A Financing-Based Misvaluation Factor and the Cross Section of Expected Returns

Hirshleifer, David and Jiang, Danling

31 October 2007

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David Hirshleifer†

Danling Jiang‡

February 10, 2010

Abstract

Behavioral theories suggest that investor misperceptions and market mispricing will be correlated across firms. We use equity and debt financing to identify common misvaluation across firms. A zero-investment portfolio (UMO, Undervalued Minus Overvalued) built from repurchase and new issue firms captures comovement in returns beyond that in some standard multi-factor models, and substantially improves the Sharpe ratio of the tangency portfolio. Loadings on UMO incrementally predict the cross-section of returns on both portfolios and individual stocks, even among firms not recently involved in external financing activities. Further evidence suggests that UMO loadings proxy for the common component of a stock's misvaluation.

[Keywords] Misvaluation, financing, new issues, repurchase, factor models, market efficiency, behavioral finance

*The paper was previously entitled "Equity Financing, Commonality in Misvaluation, and the Cross Section of Stock Returns." We appreciate helpful comments and suggestions from James Ang, Alex Butler, Karl Diether, Bing Han, Jean Helwege, Kewei Hou, Jason Karceski, Andrew Karolyi, Pete Kyle, Sonya Lim, Dave Peterson, Christof Stahel, René Stulz, Bhaskaran Swaminathan, Siew Hong Teoh; participants at the Seventh Maryland Finance Symposium, the American Finance Association meetings at New Orleans, LA, and the Western Finance Association meetings at San Diego, CA; our discussants, respectively: Jay Ritter, Kent Daniel, and Andriy Bodnaruk. We thank Jay Ritter for providing the new issue data, Evgeny Lyandres for the investment factor returns, Michael Ferguson for the leverage factor returns, Kenneth French for the 4-factor returns and industry classifications, and SuJung Choi, Yong Rin Park, and Dave Weaver for helpful research assistance.

†Professor of Finance and Merage Chair in Business Growth, Paul Merage School of Business, University of California at Irvine, (949) 824-9955, E-mail: david.h@uci.edu, http://web.merage.uci.edu/∼Hirshleifer/.

‡Assistant Professor, The College of Business, Florida State University, (850) 645-1519, E-mail: djiang@cob.fsu.edu, http://mailer.fsu.edu/∼djiang/.

A Financing-Based Misvaluation Factor and the Cross Section of Expected Returns

Behavioral theories suggest that investor misperceptions and market mispricing will be correlated across firms. We use equity and debt financing to identify common misvaluation across firms. A zero-investment portfolio (UMO, Undervalued Minus Overvalued) built from repurchase and new issue firms captures comovement in returns beyond that in some standard multifactor models, and substantially improves the Sharpe ratio of the tangency portfolio. Loadings on UMO incrementally predict the cross-section of returns on both portfolios and individual stocks, even among firms not recently involved in external financing activities. Further evidence suggests that UMO loadings proxy for the common component of a stock's misvaluation.

Introduction

Several recent behavioral models predict commonality in the misvaluation of firms. In some models, such commonality occurs because investors use past values of aggregate stock market indices as reference points (see, e.g., Barberis, Huang, and Santos (2001), Barberis and Huang (2001)). In the style investing approach of Barberis and Shleifer (2003), commonality in misvaluation arises when investors irrationally become enamored or disillusioned with publicly observable stock characteristics, inducing positive comovement among stocks with similar characteristics and negative comovement in stocks with dissimilar characteristics. In the overconfidence approach of Daniel, Hirshleifer, and Subrahmanyam (2001), investors misinterpret what they perceive to be private information about the genuine economic factors influencing firms' profits. Thus, sets of stocks with similar loadings move together as information about factors arrives, is misinterpreted, and is later corrected.

From a behavioral perspective, characteristics such as book-to-market can reflect either firm-specific mispricing or misvaluation of systematic economic factors. Thus, evidence that stock characteristics such as size, book-to-market, or momentum predict the cross section of future returns does not resolve whether there is systematic or merely firm-specific mispricing.[1]

Some theoretical arguments suggest that most mispricing will be idiosyncratic, but others suggest that common mispricing is more important. If investors devote less resources to the study of an idiosyncratic payoff component than to a common one such as the market as a whole, then we expect to see more mispricing in obscure, idiosyncratic corners of the market.[2] On the other hand, in the model of Daniel, Hirshleifer, and Subrahmanyam (2001), in frictionless markets idiosyncratic mispricing can be arbitraged away with low risk through the use of hedge portfolios; it is the mispricing of common factors that remains. Style investors and overconfident investors may trade in ways that cause either idiosyncratic or common mispricing.[3]

[1]Fama and French (1993) find that book-to-market and size effects are associated with common factors, and suggest a rational risk explanation. Carhart (1997) links the momentum effect to common factors. An additional literature refines, tests, and in some cases disputes the risk premium interpretation of the 3- or 4-factor model (e.g., Daniel and Titman (1997), Griffin and Lemmon (2002), and Hou, Peng, and Xiong (2007)).

[2]There is evidence that some anomalies are stronger within the idiosyncratic component of returns (Grundy and Martin (2001), Hou, Peng, and Xiong (2007)).

[3]Investors do seem to think that they can acquire private information about aggregate factors, as evidenced by the active industry selling macroeconomic forecasts, and the demand for industry and market earnings forecasts by stock analysts. Investors speculate based upon opposing beliefs in macroeconomic markets such as CPI futures. More generally, there are market timers who place bets against each other based on their beliefs about market aggregates,

So on prior grounds, a case can be made for either idiosyncratic or systematic mispricing. It is therefore useful to test whether or not mispriced stocks comove, and whether measures of sensitivity to factor mispricing can be used to predict the cross section of stock returns.

External financing and repurchase decisions provide a way to address these questions. Theoretical and empirical research suggest that corporate managers undertake financing decisions to take advantage of both firm-specific and common misvaluation. Theoretical models suggest that issuing or repurchasing stocks or bonds to take advantage of inefficient stock mispricing (often translated into debt mispricing) can benefit a firm's existing shareholders, and can cause such activity to predict future returns (Stein (1996), Daniel, Hirshleifer, and Subrahmanyam (1998)). Empirically, evidence from equity or debt financing and long-run returns suggests that firms tend to issue equity or risky debt when they are overvalued, and to buy back equity or retire risky debt when they are undervalued (see Section 1.3).

In this paper we use external equity and debt financing activities to identify commonality in stock misvaluation, or what we call factor mispricing, and test whether sensitivities to common movements in misvaluation predict the cross-section of asset returns. We define a misvaluation factor (or mispricing factor) as any statistical common factor in stock returns that is substantially correlated with the common mispricing of individual stocks. Commonality in misvaluation can occur when investors misinterpret signals about a fundamental economic factor, or when there are shifts in investor sentiment about firm characteristics or 'styles'.

If firms undertake new issues or repurchases to exploit mispricing, such events should reflect information possessed by managers about stock mispricing (above and beyond other observable characteristics such as equity book-to-market). Therefore, we will argue that issue and repurchase firms should have extreme sensitivities to mispricing factors. Regardless of whether the comovement in misvaluation arises from misperceptions about fundamentals, or from style-based sentiment, new issue and repurchase stocks are predicted to comove (even after controlling for familiar factors such as HML). We can therefore construct a misvaluation factor by going long on repurchase stocks and short on the new issue stocks. This misvaluation factor is predicted to have a nonnegligible positive variance, even after controlling for the market or other well-known factors. We call this misvaluation factor UMO (Undervalued Minus Overvalued).

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and investors who look for industry plays such as oil or bio-tech stocks.

We further hypothesize that the loadings of general firms (not just those firms that have recently engaged in issuance or repurchase activities) on UMO are proxies for systematic underpricing, and therefore will positively predict future returns. This hypothesis implies that firms' financing decisions contain information for predicting returns that has not hitherto been exploited.

To see why, consider for example an oil price factor that affects firms' cash flows, and suppose that investors irrationally expect oil prices to be low. Repurchasers will tend to be firms that are undervalued, which occurs if their profits are positively sensitive to oil prices (e.g., a solar power product vendor), whereas equity issuers will tend to be firms that are overvalued because their profits are negatively sensitive to oil prices (e.g., an airline). Furthermore, firms whose profits are hurt by low oil prices will load positively on UMO since UMO is long on firms that do poorly when oil prices are low. Similarly, firms that benefit from low oil prices will load negatively on UMO. In other words, the factor loading measures the degree to which an asset inherits mispricing from the mispriced factor.

Alternatively, common mispricing can be caused by shifts in investor sentiment associated with different investment styles (rather than misperceptions of signals about fundamental factors). For example, suppose that investors become enamored with high-tech firms. Then repurchases will be common among undervalued low-tech firms, and new issues among high-tech firms. Low-tech firms, in general, will tend to load positively on UMO because their returns are more highly correlated with the low-tech firms that are engaging in repurchases than with the high-tech firms that are engaging in new issue.

Both lines of reasoning imply that a firm that loads positively on the mispricing factor, UMO, will, on average, be undervalued. As a result, loadings on the mispricing factor will positively predict high subsequent returns as information about future fundamentals resolves.

