $R^*_{i,t}$ is the fundamental return on stock i in month t, $R_{F,t}$ is the riskless interest rate, and $R_{M,t}, SMB_t, HML_t$ are the Fama-French factors. Then, to a first order approximation, the market return, $R_{i,t}$ is given by:

$$R_{i,t} - R_{F,t} = \alpha_i + b_i(R_{M,t} - R_{F,t}) + c_i SMB_t + d_i HML_t + e_{i,t} \tag{7}$$

where the residual return reflects changes in the log mispricing, z_{it}, as well the fundamental idiosyncratic return, $\epsilon_{i,t}$:

$$e_{i,t} = z_{i,t} - z_{i,t-1} + \epsilon_{i,t} \tag{8}$$

[7] $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

For empirical estimation purposes, the log of the mispricing is assumed to follow an AR(1) process as in Poterba and Summers(1988):

$$z_{i,t} = \phi_1 z_{i,t-1} + \eta_{i,t} \tag{9}$$

Then, following Khil and Lee (2002), a Kalman filter is used to estimate the log mispricing, $z_{i,t}$, and the parameters of the mispricing process, ϕ_1 and σ_η, for each security from the FF3 residual returns, $e_{i,t}$. The observation equation for the Kalman filter is equation (8), and the transition equation for the unobserved state variable is equation (9). In order to identify the system, the fundamental residual return, $\epsilon_{i,t}$, is assumed to be independent of the mispricing $z_{i,t}$. Details of the Kalman filter algorithm are given in the Appendix of Brennan and Wang(2007).

In each month t from December of 1954 to December of 2004, the mispricing for security i, $z_{i,t}$ is estimated for all stocks with at least 36 prior monthly returns using the FF3 residual returns estimated over the previous 60 months as available. The Kalman filter is estimated each month and only the final value of the state variable estimate is retained, so that there is no look ahead bias in the estimation of $z_{i,t}$.

Figure 1 plots estimates of the mispricing for eight large, well-known, securities. For most of the securities shown here mispricing appears to be an episodic phenomenon. For example with IBM there are only 5 occasions on which mispricing exceeds 5%, for Microsoft 1, for Exxon none, for GM 12, 8 of which occur after 2000; for Starbucks there are 13 over a much shorter sample period, 7 of which occur during 2000; for Yahoo only 2 in seven years; for Oracle, 29 over 14 years; for 3Com 4 over 6 years (for which we can compute z). The range of estimated mispricing is much greater for Oracle and 3Com than for the other companies and the volatility of the estimated mispricing is 5.4% and 3.2% for these companies as compared with 2.7% for the average of all the companies.

4.3 Commonality in Mispricing

Since security mispricing, $z_{i,t}$, is estimated from the residual returns from the FF3 model, it is a measure of mispricing *relative* to these benchmark portfolios. Therefore, it is to be expected that the average level of mispricing for all securities in a given month, $\bar{z}_t$, will be small, and that is what we find. As reported in Panel A of Table 1, the overall average mispricing is only 7 *bp*, the minimum average mispricing in any month is -0.98 %, and the maximum is 2.93 %. The first order autocorrelation of average mispricing is 0.39. However, there is a pronounced seasonal effect in the average level of mispricing which is concentrated around the turn of the year. There is an average underpricing of 22 *bp* at the end of December, followed by 27 *bp* of overpricing at the end of January. Since our measure of average mispricing is equally weighted, this pattern is consistent with tax-loss induced selling in December and the re-establishment of positions in January concentrated among small firms.

Figures 2 and 3 plot the time series of average mispricing, $\bar{z}_t$, and the cross-sectional dispersion, $\sigma_t(z)$, of $z_{i,t}$ estimates. The cross-sectional dispersion of mispricing, $\sigma_t(z)$, has three distinct phases. It is low and roughly stable from 1954 to 1966 at about 2.5%. It then rises to 4-5% till 1986, after which it fluctuates around 5 - 8% with occasional spikes. The three phases coincide with increases in the number of stocks for which mispricing estimates can be computed. It is also consistent with Campbell *et al* (2001) who show that the idiosyncratic return volatility has increased over time.[8] The three phases of the cross-sectional dispersion of mispricing are matched by similar phases for the average values of σ_η, the volatility of shocks to z, and σ_ϵ, the volatility of the fundamental idiosyncratic return. The average value of σ_η (σ_ϵ) during these phases are 3% (4-5%), 4-6% (6-8%), 6-9% (9-14%). The average value of σ_η is 5.59% and of σ_ϵ is 8.73% so that idiosyncratic shocks to intrinsic value tend to be over 50% more volatile than shocks to mispricing.

The cross-sectional average of ϕ_1, the first order autocorrelation of mispricing, fluctuates between -0.01 and 0.11: it is negative in only 3 out of 515 months ; and the time series average is 0.06. We note that this is inconsistent with mispricing being driven by random bid-ask bounce effects.

The scaled cross-sectional dispersion, $\sigma_t^*(z_i)$ has a correlation of 0.30 with the cross-sectional mean level of mispricing, and the correlation between innovations in these variables

[8] In the subsequent empirical analysis, we scale $\sigma_t(z_i)$ by its past 60 month moving average to get $\sigma_t^*(z_i) = \sigma_t(z_i)/MA(60)$.

is 0.27. There is also a seasonal effect in the cross-sectional dispersion of mispricing. It is the highest in January (0.47%) and reaches a trough in July (-0.30%).

Panel B of Table 1 reports pair-wise correlations for both levels and innovations[9] in $\bar{z}_t$, $\sigma_t^*(z)$ and five measures of market wide trading cost or liquidity that have been used in asset pricing tests. Apart from the Amihud(2002) and Liu (2006) pair, the correlations between these variables are small. There is little correlation between the various measures of market liquidity, or between them and the two proxies that we shall use for the aggregate mispricing factor, $\bar{z}_t$ and $\sigma_t^*(z_i)$. Thus there is little evidence that episodes of market illiquidity are associated with corresponding episodes of (relative) aggregate mispricing.

Equation (1) implies that:

$$z_{i,t} = \gamma_i z_{m,t} + \xi_{i,t} \tag{10}$$

so that γ_i is a measure of the systematic mispricing risk, or "mispricing beta". Here we adopt two proxies for the aggregate mispricing state variable z_m, $\bar{z}_t$ and $\sigma_t^*(z)$, and investigate whether γ measured with respect to these two proxies for z_m are related to risk adjusted returns. First we consider the case in which $z_{m,t} = \bar{z}_t$, the cross-sectional average of security mispricing.

4.4 $z_{m,t} = \bar{z}_t$

γ_i is estimated from equation (10) in first-difference form:

$$\Delta z_i = c + \gamma_i \Delta z_m + h_i \tag{11}$$

At the end of November of each year from 1966 to 2003, mispricing betas were estimated by OLS regression using $z_{i,t}$ estimates for the preceding 60 months. Only securities for which there were at least 30 values of $z_{i,t}$ were included. The average R^2 from this first-difference regression is 3.9%. It has been increasing in recent years, reaching a maximum of 6.1% in 2001. To avoid bid-ask bounce effects, a one month lag was left before forming portfolios that are held from January to December of the following year.

[9]Innovations for all but the Pastor-Stambaugh series were computed as the residuals of regressing the levels on the corresponding lagged levels. Pastor-Stambaugh innovations were downloaded from WRDS.

Following the analysis in Section 3, decile portfolios were constructed using the absolute value of the estimated mispricing betas as a sorting instrument. Stocks were assigned in January of each year from 1967 to 2004 to one of ten equal size portfolios according to the absolute value of mispricing beta estimated at the end of the previous November. An equal investment was assumed to made in each stock in the portfolio at the beginning of the year and no rebalancing was assumed within the year.[10] The post-formation portfolio returns were then linked across time, yielding a time series of returns for each decile from January 1967 to December 2004. On average, there are about 150 stocks within each portfolio, and at no time is the number of stocks in a portfolio less than 60.

Panel A of Table 2 reports summary statistics on the decile portfolios. In the portfolio formation regressions (11), the average value of $|\gamma|$ ranges across deciles from 0.11 to 7.14, and the average R^2 ranges from close 0 to almost 12%. Firm size varies inversely with $|\gamma|$.