Of course there are rational reasons for external financing other than exploiting temporary stock misvaluation. For example, if investment is rationally undertaken in response to low project risk, then equity or debt issuances for the purpose of investment will be associated with low subsequent returns. In our tests we therefore control for sets of benchmark factors that have sometimes been interpreted as reflecting rational risk premia, including the Fama French factors, the momentum factor, the leverage factor (Ferguson and Shockley 2003), and the investment factor (Lyandres, Sun, and Zhang 2008); we also control for industry effects.[4] To the extent that these benchmark factors and/or the characteristics they are based upon reflect behavioral effects (see, e.g., Keim (1983), Loughran (1997), Baker and Wurgler (2002), Baker, Stein, and Wurgler (2003), Daniel, Hirshleifer, and Subrahmanyam (2005), Polk and Sapienza (2009)), controlling for the benchmark factors ensures that the UMO effects we identify are not just a repackaging of other known effects.

We find substantial variance in the return of UMO that is not fully explained by the returns on our benchmark factor portfolios. Furthermore, other asset portfolios have non-zero loadings on UMO even after controlling for the benchmark factors. These findings show that UMO captures commonality in stock returns beyond that implied by the benchmark factors.

We also find that the UMO factor earns abnormally high returns. UMO produces a Sharpe ratio (0.30) that is similar to that of the investment factor and higher than that of each of the other benchmark factors. Using factors that are adjusted for the five Fama-French sectors, UMO delivers the highest Sharpe ratio among all (0.39). Moreover, UMO increases the Sharpe ratio of the *ex post* tangency portfolio by about 75% relative to the Fama-French factors. MacKinlay (1995) argues that the returns provided by the Fama French factors are too large to make sense from a rational asset pricing perspective; the higher Sharpe ratio produced by UMO presents an even greater challenge. Furthermore, regressing UMO on the sets of benchmark factors yields significantly positive alphas of 6%−9% per annum, a strong abnormal performance relative to the benchmark.

We further show that at both the portfolio and the firm levels, assets with higher UMO loadings on average earn higher subsequent returns. At the portfolio level, we estimate UMO loadings from previous 5-year monthly returns. At the firm level, we obtain UMO loadings from two approaches that account for the transitory nature of firm-level mispricing. In one, we estimate UMO loadings from daily returns of individual stocks over a relatively short period, e.g., 3 to 12 months. In the other, we assign stocks the loadings of portfolios that are matched by relevant firm characteristics that are potentially related to mispricing, including size, book-to-market, and the external financing variable of Bradshaw, Richardson, and Sloan (2006).

In portfolio tests, UMO loadings predict the cross-section of portfolio returns after controlling

[4] We also consider in Section A of the Addendum other controls as robustness checks, including the macroeconomic factors suggested by Eckbo, Masulis, and Norli (2000), the new three-factor by Chen and Zhang (2010), the Fama-French factors purged of new issue firms (e.g., Loughran and Ritter (2000)), and a factor based on the asset growth variable of Cooper, Gulen, and Schill (2008).

for the loadings on the benchmark factors, with an estimated UMO premium of about 6%–9% per annum. In firm level tests, a hedge portfolio that is long the highest and short the lowest loading decile yields an annual abnormal return of 7–10% per year, and regression tests imply an abnormal return from UMO loadings of over 17% per year. UMO loadings have incremental power to predict returns after controlling for various firm characteristics.[5] The marginal effect of UMO loadings on the cross section of returns is considerably higher than that of the above return predictors.

This evidence is consistent with the proposition that the external financing decisions of managers contain information about the common component of stock mispricing, above and beyond firm characteristics such as size and book-to-market equity. The finding that UMO loadings have incremental power relative to other measures of stock mispricing (such as the net composite issuance variable of Daniel and Titman (2006) and the asset growth variable of Cooper, Gulen, and Schill (2008)) is consistent with behavioral theories that imply that both covariances and characteristics will, in general, have incremental power to predict stock returns (Daniel, Hirshleifer, and Subrahmanyam (2005)).

We also provide evidence that security loadings on the UMO factor have a period of stability much shorter than that of several well-known proposed fundamental factors. Following Fama and French (1992), we estimate the pre-ranking UMO loadings for individual stocks using 3-5 years of monthly returns and the post ranking loadings from portfolios constructed based on pre-ranking loadings. We find that, UMO loadings are much more likely to flip signs than loadings on the 3 factors, and that sorting stocks based on pre-ranking UMO loadings create little dispersion in the post-ranking period (in sharp contrast to the behavior of loadings on the Fama-French factors).

In a behavioral setting, loadings on the mispricing factor, UMO, are proxies for systematic underpricing. Overreactions to factor signals cause fundamental factors to become overpriced at certain times and underpriced at others, while shifts in investor sentiment lead investment styles to become 'hot' or 'cold' over time. As a result, individual stocks that load on the mispriced fundamental factors or style factors will inherit the factor under- and overpricing accordingly. Since UMO is constructed to be long on underpriced factors and short on overpriced ones, UMO loadings

[5] We control for size, book-to-market equity, past returns, industry dummies, the external financing variable of Bradshaw, Richardson, and Sloan (2006), the net composite issuance variable of Daniel and Titman (2006), the asset growth variable of Cooper, Gulen, and Schill (2008), the investment-asset ratio of Lyandres, Sun, and Zhang (2008), the net operating asset variable of Hirshleifer, Hou, Teoh, and Zhang (2004), the operating accruals of Sloan (1996), and the abnormal capital investment variable of Titman, Wei, and Xie (2004).

of individual stocks will shift signs to reflect the shifts in factor or style mispricing. Therefore, we expect UMO loadings to mean-revert quickly or even flip signs over a period of 3-5 years (see the discussion in Section 3.1).

1 Motivation and Hypotheses

1.1 Rational Factor Pricing Models

In rational factor pricing models such as the intertemporal CAPM, only factor covariance is 'priced,' so after controlling for factor loadings no other publicly available information can be used to predict returns. There are several possible reasons why equity financing may be correlated with risk in a rational asset pricing model. First, as discussed in the introduction, equity issuance decreases leverage, which should reduce factor loadings and premia (e.g., Eckbo, Masulis, and Norli (2000)). An implication of this argument is that shifts in leverage changes should explain the returns of new issue firms. However, the leverage effect would predict that debt financing should precede high future stock returns. Since we are examining external financing as a whole, it is unclear whether there should be a net leverage effect.

Second, a shift in a firm's loadings which decreases its risk premium/discount rate should cause it to increase planned investment (Berk, Green, and Naik 1999; Zhang 2005). This implies a greater need to issue equity or debt to fund investment, so firms that have issued to fund investment should have lower expected stock returns. This argument implies that the ability of equity/debt issuance to predict returns should be explained by investment.[6] Similarly, the ability of a financing factor to explain the cross section of returns should be largely subsumed by an investment factor.

1.2 Behavioral Models

We focus here upon the style investing model of Barberis and Shleifer (2003) and the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (2001).[7] In the model of Barberis and Shleifer

[6]Both the leverage effect and the investment effect, however, can be caused by managers exploiting irrational market valuation. So the fact that external financing is related to investments does not necessarily preclude a behavioral explanation; see Baker and Wurgler (2002), Baker, Stein, and Wurgler (2003), and Gilchrist, Himmelberg, and Huberman (2005).

[7]Several other models also imply non-fundamental commonality in asset price movements. For example, the prospect theory model of Barberis, Huang, and Santos (2001) suggests that stocks comove when investors' risk attitudes shift in response to market returns. The model of Kyle and Xiong (2001) implies common shifts in asset prices due to the simultaneous liquidation of multiple assets by convergence traders, after wealth shocks.

(2003), stocks comove with two factors, a market factor, which captures market-wide cash flows, and a style factor, which represents commonality in sentiment for styles of stocks (such as size, value versus growth, or high-tech versus low-tech). Investors shift between styles based on past relative performance. Accordingly, the demand for different kinds of stocks varies according to their sensitivity to different style factors and to past style performance. Stocks whose styles have performed well become overpriced, leading eventually to low returns. Therefore, this model predicts that common shifts in investor style investing cause commonality in mispricing.

In the model of Daniel, Hirshleifer, and Subrahmanyam (2001), overconfident investors overestimate signal precision and, accordingly, overreact to private signals about payoffs of economic factors, which creates mispricing of factor payoffs and of all securities whose cash flows are derived from these factors. In equilibrium, securities that load heavily on mispriced factors will be more misvalued. Thus, systematic mispricing results from investors' biased interpretation of factor cash flow information and reflects overreaction to cash flow news about fundamental factors.

Both behavioral models imply *excess return comovement* among securities caused by common misvaluation and correction of such mispricing. Here we define excess comovement as comovement in stock returns that deviates (either positively or negatively) from the fundamentals-based comovement that would exist in an efficient market based upon common fundamental influences. Systematic mispricing can be correlated with fundamental cash flow factors, but does not have to be.

A growing literature tests whether market inefficiency is a source of stock return comovement.[8] An advantage of using issuance/repurchase to identify commonality in misvaluation is that the decision to issue or repurchase equity or debt, under existing behavioral theories, reflects the beliefs of management about whether the stock is mispriced. It therefore provides an overall measure of mispricing based on information not otherwise detectable to the econometrician.

1.3 External Financing

Existing evidence suggests that the post-event long-run performance of new issues and repurchases reflect correction of mispricing. For example, firms that engage in IPOs and SEOs on average

[8]See Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Wurgler (2005), Goetzmann and Massa (2005), Baker and Wurgler (2006, 2007), Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2008), Boyer (2008), and Barber, Odean, and Zhu (2009).

underperform standard benchmarks for three to five years subsequent to the issue (Loughran and Ritter (1995, 2000), Spiess and Affleck-Graves (1995); using a modified benchmark, Brav, Geczy, and Gompers (2000) concur for post-SEO but not post-IPO underperformance). Since overvalued firms will tend to have both overpriced equity and risky debt, overvalued firms should tend to issue risky debt to exploit mispricing, and their equity should subsequently underperform.[9] Some recent studies further show that firm-level measures of net equity financing are negatively related to subsequent stock returns (e.g., Daniel and Titman (2006), Pontiff and Woodgate (2008), Bradshaw, Richardson, and Sloan (2006)).

Furthermore, aggregate equity issuance is correlated with market valuations and can forecast aggregate returns (e.g., Ritter (1984), Loughran, Ritter, and Rydqvist (1994), Baker and Wurgler (2000), and Lowry (2003)). This is potentially consistent with equity issuance responding to sector- or market-wide mispricing.[10]

With respect to repurchase, Lakonishok and Vermaelen (1990) and Ikenberry, Lakonishok, and Vermaelen (1995) show that the stocks of firms that buy back shares on average overperform in the subsequent three years. Similarly, the stocks of firms that reduce the outstanding debt in the face of market undervaluation tend to overperform (e.g., (Bradshaw, Richardson, and Sloan 2006)).

Graham and Harvey (2001) find that a majority of CFOs say that stock mispricing is an important motive to issue equity. Consistent with market expectational errors, Jegadeesh (2000) documents that the stock market reacts unfavorably to earnings announcements subsequent to new issues. More generally, a rational risk-based explanation for the new issues puzzle seems to require that recent issuers have unusually low risk. It has not so far been established that new issue firms are a good hedge for aggregate consumption.

Our paper differs from past work in this area in focusing on how general stocks comove with external-financing firms, and how covariance with a financing-based factor predicts future returns.

[9]This is consistent with the evidence of Stigler (1964), Spiess and Affleck-Graves (1999), Bradshaw, Richardson, and Sloan (2006), and Cooper, Gulen, and Schill (2008). Overvaluation should cause greater issuance in total, and a substitution from debt to equity issuance. Baker and Wurgler (2000) test a hypothesis about substitution based on market timing of the *relative* mispricing of equity versus debt. However, debt and equity issuance are imperfect substitutes because of agency and tax considerations. So despite the substitution effect, we do not expect the increase in total financing to be absorbed entirely by net equity issuance.

[10]Schultz (2003) suggests that the long term performance of new issues and repurchases may be a result of a pseudo market timing problem rather than market efficiency. However, a calendar-time portfolio approach as used in our paper is immune to the pseudo market timing problem.

1.4 Hypotheses

We focus our hypotheses on the predictions of behavioral models, with the predictions of rational factor pricing as the key alternative. Specifically, we hypothesize that a misvaluation factor (UMO) that is long on repurchase stocks (Undervalued) and short on new issue stocks (Overvalued) should capture comovement associated with mispricing, and that an asset's loading on UMO will positively predict future returns.

Based on the abovementioned behavioral models, we formulate the following testable hypotheses about UMO. Section C of the Addendum formally derives these predictions in a model based on the approach of Daniel, Hirshleifer, and Subrahmanyam (2001). These hypotheses, however, are intuitive and would apply in other behavioral modeling specifications as well.

We now lay out several empirical predictions and discuss the justification for each in turn.

Prediction 1: *There is incremental comovement in stock returns associated with UMO above and beyond that implied by benchmark factors.*

If there is commonality in mispricing, we expect mispricing to be shared by stocks (including those not involved with recent financing and payout activities) that load on the same mispriced fundamental factors, or that possess mispriced style characteristics. In either case, such stocks will comove with the misvaluation factor, UMO, even after controlling for proxies for possible fundamental factors.

Prediction 2: *UMO will earn abnormally high returns relative to the benchmark factors.*

Since UMO is designed to capture the spread between under and overpriced stocks, it is predicted to produce abnormal returns relative to common risk factors. In other words, we expect UMO to have a high Sharpe ratio, and to earn a significant alpha in a regression on the benchmark factors.

Prediction 3: *The loadings on UMO will forecast the cross section of stock returns.*

Under our prediction that UMO captures comovement in returns incrementally to factors such as SMB, HML, and the momentum factor (MOM), we hypothesize that securities' loadings on UMO measure the degree of underpricing deriving from common factors (membership in misvalued sectors, or style effects). In other words, a positive loading identifies the influence on the stock price of either underpriced fundamental factors, or of underpriced style characteristics. When such underpricing is subsequently corrected, securities with larger UMO loadings will earn greater returns. Stocks that load positively on UMO will behave like repurchase firms and outperform while those loaded negatively on UMO will behave like new issue firms and will underperform. Thus, the loadings on a factor that is based on new issues and repurchases can be exploited to forecast returns on general stocks including those that have *not* recently been involved in equity financing transactions.

So long as new issuance or repurchase is associated with firm-specific, not just common, mispricing, the amount of issuance or repurchase should predict returns even after controlling for the degree to which the firm partakes of common mispricing. We therefore predict that measure of external equity and/or debt financing will predict returns even after controlling for the UMO loading (see Daniel, Hirshleifer, and Subrahmanyam (2005) for a model with an analogous prediction about book-to-market and HML loadings).

2 Data

Our sample includes common stocks traded on NYSE, AMEX, and NASDAQ over the period January 1970 to December 2008. We also exclude utilities (SIC codes between 4900 and 4949) and financials (SIC codes between 6000 and 6999) since mispricing is more constrained among regulated industries. Stock returns and other trading information are from the Center for Research in Security Prices (CRSP). Accounting information is from COMPUSTAT from 1971 to 2008. Daily and monthly return series for the market factor (MKT), the size factor (SMB), and the book-to-market factor (HML), the momentum factor (MOM), and the risk-free rates are from Kenneth French's website. The investment factor (INV) is defined as the return of low investment firms minus that of high investment firms. The leverage factor (LEV) is the return of high leveraged firms minus that of low leverage firms.[11] The Appendix provides details of the construction of the two factors.

[11] We use the monthly return series of the investment factor provided by Evgeny Lyandres up to December 2005 supplemented with data from January 2006 through December 2008. We use the monthly return series of the investment factor provided by Michael Ferguson up to December 2001 and supplement it with data from January 2002 through December 2008. The results are similar if we use our own data throughout the sample period.

2.1 Main Sample

———INSERT TABLE I HERE———

Among the sample firms, we identify 7,985 initial public offerings (IPO) and 7,110 seasoned equity offerings (SEO) from the new issue data provided by Jay Ritter through the end of 2004 for IPOs and of 2001 for SEOs, supplemented by data from the SDC Global New Issues dataset through December 2008. For IPOs, we require the IPO to appear in CRSP file within six months from the offer date. For SEOs, we exclude unit offerings and pure secondary Offerings. From the SDC Global New Issues dataset we identify 6,734 debt offerings (DISSUE), including both straight (non-convertible) debt and convertible debt, among the sample firms. We require SEO and DISSUE to have valid returns at the end of the offer month in CRSP. The annual number of firms is reported in Table I.

Also shown in Table I, altogether, we identify 20,173 equity repurchases (ERP) events and 43,849 debt repurchase (DRP) events from COMPUSTAT annual statements. ERP is defined as occurring when net equity repurchases in a given fiscal year exceed 1% of the average total assets, and DRP is defined as occurring when net long-term debt reduction in a given fiscal year exceeds 1% of the average total assets. Specially, the net equity repurchase is total repurchase of common stocks minus total issuance of common stocks. Total repurchase of common stocks is the purchase of common and preferred stocks (COMPUSTAT variable PRSTKC) less any decrease in preferred stocks. Total issuance of common stocks is the sale of common and preferred stocks (SSTK) less any increase in preferred stocks. We measure preferred stocks as, in order of preference, the redemption value (PSTKRV), the liquidating value (PSTKL), or the carrying value (PSTK). Long-term debt reduction is defined as long term debt reduction (DLTR) minus long-term debt issuance (DLTIS) from the cash flow statement.

The main findings of the paper are similar if we identify IPO events as the first appearance in CRSP, if we use cash flow statement information to identify equity and/or debt issuance, if we change the cutoff of the equity/debt issuance or repurchase as a fraction of the total assets to as low as 0% or as high as 5%, if we obtain equity repurchase events (both open market and tender offer repurchases) from SDC, or if we restrict the sample of SEOs to primary offerings.

2.2 Key Variables

At the end of June of each year, we include firms with IPOs, SEOs, and debt issuances (DISSUE) in the past 24 months but not with equity repurchases (ERPs) or debt repurchases (DRPs) in the two most recent fiscal years with the fiscal year ending as of last December in portfolio 'O' (Overpriced). We include firms with DRPs or ERPs in the two most recent fiscal years with the fiscal year ending as of last December but not with IPOs, SEOs, or DISSUE in the past 24 months in portfolio 'U' (Undervalued). We require a gap of at least six months between the fiscal year end and the time of portfolio formation to ensure that repurchases by then are public information. Since prior literature shows that the long run abnormal performance of new issues and repurchases are concentrated in the first three years after events (e.g., Loughran and Ritter (1995), Ikenberry, Lakonishok, and Vermaelen (1995)), we select firms based on events that have occurred in the preceding 2 years so that the event portfolio returns cover the period from one to three years following the event. Finally, stocks with both equity issuance and repurchases or neither are included in portfolio 'N' (neutral).[12]

The three equal-weighted portfolios are held from July of year t to June of year $t+1$, and rebalanced. Following Fama and French (1993), we form a zero-investment portfolio 'UMO' (Undervaluation Minus Overvaluation), which is long on U and short on O, to capture the possible commonality in misvaluation.[13]

It could be argued that the performance of UMO comes from industry/sector-wide fundamental shocks (e.g., Hou (2007)) that are not captured by the benchmark factors. Therefore, we also consider a sector-neutral '$\mathrm{UMO}_{\perp\mathrm{SEC}}$' that minimizes sectoral effects by compute the equal-weighted returns among new issues separately within each of the five sectors, based on the Fama-French 5 industry classifications. Then we define the equal-weighted five sector returns as returns on $\mathrm{O}_{\perp\mathrm{SEC}}$. Similar procedures are used for $\mathrm{U}_{\perp\mathrm{SEC}}$. Finally, $\mathrm{UMO}_{\perp\mathrm{SEC}}$ returns are the difference between

[12] Depending on the year, on average a fraction of about 14% of event firms (standard deviation 7.7%) are excluded from portfolio O or U for being both issuers and repurchasers. Thus, an overwhelming fraction of event firms can be identified as either under or overpriced unambiguously using the external financing events.