Post-formation values of portfolio mispricing, z_{pt}, were calculated as the equally weighted average of the individual security values of z_{it} over the 12 months following portfolio formation. And post-formation portfolio mispricing betas were then estimated by regressing the changes in the resulting series of z_{pt} on changes on z_{mt} for the whole sample period. The portfolio mispricing betas range from 0.40 to 2.29. Four-factor model betas for the portfolios were estimated by regressing the post-formation excess returns on the three Fama-French factors and the Carhart momentum factor. The loadings on the market and momentum factors do not vary significantly across portfolios, while the loadings on SMB (HML) tend to increase (decrease) with the mispricing beta. To facilitate comparison with the systematic liquidity risk literature, the Pastor-Stambaugh (2003) portfolio liquidity beta was estimated for each portfolio by regressing excess portfolio returns on FF3 and the Pastor-Stambaugh liquidity factor. While the individual P-S liquidity betas are generally not statistically significant, there is a clear pattern: low γ portfolios tend to have high PS liquidity risk,and high γ portfolios tend to have low PS liquidity risk.[11] The spread of 9.6 in the estimated

[10]Since mispricing is most likely to found among small stocks, we use an equal weighting scheme to compensate for the over-representation of large, liquid, and closely followed stocks that are less likely to be subject to mispricing. Acharya and Pedersen (2005), Amihud (2002), and Chordia *et al.* (2000) adopt a similar strategy in their studies of liquidity and asset pricing.

[11]Since the estimated portfolio mispricing betas are all positive we drop reference to absolute values of the mispricing betas.

PS liquidity betas is very close to the value of 8.2 reported by Pastor and Stambaugh (2003, Table 3) . However, it is noteworthy that PS liquidity betas are inversely related to our estimated mispricing beta. Thus portfolios that tend to do well when the P-S measure of liquidity is high tend to do badly when average mispricing is high.

Panel B of Table 2 shows that the average raw returns on the portfolios are strongly increasing in the mispricing betas, the spread between the high and low γ portfolios is 85 *bp* per month and highly significant. The spread remains significant when returns are adjusted for risk using the CAPM and the Fama-French 3- and 4-factor models. For the FF3 adjusted returns, the spread is 72 *bp* per month, ($t-$statistics of 3.54), or almost 8.5 % per year.

We also formed decile portfolios using γ rather than $|\gamma|$. The patterns of raw and risk adjusted returns, not reported here, are similar to those reported in Table 2. The spread in the ex-post portfolio mispricing betas is reduced from 1.89 to 1.62, while the spread in FF3 risk adjusted returns increases by 2 *bp* per month. Although the post-ranking portfolio mispricing betas reported in Table 2 are all positive, $|\gamma|$ proved to be a more powerful instrument than γ for forming portfolios, since it yields a more monotone pattern of post-ranking portfolio γ's. Therefore, our subsequent analysis relies on portfolios formed using estimates of $|\gamma|$ as an instrument.

Since average firm size differs significantly across the portfolios, the analysis was repeated for robustness using size and book-to-market characteristic adjusted returns. At each year end, 25 equally-weighted benchmark portfolios were formed by first assigning the sample firms into size quintiles based on NYSE quintile breakpoints; then within each size quintile, assigning firms to book-to-market quintiles based on the corresponding NYSE book-to-market quintile breakpoints, where the end -June book and market value of equity were employed to ensure information availability. The characteristic adjusted stock returns are the difference between the raw returns and the returns on the corresponding benchmark portfolio. Table 3 shows the same relation between returns and γ as we found using the factor-model risk adjustments, though now it is more concentrated in the extreme portfolios: the spread between the high and the low mispricing beta portfolios is now 68 bp per month with a $t-$statistic of 3.62. The characteristic adjusted returns were further adjusted for risk using the 3 risk models and this further adjustment of the returns does not change the results.

Overall, our results show that there is a premium associated with systematic mispricing risk. And the return spreads we have documented are comparable in magnitude to those associated with liquidity risk betas reported in prior studies.

4.5 $z_{m,t} = \sigma_t^*(z)$

An alternative approach to the identification of the aggregate mispricing factor, z_m, is to assume that it is a nonnegative random variable, which increases the level of mispricing for some securities and reduces it for others. Under this assumption, the cross-sectional dispersion of mispricing, $\sigma_t(z_i)$, will proxy for $z_{m,t}$, since equation (1) implies that $\sigma_t^2(z_i) = \sigma^2(\gamma_i)z_{m,t}^2 + \sigma^2(\xi_i)$ when $cov(\gamma_i, \xi_i) = 0$, where $\sigma^2(\gamma_i)$ and $\sigma^2(\xi_i)$ are the cross-sectional variances of the mispricing betas and idiosyncratic mispricing. To allow for (slow) time variation in the cross-sectional distribution of γ and ξ, we scale $\sigma_t(z_i)$ by its past 60 month moving average, so that our proxy for the aggregate mispricing factor is:

$$z_{m,t} = \sigma_t^*(z_i) \equiv \sigma_t(z_i)/MA(60)$$

.

Given the new proxy for the market mispricing factor, the empirical analysis exactly parallels that described in the previous section. The results, which are presented in Tables 4 and 5, are very similar to those previously reported, though somewhat less strong. The spread in risk-adjusted returns between high and low mispricing beta portfolios is now about 51 *bp* instead of 71 *bp*, but it remains highly significant.

4.6 Systematic Mispricing, Mispricing Return Bias, and Liquidity Risk

Table 1 shows that our two proxies for the aggregate mispricing factor have low (maximum 0.18) correlations with both levels and innovations in the various measures of aggregate market liquidity that have been proposed in the literature, so that the systematic mispricing that we have identified appears to be distinct from the commonality in liquidity that is found to be priced in those studies. However, Tables 2 and 4 shows that there is a strong (negative) relation between the Pastor-Stambaugh betas of the portfolios and the mispricing betas of those portfolios. Therefore it is important to determine the separate effects of the mispricing beta and the various measures of the liquidity beta.

In addition, Brennan and Wang (2007) have identified empirically what they term a 'Mispricing Return Bias' (MRB). This is a Jensen's inequality effect due to mispricing which they show for a given security to be equal to

$$MRB \equiv e^{(1-\rho^1_{z_i})\sigma^2_{z_i}} - 1 \approx (1 - \rho^1_{z_i})\sigma^2_{z_i} \tag{12}$$

where $\rho^1_{z_i}$ is the first order autocorrelation of the (log) mispricing and σ_{z_i} is the volatility of mispricing for the security. They report that FF3 risk adjusted returns are closely related to this measure of return bias. MRB is highly correlated with our measure of systematic mispricing risk since for a given security, $\sigma^2_{z_i} = \gamma^2_i \sigma^2_{z_m} + \sigma^2_{\xi_i}$, where σ_{z_m} and σ_{ξ_i} are the volatilities of the stationary distributions of the aggregate mispricing factor and firm-specific mispricing. It is therefore possible that the systematic mispricing premium that we have identified is due to the mispricing return bias.

In order to determine whether the systematic mispricing premium is a phenomenon that is independent of the Mispricing Return Bias and the Systematic Liquidity Risk Premium that was found by Pastor-Stambaugh (2003), Amihud (2002), Liu (2006) and Sadka (2006), the analysis was repeated, this time forming 25 portfolios at the beginning of each year. The portfolios were formed by sorting securities first into quintiles on the absolute value of the estimated value of γ_i and then within each quintile into further quintiles based on the MRB or liquidity beta and analyzing the time series of returns on the resulting 25 portfolios; then the analysis was repeated reversing the order of the sorts. When the liquidity beta or Mispricing Return Bias is the first sorting variable, we are interested in whether γ_i has marginal explanatory power for risk and characteristic adjusted returns once the first variable is accounted for. Conversely, when $|\gamma_i|$ is the first sorting variable, we are interested in whether the second variable has marginal explanatory power. The sorting variables for each year are estimated as follows. $|\gamma_i|$ is estimated from equation (11) using the previous 60 months of estimates of z_i and z_m; MRB is calculated following equation (12) using parameter estimates from the Kalman filter. The liquidity betas are estimated by regressing the security excess returns over the previous 60 months on the FF3 factors and the innovations in each of the market liquidity proxies. Both risk- and characteristic-adjusted returns were calculated for each of the 25 portfolios. Since the results are similar, we only report only the characteristic adjusted returns.

Table 6 presents the results when $z_m = \bar{z}_i$. Panel A show that when portfolios are formed first on MRB and then on $|\gamma|$, there is still a significant 82 *bp* systematic mispricing return spread for the high MRB quintile. Similarly, when the order is reversed, there is a significant return spread of 1.02% per month associated with MRB for the high $|\gamma|$ quintile. Therefore security returns appear to be influenced both by the MRB and by the systematic mispricing premium and the effects are economically large.