[13] It is known that new issues tend to be small growth firms and repurchasers tend to be large value firms. When constructing UMO, however, we did not control for size and book-to-market. This is because behavioral theories suggest that these characteristics reflect stock mispricing, and that equal weighting the returns across size or book-to-market groups can reduce the power to detect mispricing of new issues/repurchases (Loughran and Ritter 2000). Instead, our tests perform a horse race between UMO and the size and book-to-market factors. We find that the power of UMO to explain returns is not subsumed by the size or the book-to-market effect.

$U_{\perp SEC}$ and $O_{\perp SEC}$.

———INSERT TABLE II HERE———

Table II reports the summary statistics of the event portfolios, UMO, and the other well-known factor portfolios. Since quarterly accounting information is available from 1971, the portfolio U starts from July of 1972, which limits our factor UMO to the period starting from July of 1972. As shown in Table I, the average number of firms in July of each year is 505 for O and 1695 in U, showing that UMO contains a sizable number of stocks.[14]

Consistent with the previous literature, during our sample period, repurchase stocks (U) on average outperform neutral (N) stocks while neutral stocks (N) on average outperform new issue stocks (O). UMO offers an average return 0.93% per month, or over 11% per year while $UMO_{\perp SEC}$ 0.92% per month. The two are highly correlated, with a coefficient of 0.91 as shown in Panel B. Panel B also shows that UMO has strong correlations with MKT, HML, MOM, INV, and LEV. In our subsequent tests, we estimate loadings on UMO by controlling for these benchmark factors. Thus, our findings that UMO loadings are positive predictors of the cross section of returns are not driven by these factor correlations.

UMO and $UMO_{\perp SEC}$ provide Sharpe ratios 0.30 and 0.39, respectively, which are considerably greater than those of MKT (0.08), SMB (0.05), HML (0.16), MOM (0.21), and LEV (0.11), and comparable to INV (0.30). To study the incremental contribution of UMO in improving the achievable Sharpe ratios, in Panel C, we report the weights, returns, and Sharpe ratios of the *ex post* tangency portfolios calculated following MacKinlay (1995). The tangency portfolio generates the highest Sharpe ratio by optimally combining a subset of factors. The panel shows that adding UMO to the 3 factors increases the maximum Sharpe ratio from 0.24 to 0.42, an increase close to 75%. Adding UMO to the 3 factors plus the momentum factor increases the Sharpe ratio from 0.35 to 0.44. In both cases, the tangency portfolio places a substantial weight (65% and 47%) on UMO as opposed to the other candidate factors. Adding UMO to the 3 factors greatly reduces the

[14] Although firms stay in O or U for a two-year period, the number of firms in O or U is less than twice the number of new issue or repurchase firms. This is due to at least three effects. First, multiple types of equity/debt issues can occur for one firm and are counted in O as one stock. Second, both equity and debt repurchases can occur for the same firm during a two-year period and are counted in U as one stock. Third, some new issue firms also have repurchases during a two-year window and thus do not enter O or U.

weight of SMB—from 0.17 to 0.09, and essentially eliminates the weight on HML in the tangency portfolio—a reduction from 0.58 to −0.02. This probably occurs because UMO is rather highly correlated with HML (0.65), but delivers much higher expected returns with similar volatility. This suggests that UMO is a better proxy than HML for misvaluation or for priced factors.

The improvement in the Sharpe ratio from adding UMO is observed if we include INV or LEV together with the 3 factors, although the size of the improvement differs across specifications. The highest Sharpe ratio (0.49) is achieved by combining the 3 factors with INV and UMO. Across all cases, we observe a visible reduction in the weights of SMB and HML. Overall, the results show that UMO delivers an unusually large Sharpe ratio and is an important contributor to an ex post tangency portfolio.

3 Comovement in Returns and the UMO factor

In this section, we test whether, as hypothesized, UMO captures commonality in returns, and whether UMO achieves abnormal returns relative to other benchmark factors.

3.1 Loadings of Assets on UMO

Prediction 1 implies return comovement. We first test for comovement by estimating the loadings of assets on UMO. If overpriced or underpriced general individual stocks load on some of the same mispriced fundamental factors that new issues and repurchase stocks load upon, or mispriced general stocks share some of the same style characteristics that cause mispricing in new issue and repurchase stocks, they will share incremental comovement with UMO relative to the benchmark factors during the period that mispricing is created and later corrected. However, over a long time series, if overpricing and underpricing occur about equally often, we expect individual stocks to have loadings on UMO that are close to zero.[15]

In contrast, we expect portfolios formed based on mispricing measures to have stable loadings on UMO—positive among underpriced stocks and negative among overpriced stocks. When such

[15] In the example discussed in the introduction, when investors irrationally expect low oil prices, airlines are overpriced and tend to issue, while solar product vendors are underpriced and tend to repurchase. Accordingly, firms that benefit from low oil prices will load negatively, and those that are hurt will load positively, on UMO. However, if investor sentiment shifts to an irrational belief that the oil price will be high, the industries that are issuing versus repurchasing flips. In consequence, the loadings of other firms on UMO reverses, which shows that the UMO loadings of individual stocks are transitory.

portfolios are periodically rebalanced, stocks enter or exit the portfolios according to their degree of mispricing, which tends to stabilize the degree of mispricing in the portfolio (relative to other stocks) and therefore the loadings of the portfolios on UMO. Therefore, to test for return comovement with UMO, we perform tests on portfolios which we rebalance based upon firm characteristics that are potentially related to mispricing, such as size, book-to-market, and financing-based variables. These portfolios are rebalanced once every year to make sure each continues to include similar levels of characteristics, implying similar degrees of under- or overpricing, and therefore similar loadings on UMO over time.

Using the well-known Fama-French 25 size-BM portfolios as an example, we regress value-weighted monthly returns of each portfolio on UMO together with the Fama-French 3 factors and test whether UMO loadings (β_u) are jointly different from zero.

———INSERT Figure 1 HERE———

Panel A of Figure 1 plots the UMO loadings across the size and book-to-market sorts. Results based on $\mathrm{UMO}_{\perp\mathrm{SEC}}$ or with alternative benchmark factors are similar. We focus on the smallest and the largest size groups because they exhibit distinct comovement with UMO across the book-to-market quintiles. Among the smallest size group, UMO loadings increase with the book-to-market while among the largest size group, the opposite pattern holds. In other words, small growth and large value firms tend to load negatively on UMO while small value and large growth firms tend to load positively on UMO. The pattern of UMO loadings is very similar to that of the Fama-French 3-factor alphas reported in Panel B. The mispricing of the 25 portfolios relative to the 3-factor model is highly correlated with UMO loadings, with a correlation coefficient of 0.75. This suggests that UMO helps explain the pricing errors of the 3-factor model. In addition, UMO loadings do not line up monotonically with either size or BM. This evidence indicates that UMO loadings capture different aspects of expected returns from HML and SMB loadings. The F-statistic is 8.39 ($p = 0.00$), which strongly rejects the null that all UMO loadings are jointly equal to zero.

In unreported tests, we find that UMO indeed helps reduce and even eliminate pricing errors (alphas) in time series regression. In particular, when the 3-factor model is used to price the 25 size-BM portfolios, it is well known that substantial pricing errors are present among the four corner portfolios. When UMO is additionally included, these pricing errors are substantially reduced and become insignificant for all but extreme small-growth portfolio. After adding UMO to the 3 factors, the F-statistic that tests whether the alphas are jointly equal to zero no longer rejects that null. Moreover, we also find that, relative to the 3-factor model, UMO helps reduce the pricing errors of portfolios based on other corporate events that are known to produce abnormal long-run performances, such as mergers & acquisition (Loughran and Vijh 1997), dividend initiation and resumption (Michaely, Thaler, and Womack 1995), and dividend omission (Boehme and Sorescu 2002). Overall, this evidence indicates that UMO is important for pricing stocks with a variety of characteristics, and that the anomalous returns on the corner portfolios, and on other corporate-event based portfolios result from commonality in mispricing that is captured by the UMO factor.

3.2 UMO and Other Factors

In this subsection we provide a further test of whether UMO is a source of comovement (Prediction 1) based solely on factors returns, and then test whether UMO achieves abnormal returns (Prediction 2).

In general, in a randomly formed, well-diversified, zero-investment portfolio, as the number of securities increases, both the loadings on underlying factors and idiosyncratic risk approach zero. In consequence, portfolio return variance also approaches zero. In contrast, Prediction 1 implies that forming a long-short portfolio based upon firms' financing decisions causes loading on some underlying factor(s), resulting in substantial positive variance. As a result, residual variance is predicted to be non-negligible even after regressing on the benchmark factors, and specifically, is predicted to be greater than that would be observed with equal-weighted long-short portfolios with randomly selected stocks.

In our tests, portfolios with randomly selected stocks are formed at the end of each June by randomly-selecting the equal number of stocks as that in portfolio U in the long side and as that in portfolio O in the short side. Then we calculate the equal-weighted long-short portfolio returns. We regress the randomly-selected portfolio on a set of benchmark factors and compute the variance of the residual terms. This exercise is repeated 1,000 times to generate a distribution of the standard deviation of the residual terms to compare with the standard deviation of residuals associated with UMO for the given set of benchmark factors. The regression and simulation results are reported in

Table III.

———INSERT TABLE III HERE———

Consistent with Prediction 1, we find R^2s on the order of roughly 51–57%, and the standard deviation of the residual terms are around 2.00–2.06% per month, which are significantly greater than that based on randomly selected portfolios. The low R^2s and high residual volatility suggest that new issue and repurchase stocks share incremental commonality above and beyond the comovement implied by the benchmark factors. This is consistent with UMO capturing common misvaluation factors. However, this does not rule out the possibility that the commonality comes from fundamental sources not captured by the 4 factors.

This regression also provides a test of Prediction 2, abnormal performance of UMO. Consistent with Prediction 2, as shown in Table III, the positive alphas, ranging from 0.53%–0.75% per month, show that UMO offers abnormally high returns (6.36%–9.00% per year) relative to the benchmark factors. This evidence confirms the findings of previous research of significant long-run overperformance associated with repurchases and underperformance associated with new issues.

As discussed in Section 1.1, the returns on firms with financing events may be related to a common factor in growth/investment opportunities. This is to some extent controlled for by HML, but to further test for this possibility, in Section A of the Addendum, we consider other sets of benchmark factors, including the macroeconomic factors suggested by Eckbo, Masulis, and Norli (2000), the new three-factor by Chen and Zhang (2010), the Fama-French factors purged of new issue firms (e.g., Loughran and Ritter (2000)), and a factor based on the asset growth variable of Cooper, Gulen, and Schill (2008). Even after controlling for models containing these additional factors, the R^2 of UMO is still below 56%. The residual volatility is around 2.05–2.33%, significantly higher than the simulated residual volatility based on random long-short portfolios over the same sample period.

4 Do UMO Loadings Predict the Cross Section of Asset Returns?

We now test Prediction 3, that UMO loadings predict the cross section of future asset returns. As discussed previously, behavioral models predict that UMO loadings are proxies for systematic undervaluation, and therefore will predict higher excess returns. We start by testing the ability of loadings on characteristic portfolios to predict returns, and then consider loadings on individual stocks.

4.1 UMO Loadings and the Cross Section of Portfolio Returns

UMO loadings for individual stocks tend to be unstable over time. Intuitively, different styles or economic factors can be over- and underpriced at different times, and accordingly a positive loading on certain style or economic factors can imply over- and undervaluation at different times. (Section C of the Addendum contains a proof for this assertion (see Proposition 2).) UMO is always long on the underpricing factors and short on the overpricing factors. Thus, we expect individual stocks, while having fairly persistent loadings on the style or economic factors, to have unstable loadings on UMO.

In contrast with individual stocks, portfolios that are formed based on possible mispricing proxies such as book-to-market are expected to have much more stable UMO loadings over time. Thus, we run a Fama-MacBeth regression with the 25 size-BM portfolios and test whether UMO carries a significant positive premium, in which the UMO loadings of the 25 portfolios are estimated within an annually-updated rolling 5-year window on the benchmark factors together with UMO. The mean premia and the Newey and West (1987) t-statistics are reported in Table IV.

———INSERT TABLE IV HERE———

Table IV shows that the premium of UMO is always positive, economically and statistically significant, regardless of the specifications of the model. For instance, the average premium of UMO, in regression (1) is 0.51% per month ($t = 2.54$) controlling for the market factor, in (3) is 0.75% per month ($t = 4.09$) with controls for the 3 factors, and in regression (6) is 0.73% per month ($t = 4.06$) with controls for the 4 factors.[16] In other words, the estimated UMO premium ranges from 6.12%-9.36%. Similar results are obtained after additionally controlling for INV and LEV, or replacing UMO with $\text{UMO}_{\perp\text{SEC}}$.

[16]The coefficient on UMO jumps when SMB and HML are included in the regression. A possible reason why adding factors increases the UMO premium is the omitted variable problem. If the true factor pricing model has the 3 factors plus UMO, then owing to correlations between loadings, the coefficient estimate on UMO can be downward biased when SMB and HML are omitted. For example, Panel A of Figure 1 shows that large value stocks have negative UMO loadings and positive HML loadings. Adding HML loadings to the regression therefore increases the coefficient on UMO by attributing the high returns of value stocks to high HML loadings instead of to low UMO loadings.

Lewellen, Nagel, and Shanken (2010) show that a proposed factor that is correlated (even weakly) with SMB and HML can spuriously price the 25 size-BM portfolios in the cross section. To address this possibility, in Section A of the Addendum, we use the orthogonalized UMOs (that are orthogonalized to the 3- or 4-factors) to estimate UMO loadings and then add these loadings in the Fama-MacBeth regressions to examine their incremental return predictive power. The results remain unchanged.[17]

4.2 UMO Loadings and the Cross Section of Individual Stock Returns

Behavioral theories suggest that UMO loadings should forecast not only the returns on portfolios (formed by sorting on potential mispricing proxies) but also on individual stocks. Stocks with higher sensitivity to UMO should partake of greater systematic undervaluation and have stronger return reversal when mispricing is corrected.

As discussed previously in Section 3.1, estimating UMO loadings on individual stocks is challenging due to the (theoretically predicted) instability of these loadings. We therefore adopt two different approaches to estimate UMO loadings.

4.2.1 Conditional UMO Loadings Estimated from Daily Returns over Short Windows

In the first approach, we estimate UMO loadings from daily returns over a short period, an approach also used in previous studies (e.g., Lewellen and Nagel (2006)). In our context, loadings are unstable because misvaluation is temporary, and over a sufficiently long horizon should on average vanish.

Specifically, we estimate firm-level UMO loadings using at least 100 daily returns over the most recent 12-month period with controls for the 3 factors. We call the estimated UMO loading the pre-formation loading, denoted as β_u^{pre}. (Reducing the estimation period to three months yields similar results.)

———INSERT TABLE V HERE———

After obtaining β_u^{pre}, we sort stocks based on β_u^{pre} into deciles and calculate both the equal-weighted decile returns in the following month. As shown in Table V, the decile returns tend to

[17]Similar results also obtain for various sets of portfolios sorted based on size, book-to-market equity, external financing (EXFIN), and net composite issuance (IR).

increase with β_u^{pre}. The return differentials between the highest and the lowest β_u^{pre} deciles is 0.77% per month ($t = 3.75$), or 9.24% per annum. The alphas from the CAPM and the 3 factor model remain sizable and statistically significant, suggesting an annual abnormal return of 7.6-10.8%. After excluding firms in UMO, also shown in Table V, we observe that the results remain strong with a slight reduction in the size of the long-short returns. The post-ranking UMO loadings, β_u^{post}, generally monotonically increase with the pre-ranking loading ranks, suggesting that over a 12-13 month period, UMO loadings are persistent during the window. Overall, the results show an economically and statistically significant premium on UMO at the firm level, even among those firms that are not recently involved in external issuances or repurchases.

4.2.2 Conditional UMO Loadings Estimated from Characteristics Portfolios

The advantage of the first approach is that it obtains firm-level UMO loadings directly from individual stock returns. This method, however, is known to generate relatively imprecise loadings since firm-level loadings tend to be more subject to regression-to-the-mean, which in our context means a greater tendency to reverse out. Thus, it is difficult to assess whether UMO loadings add incremental predictive power relative to existing firm-level return predictors.

To obtain more precise UMO loadings, in the second approach, we employ a modified version of the estimation procedure by Fama and French (1992), known as the portfolio shrinkage method. However, instead of estimating unconditional UMO loadings using past 3-5 year firm-level returns as in Fama and French (1992), we estimate conditional security UMO loadings from annually-balanced portfolios sorted by mispricing proxies. Again, this is because mispricing tends to be temporary and reverses out during a period of 3-5 years.

In this procedure, at the end of each month from June of year t through May of year $t+1$, we first sort all stocks into 100 portfolios according to two firm characteristics that proxy for misvaluation, such as firm size (ME) during the most recent June and the external financing variable (EXFIN) calculated at the fiscal year ending as of December of year $t-1$. Results using various combinations of ME, BM, EXFIN, and IR are similar and thus unreported. By sorting stocks based on firm mispricing proxies, we create dispersion in the sensitivities to UMO. We then estimate the UMO loadings for each of the 100 equal-weighted portfolios using at least 36-month returns, from July of

1972 through month $t-1$, in a time-series regression with controls for the 4 factors.[18] Finally, each individual stock assumes the portfolio loading according to which portfolio it belongs in month $t-1$.[19]

We denote the conditional UMO loadings as β^{UMO} and use these loadings to forecast stock returns in month t with controls for a set of standard predictors, which include logarithmic firm size, LOG(ME), logarithmic book-to-market, LOG(BM), past one month return, $r_{(t-1)}$, past returns from month $t-12$ to $t-2$, $r_{(t-12,t-2)}$, past returns from month $t-36$ to $t-13$, $r_{(t-36,t-13)}$, industry dummies based on the Fama-French 49 industry classifications, and the 3-factor loadings.[20] The past return measures are expressed on a monthly basis. UMO loadings are normalized and standardized to have zero mean and unit variance. The estimated coefficients are averaged across time and reported in Table VI. A positive average coefficient of UMO loading will indicate that high UMO loading stocks tend to earn higher returns on top of the controls.