When portfolios were formed first on one of the liquidity betas and then on $|\gamma|$, there is a significant return spread associated with mispricing betas, especially for the high and low liquidity beta quintiles. For these extreme liquidity beta quintiles, the spread in size and BM adjusted returns between the low and high $|\gamma|$ portfolios are both statistically and economically significant, ranging from 47 to 73 *bp* per month. In contrast, when portfolios were formed first on $|\gamma|$, and then on the liquidity beta, the return spread associated with the liquidity beta is never significant. The point estimates of the return spread range from -34 bp per month when liquidty risk is measured against Liu's market *illiquidity* proxy, to 24 *bp* per month where liquidity risk is measured against P-S market *liquidity* proxy.

Overall, there is strong evidence for a systematic mispricing premium, that is independent of the Mispricing Return Bias and of systematic liquidity risk.

Table 7 summarizes the analogous results when the proxy for the aggregate mispricing factor, $z_{m,t}$, is $\sigma_t^*(z_i)$. The results are strikingly similar to those reported in Table 6, despite the difference in the proxy used for the aggregate mispricing factor. When the portfolios are sorted first on MRB and then on γ, for the high MRB quintile the size and book-to-market adjusted spread between high and low $|\gamma|$ quintiles is 75 *bp* per month which is highly significant; the spreads for the other quintiles are not significant. Similarly, when the order of the sorts is reversed, there is a 110 *bp* spread between high and low MRB portfolios for the high $|\gamma|$ quintile, while the spreads are not significant for the other quintiles.

When the analysis is repeated using the liquidity betas of Pastor-Stambaugh, Liu and Amihud, we find in every case that the adjusted returns are increasing in $|\gamma|$ for every quintile of the liquidity beta and the spreads between low and high γ quintiles are significant in 2 out of the 3 quintiles reported except when the Pastor-Stambaugh beta is the first sorting variable: in this case while the spreads are positive in every case, it is only significant for the low β^{PS} quintile. The spreads between returns on high and low $|\gamma|$ quintiles are also economically significant, reaching 50-60 *bp* per month holding constant the liquidity beta quintile. In striking contrast, when the quintiles are formed first on γ and then on the liquidity betas, in no case is the spread between high and low liquidity beta quintiles significant, the spreads are sometimes positive and sometimes negative, and the maximum spread is no more than 15 *bp* per month. There is no evidence that the liquidity betas have any explanatory power for size and book to market adjusted returns once systematic mispricing risk is taken account for.

5 Conclusion

In this paper we have calculated a statistical measure of individual security mispricing by applying a Kalman filter to the residuals from the Fama-French (1993) 3 factor model of returns, under the assumption that mispricing follows an AR1 process. The estimated mispricing is *relative* in the sense that it presupposes that the 3 FF portfolios are correctly priced. Despite this, we find evidence of significant commonality in mispricing. An aggregate mispricing factor is proxied by both the arithmetic cross-sectional average of individual security mispricing, $\bar{z}_t$, and the cross-sectional dispersion of mispricing, $\sigma_t(z_i)$. First difference regressions show that the aggregate mispricing factor proxy, $\bar{z}_t$, explains almost 4% of monthly changes in individual security mispricing for the average security, and as much as 11.9% for the high mispricing beta decile of securities. When $\sigma_t(z_i)$ is used as the proxy the corresponding figures are about 3% and 9.2%, respectively.

Ten portfolios were formed by ranking each year on estimates of $|\gamma_i|$, where γ_i is the 'mispricing beta' which is estimated by regressing changes in individual security mispricing on the aggregate mispricing factor proxy. Returns on the portfolios were found to vary significantly with this measure of systematic mispricing risk after adjusting for risk using the CAPM and 3- and 4-factor versions of the Fama-French model. The spread in risk adjusted returns between high and low systematic mispricing risk portfolios was 50-70 *bp* per month or 6-8.5% on an annualized basis depending on which of the aggregate mispricing factor proxies were used. Similar return spreads were obtained when the raw returns were adjusted for risk by subtracting the returns on size and book-to-market characteristic matched portfolios. Thus, there is robust evidence that there is a return premium associated with systematic mispricing risk.

To explore the relation between the systematic mispricing risk premium and the systematic liquidity risk premium that has been documented in previous studies, 25 portfolios were formed by ranking on estimates of both the systematic mispricing risk and estimates of systematic liquidity risk, following Amihud, Liu and Pastor-Stambaugh. Risk-adjusted returns on these portfolios vary significantly with systematic mispricing risk holding constant each of the measures of systematic liquidity risk, but do not vary significantly with any of the measures of systematic liquidity risk when systematic mispricing risk is held constant.

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Table 1: Proxies for the Aggregate Mispricing Factor and Market Liquidity $\bar{z}_t$ is the cross-sectional arithmetic average and $\sigma_t(z_i)$ is the cross-sectional dispersion of the individual security mispricing estimates. $\sigma_t^*(z_i) \equiv \frac{\sigma_t(z_i)}{MA(60M)}$ is the cross-sectional dispersion normalized by a moving average of the values over the previous 60 months.''*Amihud*', '*Liu*', '*PS*', '$Sadka^{FC}$', and '$Sadka^{VC}$' are the measures of market liquidity used in Amihud (2002), Liu(2006), Pastor and Stambaugh (2003) and the fixed cost (FC) and variable cost (VC) of transacting estimates from Sadka(2006). All statistics are derived from monthly data for the period 1962.08 - 2004.11.

Panel A: Summary Statistics on Mispricing Factor Proxies

	Min	10%	Median	90%	Max	Mean	Stdev	ρ_1
$\bar{z}_t(\%)$	-0.98	-0.29	0.06	0.43	2.93	0.07	0.32	0.39
$\sigma_t(z_i)(\%)$	1.88	2.80	4.32	6.43	13.48	4.59	1.66	0.90
$\sigma_t^*(z_i)$	0.70	0.85	1.04	1.31	2.34	1.07	0.21	0.76

Additive Seasonal Adjustment Factors (%)

	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
$\bar{z}_t$	0.27	0.07	0.08	-0.05	0.01	-0.08	-0.03	-0.06	-0.03	0.05	-0.02	-0.22
$\sigma_t(z_i)$	0.47	0.10	0.06	-0.02	-0.04	-0.16	-0.30	-0.02	-0.05	-0.05	-0.04	0.04
$\sigma_t^*(z_i)$	0.10	0.02	0.03	0.01	0.00	-0.03	-0.06	-0.02	-0.01	-0.01	-0.02	0.01

Panel B: Correlations between Mispricing Factor Proxies and Measures of Market Liqudity

Correlations of Levels

	Amihud	*Liu*	*PS*	$Sadka_{FC}$	$Sadka_{VC}$	$\bar{z}_t$
Liu	0.71					
PS	-0.14	-0.03				
$Sadka_{FC}$	-0.09	0.03	0.05			
$Sadka_{VC}$	-0.08	0.06	0.14	0.19		
$\bar{z}_t$	0.10	0.10	-0.09	0.15	-0.06	
$\sigma_t^*(z_i)$	0.12	0.18	0.09	0.07	-0.03	0.30

Correlations of Innovations

	Amihud	*Liu*	*PS*	$Sadka_FC$	$Sadka_VC$	$\bar{z}_t$
Liu	0.16					
PS	-0.12	0.05				
$Sadka_{FC}$	-0.05	-0.08	0.08			
$Sadka_{VC}$	-0.06	0.12	0.22	0.19		
$\bar{z}_t$	-0.02	0.02	-0.04	0.11	-0.10	
$\sigma_t^*(z_i)$	0.01	-0.07	0.12	-0.06	-0.12	0.27

Table 2: Properties of equally-weighted decile portfolios formed each year from January 1967 to December 2004 on Kalman Filter estimates of the absolute value of γ the 'mispricing beta' using *Average Mispricing* **as a proxy for the Aggregate Mispricing Factor: $\Delta z_{i,t} = c + \gamma \Delta z_{m,t}$, where**

$$z_{m,t} = \bar{z}_t.$$

$|\gamma|$ is the average of the absolute values of the pre-portfolio formation estimates of γ for the securities within each portfolio. R^2 is the average value of R^2 from the first difference regressions used to estimate γ. *Size* is the time series mean firm size in billion \$. The portfolio 'mispricing beta', γ, is the coefficient from the regression of changes in post-formation portfolio mispricing, Δz_p, on changes in the aggregate mispricing factor proxy. The $\beta's$ are the loadings of the post-formation portfolio excess returns on the 3 Fama-French factors, the Carhart Momentum factor, and the Pastor-Stambaugh market liquidity innovations. Panel C reports raw returns and the intercepts (α) from regressions of excess returns on the market excess returns (CAPM), the 3 Fama-French factors (FF3), and the 3 Fama-French factors plus the Carhart Momentum factor (FF4). The returns and $\alpha's$ are in *per cent* per month, and t-statistics which are adjusted for autocorrelation and heteroscedasticity are in parentheses.