———INSERT TABLE VI HERE———

Consistent with Prediction 3, as shown in Specifications (1) and (2) in Panel A of Table VI, the average coefficients of β^{UMO} are all positive and statistically significant, before and after adding the standard controls. Before controlling for the standard return predictors, the coefficient of β^{UMO} is 0.48 ($t = 6.87$). After adding the controls, the coefficient of β^{UMO} is 0.35 ($t = 7.80$). This implies that, moving from the lowest (with mean β^{UMO} of -1.78) to the highest (with mean β^{UMO} of 1.78) decile, the marginal effect (abnormal return) is 15.14% ($= (1.78 - (-1.78)) \times 0.35\% \times 12$).

In Panel B, we exclude stocks in the dependent variable used to form UMO of the current year. The results are similar. The coefficient of β^{UMO} is 0.44 ($t = 6.21$) before adding the controls and 0.33 ($t = 6.74$) after adding the controls. The coefficient with controls implies a marginal effect of 14.29% per annum, moving from the lowest to the highest β^{UMO} decile. So this evidence shows that stocks that load heavily on UMO on average earn higher returns, even after controlling for the standard predictors of the cross section of stock returns. This predictive ability of UMO loadings

[18] Using a rolling window over the past 60 months to estimate UMO loadings produces qualitatively similar results.

[19] The results are similar if size and book-to-market, or book-to-market and IR, are used to sort the characteristic portfolios. We expect to obtain appropriate estimates of UMO loadings so long as the characteristic variables are sufficiently good proxies for stock mispricing to create substantial large dispersion in UMO loadings.

[20] The predictors are designed to capture the size effect, the book-to-market effect, the short-term return contrarian effect, the momentum effect, the long-term reversal effect, the industry effects, and systematic risks.

applies not only to firms involved in equity financing events, but to those that have not recently been engaged in either new issues or repurchases.

Next, we run a horse race between UMO loadings and a set of other return predictors documented in recent literature, including external financing (EXFIN) as in Bradshaw, Richardson, and Sloan (2006), net composite issuance (IR) as in Daniel and Titman (2006), the investment-asset ratio (IVA) as in Lyandres, Sun, and Zhang (2008), net operating assets (NOA) as in Hirshleifer, Hou, Teoh, and Zhang (2004), operating accruals (ACCRUALS) as in Teoh, Welch, and Wong (1998b, 1998a), and the abnormal capital investment (CI) of Titman, Wei, and Xie (2004). This test serves two purposes. First, some or all of these characteristics have been interpreted as proxies for firm-level mispricing. Daniel, Hirshleifer, and Subrahmanyam (2005) describe a behavioral setting with no risk premia, in which both characteristics and covariances have incremental predictive power to predict returns.[21] Thus, it is interesting to test whether UMO loadings as proxies for systematic underpricing can pick up incremental return predictability beyond that captured by firm characteristics. Second, regardless of whether these characteristics variables are interpreted as proxies for risk or mispricing, it is useful to see whether UMO loadings have an ability to predict the cross section of returns incremental to known predictors.

In Table VI, from regressions (3)-(9), we run the Fama-MacBeth regressions on UMO loadings, the set of standard controls, and each of the seven new return predictors. As with the UMO loadings, these new predictors are normalized and standardized to have zero mean and unit variance. The results confirm the ability of UMO loadings to positively forecast returns after controlling for these additional predictors. The coefficients on the normalized UMO loadings range from 0.25 to 0.35, indicating a marginal effect on returns of 10.73% to 15.05%. The coefficients on the seven other predictors (from -0.07 to -0.35) all imply a smaller marginal effect. For example, the net issuance variable IR has the largest marginal effect among these predictors. Moving from the highest to the lowest IR decile, the coefficient -0.19 implies an increase in decile returns by 7.82%, which is

[21] In their model, when both factor and firm-specific cash flow components are mispriced, characteristics are proxies for both factor mispricing and the mispricing of firm-specific (idiosyncratic) cash flow components; loadings on a price-characteristic-based factor portfolio (such as HML) are proxies for factor mispricing. In a cross-sectional regression of returns on both characteristics and covariances, the coefficient on the characteristic implicitly forces the coefficients on the factor mispricing and the idiosyncratic mispricing to be the same. When factor mispricing is stronger than firm-specific mispricing, loadings pick up the difference and therefore are positive incremental return predictors. Daniel, Hirshleifer, and Subrahmanyam (2005) consider characteristics and characteristics-based factors formed on the basis of market price rather than on the basis of managerial actions such as issuance and repurchase, but a similar intuition applies.

considerably smaller than that of UMO loadings.[22] In unreported analyses, we also find that when we run a horse race between UMO loadings and the seven other predictors (together with the set of standard controls), UMO loadings remain positive and significant.

In Panel B, we run Fama-MacBeth regressions using for our cross-section only firms that are excluded from UMO for a given month. Again, we find that UMO loadings have significant power to forecast the cross section of stock returns incremental to known return predictors. The finding that both UMO loadings and firm characteristics contain distinct incremental power to forecast returns is consistent with the hypothesis that UMO loadings contain information about firms' systematic mispricing and that the characteristics contain information about firm specific mispricing; as compared with the rational factor pricing prediction that only covariances matter.

An alternative explanation for the finding that UMO loadings strongly predict returns but that the characteristics also incrementally predict returns is that markets are efficient, that the loadings on an underlying new issue/repurchase factor is priced, but that UMO is a poor proxy for that factor. However, if so, then the unobserved risk factor must have a large risk premium to explain both the high Sharpe ratio of UMO, and the incremental ability of the characteristic to predict returns. As discussed earlier, the Sharpe ratio of UMO is about 2 1/2 times as large as that of the market portfolio, and is considerably higher than that of HML.

The high Sharpe ratio of the market (the equity premium puzzle) is already viewed as a challenge to rational asset pricing; MacKinlay (1995) describes the Sharpe ratio achievable with the Fama French factors as a further challenge. UMO sharpens the challenge in two ways. First, its Sharpe ratio exceeds those of the Fama French and momentum factors. Second, the incremental power of the characteristics to predict returns implies that an even higher Sharpe ratio than that of UMO can potentially be achieved by combining UMO with financing variable-based portfolios.

A different possibility is that UMO is the correct risk factor, but that loadings are estimated with noise, causing them to predict returns imperfectly. Such noise can derive from limited sample size or from time variation in loadings. If so, characteristics may incrementally predict returns because they are proxies for true UMO loadings. However, the same objection applies to this explanation: that the Sharpe ratios that are in principle achievable using UMO and the characteristics are

[22]In Panel A, the variables IVA and CI are statistically significant as return predictors when UMO loadings are excluded, but not when UMO loadings are included. So UMO loadings subsume the predictive power of these variables.

surprisingly high.

Section B and Table A-3 of the Addendum provides evidence suggesting that stocks with extreme UMO loadings tend to be hard to value or to arbitrage. This may help explain why the mispricing associated with extreme UMO loadings can persist.

5 Are UMO Loadings Stable?

Finally, we examine whether UMO loadings are fairly stable over periods of 3 to 5 years. The presumption for a pure mispricing factor is that the loadings are unstable over the typical frequency at which mispricing appears and corrects, i.e., as a stock shifts between being over- versus underpriced. In contrast, for a rational priced factor there is no presumption that loadings will be unstable. A common presumption for tests of rational asset pricing has been that loadings are stable for periods of 3-5 years.

To estimate the systematic risk of stocks, it is a common practice to estimate loadings on a fundamental risk factor (such as the market) by sorting stocks based on pre-ranking loadings that are estimated from the previous 3 to 5 years (Fama and MacBeth (1973), Ferson and Harvey (1991), and Fama and French (1992)). The presumption underlying this practice is that firm fundamentals evolve gradually, so that a firm's sensitivity to cash flow factors usually does not change dramatically during a relatively short period of time.

Under the hypothesis that securities have fairly stable loadings on fundamental economic risks, pre-ranking loadings should be highly positively correlated with post-ranking loadings. Thus, sorting firms by pre-ranking loadings should create a large dispersion in post-ranking loadings. In contrast, if UMO loadings reflect mispricing, they are likely to be unstable over periods as long as five years. Therefore pre-ranking loadings should be very poor proxies for misvaluation, and should have little power to predict post-ranking loadings. Additionally, sorting firms based on pre-ranking loadings should create little dispersion in post-ranking loadings.

Following Fama and French (1992), we estimate UMO pre-ranking loadings ($b^{\text{UMO}}_{\text{pre}}$) by regressing individual stock monthly returns from the previous 36 to 60 months on UMO together with the FF 3 factors, and sort stocks into 100 portfolios based on their $b^{\text{UMO}}_{\text{pre}}$. Using the full sample equal-weighted returns of the 100 portfolios, we estimate the post-ranking UMO loadings ($b^{\text{UMO}}_{\text{post}}$) in a multi-factor regression for each portfolio. We report the average $b_{\text{pre}}^{\text{UMO}}$ and the estimated $b_{\text{post}}^{\text{UMO}}$ for the 100 portfolios in Table VII.

Our preliminary analyses show that the average loadings on MKT and SMB are positive while those on HML and UMO close to zero. To facilitate the comparison across different factors, we subtract the means from the pre- and post-ranking loadings. For pre-ranking loadings, the monthly mean loadings are used. Since the loadings are demeaned, we expect a reasonable number of portfolios with moderate loadings to flip signs simply due to the changes in the means (or simply random errors in estimation). Thus, we focus on the 20 extreme-loadings portfolios which include the top and the bottom 10. The loadings of firms in these portfolios are the least likely to flip signs. If firms have reasonably persistent sensitivity to UMO as a stable risk factor, we expect UMO loadings to retain their signs and pre-ranking ranks during the post-formation period. In contrast, if UMO is a mispricing factor, the extreme loadings can change rapidly, and even flip signs. Our results support the latter prediction.

———INSERT TABLE VII AND FIGURE 2 HERE———

In Panel A of Table VII, we report the average demeaned pre-ranking loadings of the 100 UMO loading portfolios and in Panel B, we report the demeaned post-ranking portfolio loadings. We focus on the 20 extreme loading portfolios (either positive or negative) since these loadings are the least likely to flip signs if UMO loadings are proxies for stable risk. Contrary to the hypothesis that factor loadings are persistent for substantial periods, 10 out of the 20 extreme portfolios switch the signs of their $b_{\text{pre}}^{\text{UMO}}$'s in the subsequent one year, shown in Panel B and summarized in Panel C. This finding is not driven solely by new issues or repurchase stocks; after excluding the firms in UMO, we still observe 10 out of the 20 extreme portfolios switching signs from pre-ranking to post-ranking periods.

These numbers are substantially greater than those associated with MKT, SMB and HML when we use the same method to estimate market beta and loadings on SMB and HML. As reported in Panel C, there are no MKT and HML loading portfolios and only one SMB loading portfolio among the extreme 50 have opposite comovement with their corresponding factor before and after the portfolio formation. The inferences remain similar if we use raw, rather than demeaned, loadings.

Overall, a strong majority, 73 out of 100 UMO loading portfolios have essentially zero post-ranking loadings, suggesting that sorting stocks based on $b_{\text{pre}}^{\text{UMO}}$'s creates little dispersion in $b_{\text{post}}^{\text{UMO}}$'s. (The results are similar if we exclude firms in UMO from our analyses of loadings.) In contrast, by applying the same method to MKT, SMB, and HML, we find that *none* of the market beta and SMB loading portfolios, and only seven HML loading portfolios carry post-ranking loadings that are insignificantly different from zero.[23] These patterns are also evidenced in Figure 2, which plots the pre- and post-ranking loadings associated with UMO and the 3 factors.

The time series average of the cross-sectional correlations between pre- and post-ranking loadings again indicate that UMO loadings are much less persistent than those on MKT, SMB, and HML. This correlation is between 0.88 to 0.89 for the 3 factors but merely 0.20 for UMO for general firms and 0.18 after excluding firms in UMO.[24] The substantially lower correlation in pre- and post-ranking UMO loadings is consistent with our findings that UMO loadings tend to flip signs and are unstable over periods of several years.

Taken together, our evidence suggests that UMO loadings shift too rapidly to be captured by long-window estimates. This seems to be at odds with the view that firms' fundamental and exposure to systematic risk are persistent and evolve gradually. Thus, we conclude that the sensitivities of stock returns to UMO have much lower persistence than the loadings on other proposed fundamental risk factors in previous literature.

6 Conclusion

Behavioral approaches to asset pricing imply that there is common misvaluation across firms, and that there is systematic comovement associated with firms that are similarly misvalued. This study documents that, over the period 1972–2008, returns on issuing and repurchasing firms can be used to identify commonality in returns, and provides evidence suggesting that this return commonality derives from commonality in misvaluation.

Existing research has proposed that firms undertake equity issues in response to overpricing and

[23]It is possible that more pre-ranking UMO loadings are close to zero than are the pre-ranking MKT, SMB, or HML loadings. If so, this would only reinforce the point that loadings on UMO are not stable over periods as long as five years.

[24]The greater the extent to which loadings capture persistent fundamental risks rather than mispriced factors, the more stable we expect these loadings to be. So the relative instability of UMO loadings suggests that UMO is a purer proxy for misvaluation than the Fama/French factors.

repurchases in response to underpricing. These financing events seem to reflect stock mispricing perceived by managers that is not fully captured by firm characteristics such as book-to-market equity. Building upon this literature, our evidence indicates that there is comovement in returns associated with financing events, and that firms that engage in similar events subsequently move together more. However, this comovement is not unique to firms that that are involved with these transactions—it is shared by general firms that load upon our misvaluation factor.

Probably the most surprising results here are the exceptionally high Sharpe ratio of UMO and the strong ability of UMO loadings to predict the cross section of stock returns. When UMO competes with the 3 Fama-French factors, the momentum factor, and the leverage factor, the ex post tangency portfolio places a much higher weight on UMO than on the other factors. When we regress UMO on the set of benchmark factors, UMO produces consistently positive alphas and large residual variance. This evidence confirms that, despite some critiques of the new issue and repurchase puzzles in the literature (e.g., Brav, Geczy, and Gompers (2000), Butler, Grullon, and Weston (2005)), new issue and repurchase events do indeed contain important information for predicting returns. Moreover, the UMO loading is a strong predictor of the cross sectional stock returns, with a marginal effect that is considerably greater than those of the other firm characteristics that we consider. The fact that UMO loadings show a strong and distinct ability to forecast the cross section of portfolio and stock returns suggests that firm external financing activities convey information about the systematic component of stock misvaluation.

Although it is hard to rule out frictionless rational factor pricing explanations for return predictability conclusively, taken together, we view this evidence as most supportive of commonality in misvaluation that can be identified by means of financing events. However, we do not attempt to test possible explanations (not necessarily mutually exclusive) based upon market frictions. For example, market frictions such as illiquidity may make it hard to realize the high Sharpe ratios associated with financing-based portfolios.

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Appendix

Book-to-market equity (BM): Following Polk and Sapienza (2009), we define BE as stockholders' equity, plus balance sheet deferred taxes (TXDB) and investment tax credit (ITCB, set to zero if unavailable), plus postretirement benefit liabilities (PRBA), minus the book value of preference stocks. Depending on availability, in order of preference, we use redemption (PSTKRV), liquidation (PSTKL), or carrying value (PSTK). Stockholders' equity is measured as the book value of common equity (SEQ), plus the book value of preferred stock. If common equity is not available, we use the book value of assets (AT) minus total liabilities (LT). To compute BM, we match BE for all fiscal year-ends in calendar year $t-1$ with the firm's market equity at the end of December of year $t-1$.

Investment/asset ratio (IVA): Following Lyandres, Sun, and Zhang (2008), we measure investment-to-assets as the annual change in gross property, plant, and equipment (PPEGT) plus the annual change in inventories (INVT) divided by the lagged book value of assets (AT). We perform a triple sort on size, book-to-market, and investment-to-assets based on the breakpoint of the top 30% and the bottom 30% into 27 portfolios. We define the investment factor (INV) as the average value-weighted returns of the nine low investment-to-assets portfolios minus the average returns of the nine high investment-to-assets portfolios.

Leverage (LEV): Following Ferguson and Shockley (2003), we measure leverage (BD/ME) as the book value of total liabilities (LT) over the market value of equity. We match LT for all fiscal year-ends in calendar year $t-1$ with the firm's market equity at the end of December of year $t-1$. We perform a triple sort on size, book-to-market, and BD/ME based on the breakpoint of the top 30% and the bottom 30% to form 27 portfolios. We define the leverage factor as the average value-weighted returns of the nine high-leverage portfolios minus the average returns of the nine low-leverage portfolios.

External Financing (EXFIN): Following Bradshaw, Richardson, and Sloan (2006), external financing (EXFIN) is defined as the net amount of cash flow received from external financing activities, including net equity and debt financing, scaled by total assets (AT). Net equity financing is defined as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC) minus cash dividends paid (DV). Net debt financing is defined as the issuance of long-term debt (DLTIS) minus the reduction in long-term debt (DLTR). Unlike Bradshaw, Richardson, and Sloan (2006), we do not include change in current debt in calculating net debt financing to avoid including natural retirement of short-term debt (which is not a market timing choice) as opposed to debt repurchases.

The net composite issuance variable (IR): Following Daniel and Titman (2006), IR is defined as

$$\mathrm{IR}_{\mathrm{t}-1} = \log\left(\frac{\mathrm{ME}_{t-1}}{\mathrm{ME}_{t-60}}\right) - r(t-60, t-1),$$

where ME is the market equity with the subscripts referring to the month, $r(t-60, t-1)$ is the stock return in the previous 60 months from month $t-60$ through $t-1$, adjusted for stock splits and stock dividends. IR captures the part of the growth of the market value that is not attributed to stock returns, i.e., which is due instead to new issue, repurchase, and other activities that affect market value.

Net operating assets (NOA): Following Hirshleifer, Hou, Teoh, and Zhang (2004), net operating assets are defined as the difference of operating assets minus operating liabilities over total assets. Operating assets are total assets (AT) minus cash and short-term Investment (CHE). Operating liabilities are total assets (AT) minus the sum of short-term debt (DLC), long-term debt (DLTT), minority interest (MIB), preferred stock (PSTK), and common equity (CEQ), deflated by the lagged total assets (AT).