Portfolio	1	2	3	4	5	6	7	8	9	10	
Panel A: Pre-formation Portfolio Characteristics											
$\lvert\gamma\rvert$	0.11	0.32	0.55	0.81	1.10	1.46	1.90	2.52	3.54	7.14	
$R^2(\%)$	0.07	0.43	0.89	1.52	2.28	3.15	4.10	5.57	7.68	11.87	
Size (\$ B)	1.80	1.97	1.84	1.38	1.41	1.44	0.87	0.79	0.53	0.20	
Number of Stocks											
Mean	154	155	154	154	155	154	154	153	152	152	
Minimum	68	67	68	66	69	65	66	68	64	61	
Panel B: Post-formation Portfolio Characteristics											
γ	0.40	0.33	0.46	0.46	0.68	0.63	0.74	0.99	1.35	2.29	
	(8.78)	(5.70)	(8.64)	(8.92)	(16.97)	(11.40)	(7.98)	(10.18)	(17.03)	(14.35)	
β_{mkt}	0.99	0.94	0.96	0.98	0.95	1.00	0.98	1.01	1.00	1.04	
	(31.09)	(44.10)	(44.24)	(39.12)	(42.29)	(37.40)	(46.64)	(43.64)	(35.10)	(20.85)	
β_{SMB}	0.51	0.54	0.57	0.58	0.68	0.62	0.74	0.86	0.97	1.31	
	(7.98)	(13.26)	(9.88)	(11.94)	(24.43)	(9.89)	(17.94)	(21.99)	(22.55)	(15.84)	
β_{HML}	0.46	0.45	0.42	0.43	0.36	0.41	0.39	0.29	0.26	0.22	
	(8.01)	(11.01)	(8.96)	(8.52)	(11.61)	(8.54)	(8.85)	(6.46)	(4.72)	(2.05)	
β_{MOM}	-0.03	-0.02	-0.05	-0.02	-0.03	-0.08	-0.03	-0.02	-0.03	-0.05	
	(-0.71)	(-0.60)	(-1.36)	(-0.79)	(-0.96)	(-1.84)	(-0.75)	(-0.42)	(-0.73)	(-0.49)	
β^{PS}	2.37	3.88	1.74	0.53	0.34	0.60	0.70	-1.37	-1.69	-7.26	
	(1.37)	(2.84)	(1.30)	(0.33)	(0.24)	(0.32)	(0.45)	(-0.76)	(-0.82)	(-1.90)	
Panel C: Returns (*per cent* per month)											
Raw Return	1.36	1.32	1.50	1.46	1.46	1.42	1.61	1.56	1.65	2.21	0.85
	(5.37)	(5.32)	(5.90)	(5.74)	(5.61)	(5.49)	(5.78)	(5.36)	(5.26)	(5.44)	3.59
Capm α	0.41	0.38	0.54	0.50	0.49	0.45	0.62	0.54	0.62	1.12	0.71
	(2.95)	(2.93)	(3.99)	(3.74)	(3.63)	(3.04)	(4.13)	(3.48)	(3.45)	(3.99)	(3.20)
FF3 α	0.06	0.04	0.21	0.16	0.17	0.10	0.28	0.24	0.32	0.78	0.72
	(0.80)	(0.61)	(3.01)	(2.24)	(2.60)	(1.39)	(3.99)	(2.82)	(3.05)	(3.84)	(3.54)
FF4 α	0.09	0.06	0.26	0.18	0.20	0.18	0.31	0.25	0.35	0.84	0.74
	(1.18)	(0.92)	(3.78)	(2.66)	(2.91)	(2.18)	(3.76)	(2.73)	(2.98)	(3.38)	(3.10)

Table 3: Size and book-to-market adjusted returns for equally-weighted decile portfolios formed each year from January 1973 to December 2004 on Kalman Filter Estimates of the absolute value of γ the 'mispricing beta' using *Average Mispricing* as a proxy for the Aggregate Mispricing Factor: $\Delta z_{i,t} = c + \gamma \Delta z_{m,t}$, where

$$z_{m,t} = \bar{z}_{i,t}.$$

The portfolio mispricing beta, γ, is the coefficient from the regression of changes in post-formation portfolio mispricing, Δz_p, on changes in the aggregate mispricing factor proxy. Panel B reports size and book-to-market adjusted returns and the intercepts (α) from regressions of size and book-to-market adjusted returns on the market excess returns (CAPM), the 3 Fama-French factors (FF3), and the 3 Fama-French factors plus the Carhart Momentum factor (FF4). The returns and $\alpha's$ are in *per cent* per month, and the t-statistics which are adjusted for autocorrelation and heteroscedasticity are in parentheses.

Portfolio	1	2	3	4	5	6	7	8	9	10	Spread 10 − 1
Panel A: Post-formation Portfolio Mispricing Beta											
γ	0.39	0.31	0.43	0.45	0.64	0.62	0.71	0.99	1.25	2.26	
t-statistic	8.76	5.06	6.60	8.15	12.02	11.58	6.51	11.28	16.87	14.33	
Panel B: Returns (*per cent* per month)											
Adjusted	-0.13	-0.23	0.00	-0.08	-0.13	-0.16	0.04	-0.04	-0.08	0.54	0.68
Return	(-2.40)	(-3.65)	(-0.02)	(-1.51)	(-2.81)	(-2.95)	(0.64)	(-0.65)	(-0.97)	(3.56)	(3.62)
Capm α	-0.10	-0.19	0.02	-0.07	-0.11	-0.16	0.04	-0.07	-0.13	0.45	0.56
	(-1.87)	(-3.10)	(0.35)	(-1.23)	(-2.45)	(-2.96)	(0.68)	(-1.20)	(-1.63)	(3.12)	(3.15)
FF3 α	-0.11	-0.20	0.01	-0.08	-0.09	-0.17	0.06	-0.03	-0.05	0.58	0.69
	(-1.96)	(-3.34)	(0.21)	(-1.47)	(-1.88)	(-2.90)	(1.02)	(-0.63)	(-0.58)	(3.90)	(3.82)
FF4 α	-0.18	-0.28	-0.04	-0.16	-0.15	-0.18	-0.01	-0.08	-0.11	0.50	0.68
	(-3.12)	(-4.63)	(-0.80)	(-2.69)	(-3.02)	(-2.82)	(-0.17)	(-1.39)	(-1.40)	(3.03)	(3.34)

Table 4: Properties of equally-weighted decile portfolios formed each year from January 1967 to December 2004 on Kalman Filter estimates of the absolute value of γ the 'mispricing beta' using *Mispricing Dispersion* **as a proxy for the Aggregate Mispricing Factor:** $\Delta z_{i,t} = c + \gamma \Delta z_{m,t}$**, where**

$$z_{m,t} = \sigma_t^*(z)$$

$\sigma_t^*(z)$ is the dispersion of mispricing estimates in month t divided by its 60 month moving average. $|\gamma|$ is the average of the absolute values of the pre-portfolio formation estimates of γ of the securities within each portfolio. R^2 is the average value of R^2 from the first difference regressions used to estimate γ. *Size* is the time series mean firm size in billion \$. The portfolio mispricing 'beta', γ, is the coefficient from the regression of changes in post-formation portfolio mispricing, Δz_p, on changes in the aggregate mispricing factor proxy. The $\beta's$ are the loadings of the post-formation portfolio excess returns on the 3 Fama-French factors, the Carhart Momentum factor, and the Pastor-Stambaugh market liquidity innovations. Panel C reports raw returns and the intercepts (α) from regressions of excess returns on the market excess returns (CAPM), the 3 Fama-French factors (FF3), and the 3 Fama-French factors plus the Carhart Momentum factor (FF4). The returns and $\alpha's$ are in *per cent* per month, and t-statistics which are adjusted for autocorrelation and heteroscedasticity are in parentheses.

Portfolio	1	2	3	4	5	6	7	8	9	10	
Panel A: Pre-formation Portfolio Characteristics											
$\|\gamma\|$	0.19	0.57	0.98	1.44	1.96	2.58	3.36	4.48	6.30	12.81	
R^2(%)	0.05	0.29	0.65	1.10	1.61	2.23	2.99	3.95	5.57	9.22	
Size	1.81	1.66	1.69	1.53	1.24	1.30	1.08	1.04	0.61	0.30	
Mean	154	154	154	155	154	154	154	154	153	152	
Min.	66	68	64	68	67	68	68	66	61	67	
Panel B: Panel B: Post-formation Portfolio Characteristics											
γ	0.22	0.27	0.35	0.25	0.17	0.44	0.24	0.76	0.92	1.36	
	(0.69)	(1.22)	(1.02)	(1.30)	(0.52)	(1.75)	(0.93)	(2.06)	(2.01)	(1.76)	
β_{mkt}	0.96	0.94	0.95	0.99	0.98	0.99	1.00	0.98	1.02	1.04	
	(46.43)	(37.76)	(43.50)	(38.27)	(42.00)	(38.37)	(47.05)	(35.52)	(38.16)	(23.07)	
β_{SMB}	0.51	0.57	0.58	0.68	0.68	0.68	0.82	0.79	0.89	1.23	
	(11.56)	(16.09)	(14.19)	(12.28)	(20.58)	(13.49)	(24.31)	(12.65)	(18.71)	(17.17)	
β_{HML}	0.36	0.41	0.42	0.41	0.41	0.41	0.35	0.38	0.32	0.18	
	(9.16)	(10.77)	(9.53)	(8.29)	(10.82)	(10.23)	(8.02)	(6.83)	(6.23)	(1.92)	
β_{MOM}	-0.07	-0.02	-0.04	0.01	-0.01	-0.03	0.01	-0.04	-0.06	-0.07	
	(-1.95)	(-0.68)	(-1.22)	(0.20)	(-0.39)	(-0.83)	(0.38)	(-1.05)	(-1.31)	(-0.82)	
β^{PS}	3.15	1.23	1.13	-3.07	-0.57	2.69	-1.20	2.00	1.39	-6.73	
	(2.31)	(0.82)	(0.72)	(-1.45)	(-0.35)	(1.58)	(-0.74)	(0.96)	(0.72)	(-1.98)	
Panel C: Returns (*per cent* per month)											
Return	1.38	1.40	1.50	1.52	1.56	1.44	1.51	1.55	1.66	2.03	0.65
	(5.52)	(5.70)	(5.89)	(5.60)	(6.05)	(5.35)	(5.32)	(5.47)	(5.33)	(5.30)	(3.13)
Capm α	0.42	0.46	0.55	0.55	0.59	0.47	0.51	0.56	0.63	0.94	0.51
	(3.29)	(3.48)	(3.92)	(3.82)	(4.08)	(3.16)	(3.38)	(3.46)	(3.54)	(3.81)	(2.68)
FF3 α	0.13	0.13	0.21	0.21	0.24	0.12	0.18	0.21	0.31	0.64	0.51
	(1.63)	(1.82)	(2.57)	(2.47)	(3.53)	(1.67)	(2.50)	(2.44)	(3.17)	(3.73)	(2.97)
FF4 α	0.20	0.16	0.26	0.20	0.25	0.15	0.18	0.26	0.37	0.71	0.51
	(2.53)	(2.19)	(3.00)	(2.36)	(3.51)	(1.91)	(2.39)	(2.82)	(3.09)	(3.43)	(2.61)

Table 5: Size and book-to-market adjusted returns for equally-weighted decile portfolios formed each year from January 1973 to December 2004 on Kalman Filter estimates of the absolute value of γ the 'mispricing beta' using *Mispricing Dispersion* as a proxy for the Aggregate Mispricing Factor: $\Delta z_{i,t} = c + \gamma \Delta z_{m,t}$, where

$$z_{m,t} = \sigma^*(z)$$

$\sigma^*(z)$ is the dispersion of estimated mispricing in month t. The portfolio mispricing beta, γ, is the coefficient from the regression of changes in post-formation portfolio mispricing, Δz_p, on changes in the aggregate mispricing factor proxy. Panel B reports size and book-to-market adjusted returns and the intercepts (α) from regressions of size and book-to-market adjusted returns on the market excess returns (CAPM), the 3 Fama-French factors (FF3), and the 3 Fama-French factors plus the Carhart Momentum factor (FF4). The returns and $\alpha's$ are in *per cent* per month, and the t-statistics which are adjusted for autocorrelation and heteroscedasticity are in parentheses.

	Portfolio 1	2	3	4	5	6	7	8	9	10	Spread $10-1$
Panel A: Portfolio Post-formation Mispricing Beta											
γ	0.20	0.20	0.28	0.19	0.11	0.47	0.25	0.76	1.06	1.59	
	0.54	0.84	0.68	0.87	0.30	1.57	0.93	1.85	2.23	1.86	
Panel B: Size and Book-to-Market Adjusted Returns (*per cent* per month)											
Adjusted	-0.13	-0.17	-0.08	0.01	-0.05	-0.11	-0.08	-0.07	0.01	0.38	0.51
Return	(-2.56)	(-2.80)	(-1.38)	(0.11)	(-0.78)	(-2.36)	(-1.35)	(-1.12)	(0.12)	(2.63)	(3.06)
Capm α	-0.11	-0.13	-0.05	0.01	-0.04	-0.11	-0.10	-0.08	-0.02	0.30	0.40
	(-2.18)	(-2.27)	(-0.92)	(0.10)	(-0.61)	(-2.27)	(-1.61)	(-1.33)	(-0.39)	(2.13)	(2.54)
FF3 α	-0.08	-0.13	-0.05	0.02	-0.05	-0.11	-0.09	-0.06	0.05	0.43	0.51
	(-1.54)	(-2.21)	(-0.82)	(0.19)	(-0.78)	(-2.32)	(-1.55)	(-0.95)	(0.81)	(3.05)	(3.15)
FF4 α	-0.11	-0.20	-0.10	-0.09	-0.14	-0.16	-0.17	-0.11	0.01	0.38	0.49
	(-1.96)	(-3.53)	(-1.75)	(-1.47)	(-2.43)	(-2.95)	(-2.48)	(-1.97)	(0.08)	(2.40)	(2.64)

Table 6 $z_{m,t} = \bar{z}_t$: Properties of equally-weighted 5 by 5 portfolios returns adjusted for size and book-to-market ratio, sorted on $|\gamma|$ and either the Mispricing Return Bias, or one of three measures of liquidity beta. β^{PS}, and $|\gamma|$ - this version uses from January 1973 to December 2004. At the end of each year from 1972 to 2003, stocks are sorted into β^{PS} or *Bias*, quintile portfolios; within each quintile, they are further sorted into 5 $|\gamma|$ portfolios; vice versa. The table reports returns adjusted for size and book-to-market ratios. The returns are in *per cent* per month, and the *t*-statistics are adjusted for autocorrelation and heteroscedasticity.

	Size and B/M Matched Returns (%)						t-statistic					
	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)
Hi Bias	-0.02	0.13	0.22	0.39	0.80	0.82	-0.15	1.08	1.64	2.20	3.69	3.79
3	-0.15	-0.14	-0.25	0.12	-0.12	0.04	-1.77	-1.85	-2.77	1.32	-1.21	0.27
Lo Bias	-0.16	-0.15	-0.21	-0.21	0.00	0.16	-1.85	-1.61	-2.61	-2.76	0.00	1.05
	Lo Bias	2	3	4	Hi Bias	Spread (5-1)	Lo Bias	2	3	4	Hi Bias	Spread (5-1)
Hi $\|\gamma\|$	-0.08	0.03	-0.13	0.43	0.93	1.02	-0.66	0.24	-1.18	3.03	3.59	3.83
3	-0.31	-0.03	-0.22	-0.17	-0.02	0.29	-4.00	-0.35	-2.46	-2.50	-0.17	1.88
Lo $\|\gamma\|$	-0.17	-0.20	-0.18	-0.22	-0.13	0.03	-1.89	-2.58	-2.57	-2.41	-1.60	0.26
	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)
Hi β^{PS}	-0.07	-0.07	0.09	0.36	0.48	0.55	-0.71	-0.69	0.95	2.53	2.25	2.30
3	-0.16	-0.10	-0.08	-0.11	0.21	0.37	-1.75	-1.16	-1.00	-1.48	1.77	2.27
Lo β^{PS}	-0.21	0.01	-0.08	-0.08	0.26	0.47	-2.34	0.09	-0.86	-0.70	1.65	2.48
	Lo β^{PS}	2	3	4	Hi β^{PS}	Spread (5-1)	Lo β^{PS}	2	3	4	Hi β^{PS}	Spread (5-1)
Hi $\|\gamma\|$	0.33	-0.01	0.16	0.11	0.57	0.24	2.11	-0.06	1.39	1.05	2.49	1.10
3	-0.13	-0.15	-0.16	-0.22	-0.04	0.09	-1.52	-1.93	-1.89	-3.04	-0.39	0.70
Lo $\|\gamma\|$	-0.30	-0.14	-0.19	-0.12	-0.19	0.10	-3.34	-1.69	-2.22	-1.40	-2.04	0.78
	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)
Hi β^{Liu}	-0.18	-0.06	-0.18	0.17	0.32	0.49	-1.79	-0.65	-1.90	1.48	2.18	2.70
3	-0.10	-0.12	-0.15	-0.12	-0.09	0.01	-1.13	-1.43	-1.83	-1.63	-0.71	0.09
Lo β^{Liu}	-0.09	-0.06	0.24	0.13	0.64	0.73	-0.86	-0.59	1.87	0.87	2.80	3.02
	Lo β^{Liu}	2	3	4	Hi β^{Liu}	Spread (5-1)	Lo β^{Liu}	2	3	4	Hi β^{Liu}	Spread (5-1)
Hi $\|\gamma\|$	0.69	0.06	0.24	-0.03	0.36	-0.34	2.90	0.47	2.19	-0.18	2.43	-1.47
3	-0.10	-0.21	-0.24	-0.09	-0.11	-0.01	-0.97	-2.80	-2.65	-1.13	-1.03	-0.04
Lo $\|\gamma\|$	-0.21	-0.18	-0.15	-0.11	-0.22	-0.01	-2.41	-2.09	-1.69	-1.26	-2.38	-0.07
	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)	Lo $\|\gamma\|$	2	3	4	Hi $\|\gamma\|$	Spread (5-1)
Hi β^{Amihud}	-0.24	-0.11	-0.20	0.11	0.38	0.61	-2.91	-1.40	-2.17	0.82	1.99	3.12
3	-0.09	0.00	-0.21	-0.19	0.16	0.25	-1.08	-0.03	-2.22	-2.44	1.40	1.68
Lo β^{Amihud}	0.00	-0.02	-0.04	-0.03	0.57	0.58	-0.01	-0.21	-0.40	-0.18	2.94	2.82
	Lo β^{Amihud}	2	3	4	Hi β^{Amihud}	Spread (5-1)	Lo β^{Amihud}	2	3	4	Hi β^{Amihud}	Spread (5-1)
Hi $\|\gamma\|$	0.33	0.11	0.14	0.17	0.49	0.16	1.72	0.81	0.88	1.37	2.39	0.63
3	-0.18	-0.11	-0.17	-0.11	-0.18	-0.01	-1.78	-1.17	-1.80	-1.50	-2.02	-0.04
Lo $\|\gamma\|$	-0.20	-0.12	-0.10	-0.21	-0.29	-0.09	-2.05	-1.32	-1.09	-2.52	-3.74	-0.65

Table 7 $z_{m,t} = \sigma_t(z_i)/MA(60)$: Properties of equally-weighted 5 by 5 portfolio returns adjusted for size and book-to-market ratio, sorted on $|\gamma|$ and either the Mispricing Return Bias, or one of three measures of liquidity beta. β^{PS}, and $|\gamma|$ - this version uses from January 1973 to December 2004. At the end of each year from 1972 to 2003, stocks are sorted into β^{PS} (or *Bias*, quintile portfolios; within each quintile, they are further sorted into 5 $|\gamma|$ portfolios; vice versa. The table reports returns adjusted for size and book-to-market ratios. The returns are in *per cent* per month, and the *t*-statistics are adjusted for autocorrelation and heteroscedasticity.

	Size and B/M Matched Returns (%)						t-statistic					
	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)
Hi Bias	0.04	0.04	0.20	0.42	0.79	0.75	0.20	0.33	1.52	3.13	3.26	3.09
3	-0.07	-0.01	-0.05	-0.15	-0.25	-0.18	-0.85	-0.17	-0.72	-1.73	-2.62	-1.42
Lo Bias	-0.26	-0.15	-0.07	-0.11	-0.09	0.17	-3.32	-1.79	-0.61	-1.33	-0.89	1.46
	Lo Bias	2	3	4	Hi Bias	Spread (5-1)	Lo Bias	2	3	4	Hi Bias	Spread (5-1)
Hi $\lvert\gamma\rvert$	-0.14	-0.05	-0.12	0.24	1.02	1.16	-1.39	-0.52	-1.07	1.86	3.96	4.28
3	-0.16	-0.07	-0.08	0.03	-0.04	0.12	-2.21	-0.89	-1.10	0.34	-0.34	0.81
Lo $\lvert\gamma\rvert$	-0.18	-0.22	-0.13	-0.10	-0.12	0.06	-2.15	-2.50	-1.80	-1.24	-1.07	0.38
	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)
Hi β^{PS}	-0.02	0.14	0.03	0.14	0.49	0.51	-0.22	0.78	0.28	1.40	2.60	2.39
3	-0.08	0.04	-0.18	-0.12	0.13	0.21	-0.95	0.49	-1.91	-1.46	1.06	1.35
Lo β^{PS}	-0.19	0.03	-0.09	0.00	0.11	0.30	-2.00	0.20	-0.95	0.00	0.75	1.87
	Lo β^{PS}	2	3	4	Hi β^{PS}	Spread (5-1)	Lo β^{PS}	2	3	4	Hi β^{PS}	Spread (5-1)
Hi $\lvert\gamma\rvert$	0.33	0.02	0.12	0.00	0.49	0.16	2.14	0.14	0.96	-0.04	2.74	0.81
3	0.01	-0.12	-0.17	-0.09	-0.02	-0.03	0.06	-1.51	-1.97	-1.20	-0.21	-0.22
Lo $\lvert\gamma\rvert$	-0.17	-0.18	-0.14	-0.11	-0.09	0.08	-1.94	-2.16	-1.65	-1.41	-0.91	0.59
	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)
Hi β^{Liu}	-0.11	-0.04	0.00	-0.04	0.27	0.38	-1.09	-0.51	-0.03	-0.39	2.00	2.77
3	-0.19	-0.19	-0.05	-0.08	-0.07	0.12	-1.94	-2.74	-0.58	-0.96	-0.74	0.82
Lo β^{Liu}	-0.08	0.27	0.01	0.04	0.57	0.64	-0.69	1.31	0.07	0.31	2.60	2.71
	Lo β^{Liu}	2	3	4	Hi β^{Liu}	Spread (5-1)	Lo β^{Liu}	2	3	4	Hi β^{Liu}	Spread (5-1)
Hi $\lvert\gamma\rvert$	0.39	0.26	0.01	0.09	0.33	-0.07	1.95	2.00	0.10	0.69	2.27	-0.30
3	0.04	-0.28	0.03	-0.13	0.02	-0.03	0.41	-3.18	0.35	-1.60	0.17	-0.21
Lo $\lvert\gamma\rvert$	-0.18	-0.18	-0.20	-0.19	-0.02	0.16	-1.64	-2.07	-2.17	-2.36	-0.20	0.97
	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)	Lo $\lvert\gamma\rvert$	2	3	4	Hi $\lvert\gamma\rvert$	Spread (5-1)
Hi β^{Amihud}	-0.12	-0.14	-0.09	-0.06	0.37	0.48	-1.41	-1.24	-1.08	-0.47	1.98	2.43
3	-0.05	-0.16	-0.09	-0.02	0.01	0.06	-0.57	-1.89	-1.11	-0.26	0.06	0.45
Lo β^{Amihud}	-0.21	0.26	-0.11	0.14	0.37	0.59	-1.84	1.92	-0.91	1.21	1.98	2.95
	Lo β^{Amihud}	2	3	4	Hi β^{Amihud}	Spread (5-1)	Lo β^{Amihud}	2	3	4	Hi β^{Amihud}	Spread (5-1)
Hi $\lvert\gamma\rvert$	0.36	0.19	-0.03	0.15	0.34	-0.02	1.96	1.50	-0.26	1.41	1.94	-0.08
3	-0.03	-0.03	-0.05	-0.07	-0.17	-0.14	-0.30	-0.32	-0.67	-0.90	-1.83	-1.02
Lo $\lvert\gamma\rvert$	-0.23	-0.13	-0.02	-0.20	-0.16	0.07	-2.37	-1.47	-0.21	-2.43	-2.02	0.54

Figure 1: Mispricing Measures, z_i, for Sample Firms in per cent

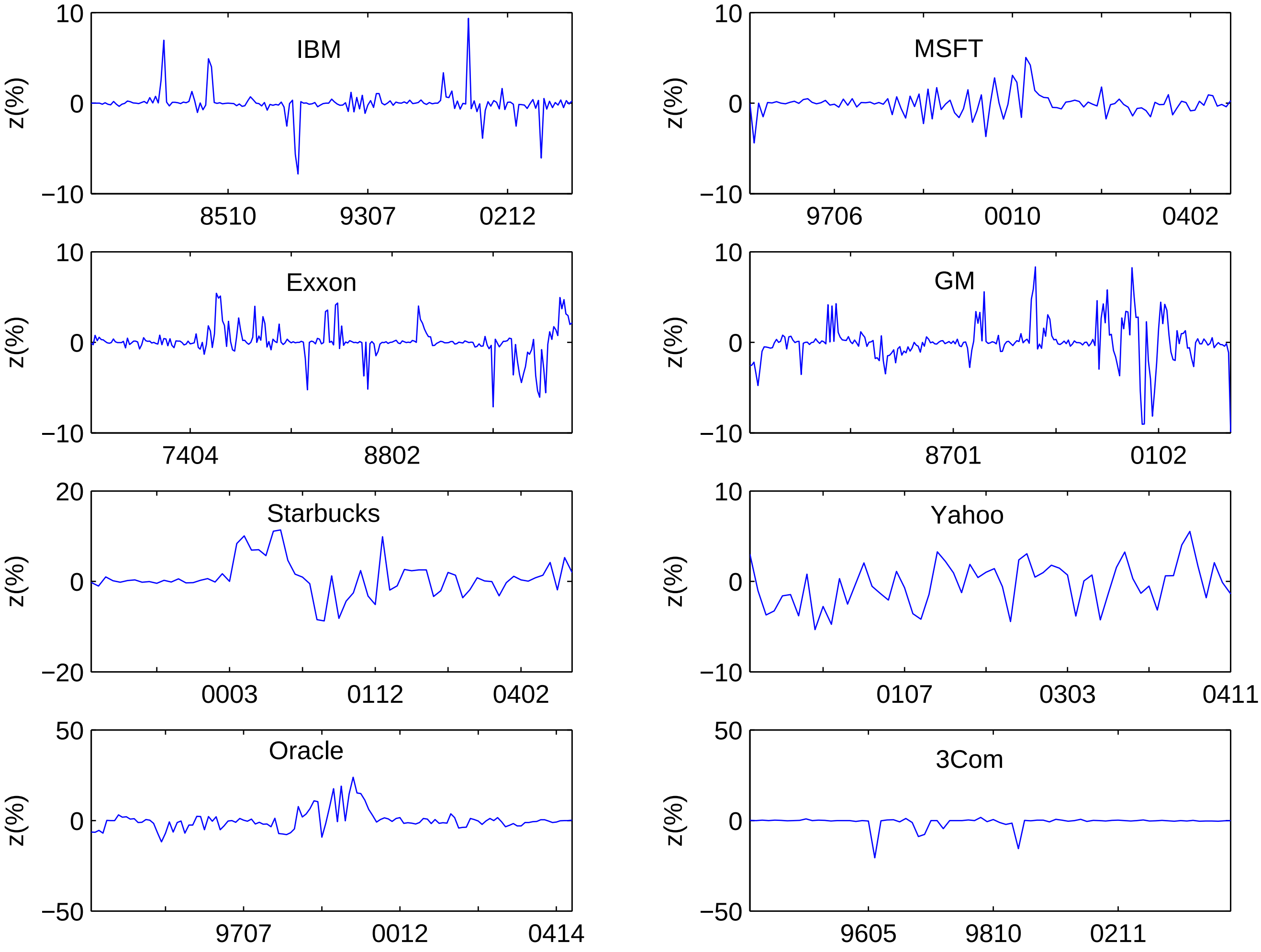

Figure 2: Time Series of the Mean level of Mispricing $\bar{z}_{i,t}$ in per cent

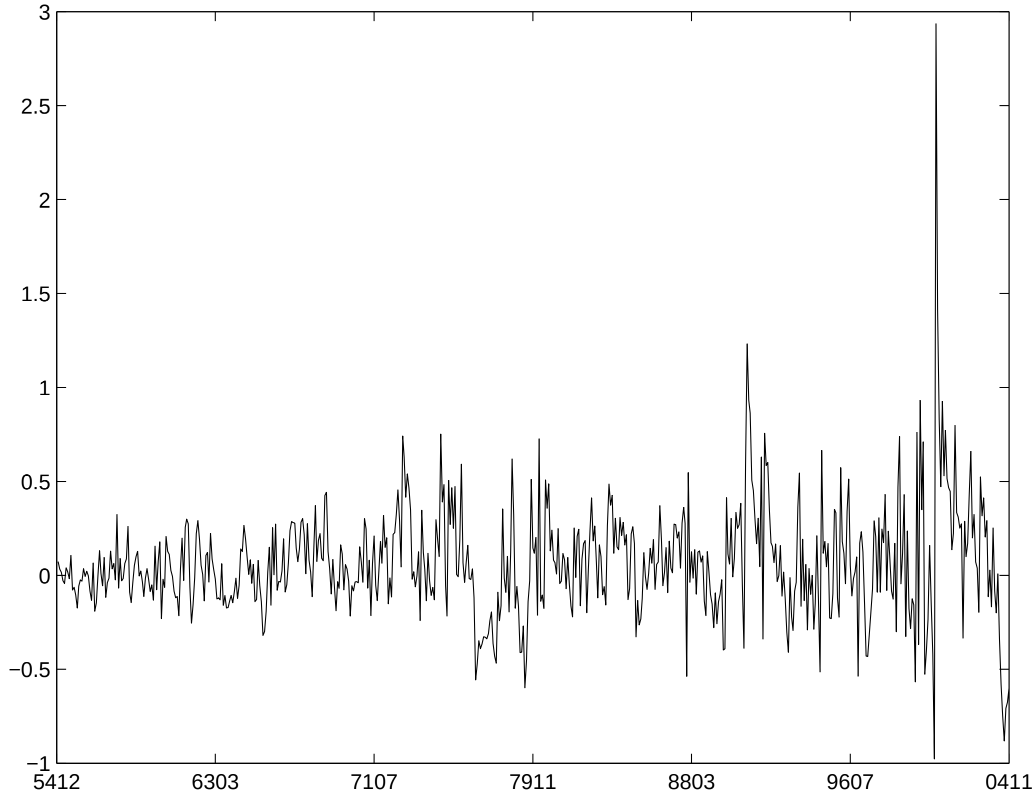

Figure 3: Time Series of Cross-sectional Dispersion of Mispricing ($\sigma_t(z_i)$) and Number of Stocks

Dashed line is for the cross-sectional dispersion of individual security mispricing in per cent, and the solid line is for the number of stocks in thousands at the end of each month.

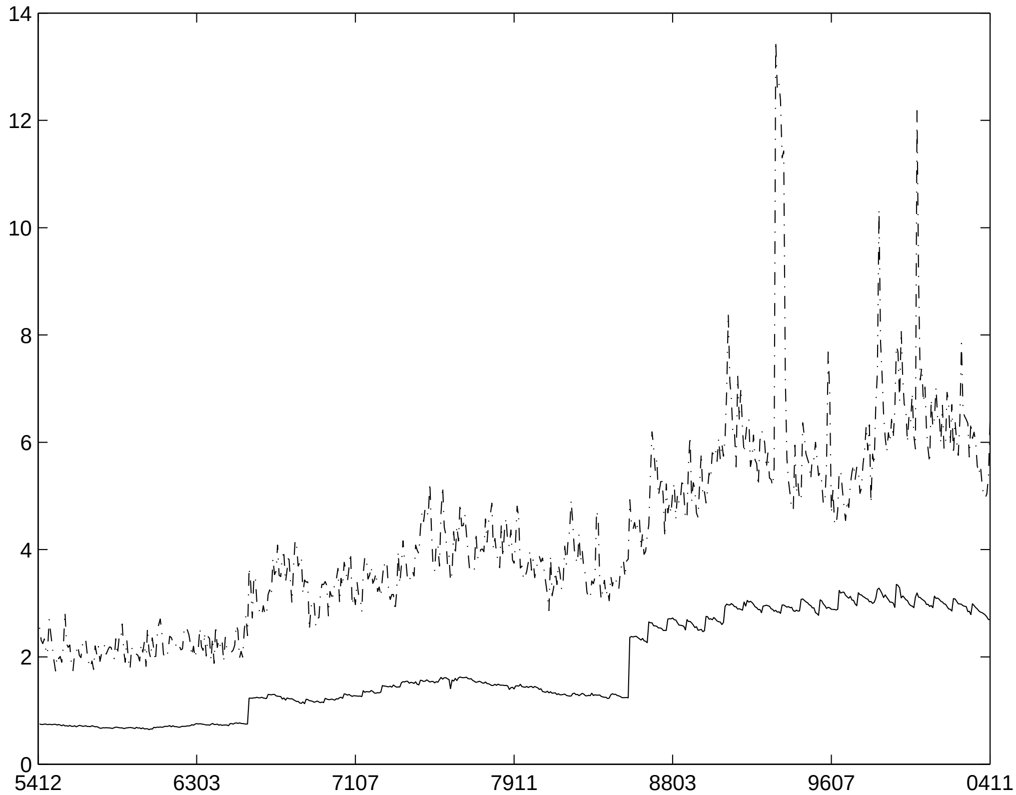

Figure 4: Post-formation Mispricing Bias Beta and FF3 Alpha

Blue stars plot monthly FF3 alphas in *per cent* against post-formation mispricing bias beta for decile portfolios sorted on $|\gamma|$, while red circles are for decile portfolios sorted on γ.

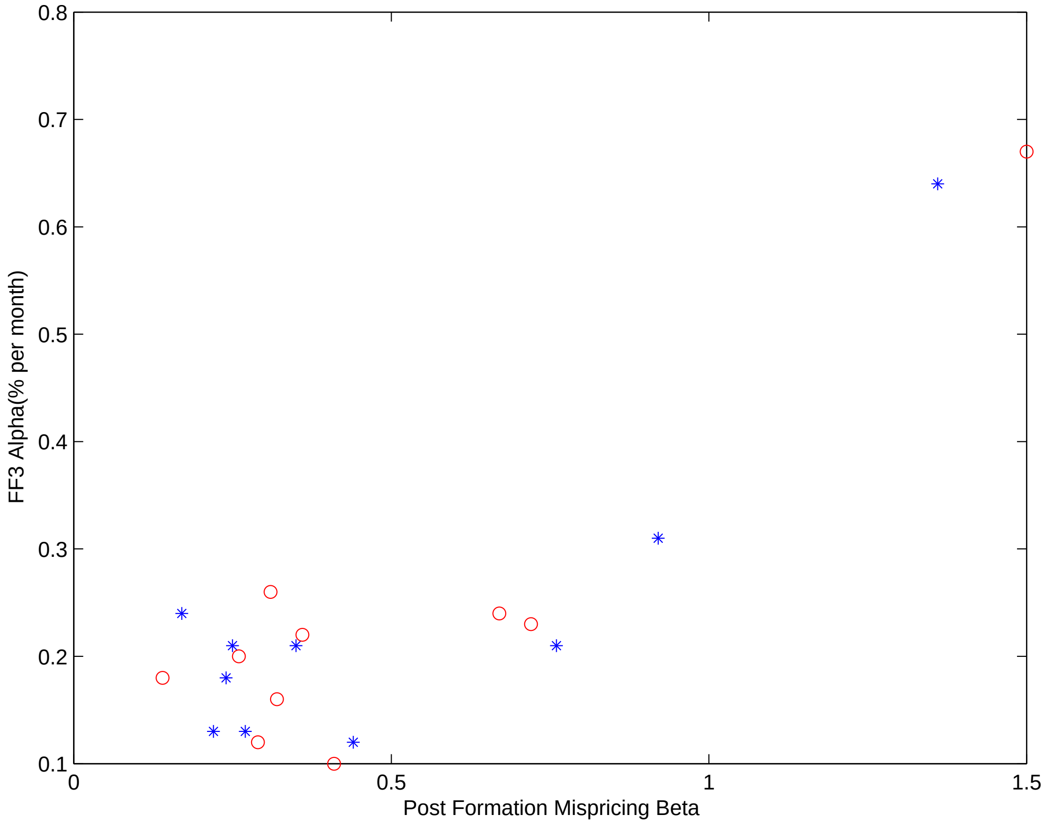

Figure 5: Figure 1A: Mispricing Measures, z_i, for Sample Firms in per cent

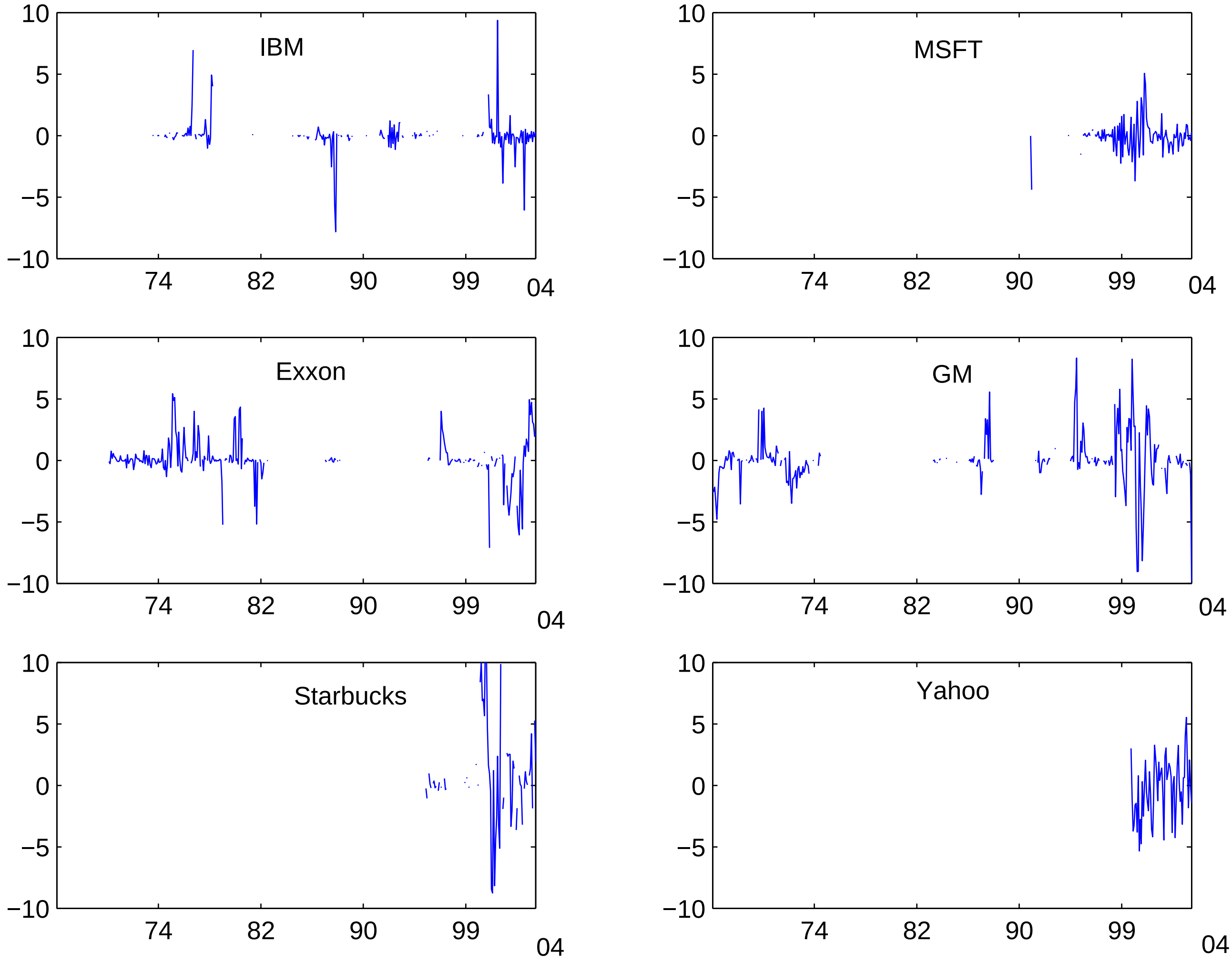

Figure 6: Figure 1B: Mispricing Measures, z_i, for Sample Firms in per cent