Operating accruals (ACC): Following Hirshleifer, Hou, Teoh, and Zhang (2004), operating accruals are defined as changes in current assets (ACT) minus changes in cash (CH), changes in current liabilities (LCT) plus the sum of changes in short-term debt (DLC) and changes in taxes payable (TXP), and minus depreciation and amortization expense (DP), deflated by the lagged total assets (AT).

Abnormal capital investment (CI): Following Titman, Wei, and Xie (2004), the abnormal capital investment (CI) is defined as a firm's capital expenditures (CAPX) scaled by the moving-average of its capital expenditures over the previous three years.

Table I: Number of firms with events and in event portfolios

This table reports the number of event firms with initial public offerings (IPO), seasoned equity offerings (SEO), debt offerings (DISSUE) (including both straight and convertible debt offerings), equity repurchases (ERP), and debt repurchases (DRP) for each year over the period 1970–2008, and the number of firms in the event portfolios O, N, and U in the beginning of July of each year from 1972 through 2008. At the end of June of each year, firms issuing IPOs, SEOs, or/and DISSUE in the last 24 months but not involving in stock repurchases during the most recent two fiscal years with the fiscal year ending as of last December are included in portfolio O (Overpriced). Firms with ERP or/and DRP made during the most recent two fiscal years with the fiscal year ending as of last December but not issuing IPOs, SEOs, or/and DISSUE in the last 24 months are included portfolio U (Underpriced). Firms that involve both equity/debt offerings and repurchases or neither of the two are included portfolio N (Neutral).

Year	IPO	SEO	DISSUE	ERP	DRP	O	N	U
1970	3	39	25					
1971	12	123	44	68	430			
1972	19	87	21	93	525	193	1477	419
1973	184	37	6	307	769	340	3193	761
1974	4	19	6	224	839	209	2527	1204
1975	11	48	12	212	1127	51	2241	1496
1976	26	72	17	246	1230	105	2068	1664
1977	21	41	10	324	926	120	1883	1805
1978	30	74	13	278	828	83	1880	1692
1979	49	75	15	326	860	133	2004	1489
1980	110	225	69	277	961	201	2018	1428
1981	300	220	62	274	1028	484	2075	1407
1982	81	170	53	329	1067	597	2008	1421
1983	506	481	152	296	1301	575	2122	1482
1984	307	95	143	441	1191	965	2139	1486
1985	224	191	273	472	1168	768	2111	1569
1986	410	225	415	473	1245	664	2186	1642
1987	401	203	274	632	1389	969	2142	1584
1988	146	84	155	719	1361	756	2074	1755
1989	146	139	178	555	1325	398	1949	2012
1990	153	128	163	618	1341	400	1890	1986
1991	277	246	389	500	1541	399	1918	1917
1992	404	312	362	458	1672	658	1859	1859
1993	496	438	459	489	1686	783	2015	1809
1994	489	291	268	556	1571	920	2295	1886
1995	432	421	380	651	1482	844	2402	1950
1996	701	505	381	691	1606	1008	2577	2012
1997	453	364	366	845	1505	1190	2636	1961
1998	264	231	453	1055	1276	986	2710	2009
1999	414	285	272	1125	1230	706	2456	2066
2000	366	287	201	986	1288	760	2185	2207
2001	57	152	265	674	1239	621	1936	2084
2002	61	107	233	630	1327	333	1844	2052
2003	41	127	170	545	1173	192	1646	1980
2004	137	141	100	547	1037	231	1578	1901
2005	87	123	87	676	925	291	1649	1737
2006	73	114	91	769	842	266	1686	1647
2007	71	111	97	832	766	262	1617	1664
2008	19	79	54	980	772	228	1524	1690
All	7985	7110	6734	20173	43849	18689	76520	62733
Mean	205	182	173	531	1154	505	2068	1695

Table II: Summary statistics of event and factor portfolios

Panel A reports the summary statistics of the event portfolios and the factor portfolio percentage returns from July 1972 through December 2008. The event portfolios U, N, O are defined in Table I. UMO (Underpricing Minus Overpricing) is the misvaluation factor that is long on U and short on O. $\mathrm{UMO}_{\perp\mathrm{SEC}}$ controls for the sector influences in UMO by taking the average returns of new issues and repurchases within each of the five sectors before taking the mean returns across the five sectors. The five sectors are defined based on Fama-French 5 industry classifications. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). INV is the investment factor of Lyandres, Sun, and Zhang (2008). LEV is the leverage factor of Ferguson and Shockley (2003). The Sharpe ratio (SR) for U, N, and O is the ratio of mean monthly returns in excess of the one-month riskfree rate divided by return standard deviation; for the factor portfolios, is the ratio of the mean monthly returns over return standard deviation. The variables ME (in millions) and BM are the average monthly market value and book-to-market equity of firms included in U, N, or O. Panel B reports the Pearson correlations among the factor portfolios. Panel C reports the summary statistics of the *ex post* tangency portfolio. The tangency portfolio correctly prices the candidate portfolios with non-zero weights and delivers the highest Sharpe ratio by optimally combining these candidate portfolios. The portfolio weights are calculated as $(\iota' V^{-1}\mu)^{-1}V^{-1}\mu$, where ι is a k×1 vector of ones, V is the covariance matrix of the factor returns, and μ is the mean factor returns.

Panel A: Portfolio returns

	Mean	Std	t-stat	SR	ME	BM
U	1.38	6.19	4.68	0.15	1049	0.88
N	1.06	6.64	3.33	0.09	1001	0.81
O	0.46	7.94	1.20	0.00	1323	0.52
UMO	0.93	3.08	6.30	0.30		
$\mathrm{UMO}_{\perp\mathrm{SEC}}$	0.92	2.39	8.11	0.39		
MKT	0.37	4.61	1.69	0.08		
SMB	0.17	3.24	1.11	0.05		
HML	0.48	3.04	3.31	0.16		
MOM	0.88	4.25	4.36	0.21		
INV	0.52	1.71	6.34	0.30		
LEV	0.38	3.44	2.29	0.11		

Panel B: Correlation matrix of factor mimicking portfolios

	UMO	$\mathrm{UMO}_{\perp\mathrm{SEC}}$	MKT	SMB	HML	MOM	INV
$\mathrm{UMO}_{\perp\mathrm{SEC}}$	0.91						
MKT	−0.53	−0.48					
SMB	−0.21	−0.11	0.26				
HML	0.65	0.58	−0.42	−0.28			
MOM	0.22	0.17	−0.10	0.01	−0.13		
INV	0.37	0.32	−0.29	−0.12	0.19	0.19	
LEV	0.42	0.37	−0.16	0.14	0.61	−0.20	0.07

Table II: Summary statistics of event and factor portfolios (cont'd)

Panel C: Ex post tangency portfolio										
	Portfolio Weights							Tangency Portfolio		
	MKT	SMB	HML	MOM	INV	LEV	UMO	Mean	Std	SR
(1)	0.25	0.17	0.58					0.40	1.68	0.24
(2)	0.20	0.11	0.43	0.27				0.54	1.52	0.35
(3)	0.15	0.08	0.20		0.56			0.46	1.13	0.41
(4)	0.25	0.20	0.65			−0.10		0.40	1.66	0.24
(5)	0.28	0.09	−0.02				0.65	0.71	1.70	0.42
(6)	0.25	0.08	0.07	0.13			0.47	0.69	1.57	0.44
(7)	0.20	0.06	0.02		0.40		0.33	0.60	1.24	0.49
(8)	0.28	0.12	0.07			−0.11	0.64	0.71	1.67	0.43

Table III: Regressions of UMO on benchmark factors

This table reports the time-series regression of UMO on a set of benchmark factors from July 1972 through December 2008. The dependent variable is monthly returns on UMO. The independent variables are the benchmark factors, including MKT, HML, SMB, MOM, INV, and LEV, all defined in Table II. Robust Newey-West (1987) t-statistics are reported in square bracket. The R^2s are adjusted for degree of freedom. The variable $\sigma(\epsilon)$ is the standard deviation of the regression error term. In square bracket underneath is the 1% confidence interval of the standard deviation of the residual terms based on long-short portfolios with randomly selected stocks. Specifically, we form portfolios with randomly selected stocks at the end of each June with the equal number of stocks as that in portfolio U in the long side and as that in portfolio O in the short side. Then we calculate the equal-weighted long-short portfolio returns. We regress the randomly-selected portfolio returns on a set of benchmark factors and compute the standard deviation of the residual terms. This exercise is repeated 1,000 times to generate a distribution of the standard deviation and we report the 1% confidence interval based on this distribution. An observed standard deviation of the residual terms from regressions of UMO is statistically significant when it is above the right end of the confidence interval.

	Intercept	MKT	SMB	HML	MOM	INV	LEV	R^2	$\sigma(\epsilon)$
(1)	0.75	−0.21	0.02	0.54				51%	2.16
	[7.19]	[5.92]	[0.28]	[7.82]					[0.977, 1.217]
(2)	0.53	−0.18	0.02	0.59	0.20			57%	2.00
	[5.12]	[5.73]	[0.36]	[10.31]	[4.47]				[0.977,1.217]
(3)	0.56	−0.18	0.03	0.52		0.36		54%	2.08
	[5.22]	[5.48]	[0.49]	[8.89]		[3.50]			[0.977, 1.219]
(4)	0.75	−0.21	−0.01	0.47			0.08	51%	2.15
	[7.35]	[5.95]	[0.15]	[7.11]			[1.45]		[0.977, 1.219]

Table IV: Fama-MacBeth regressions at the portfolio level

This table reports the Fama-MacBeth regression results using the 25 size and book-to-market portfolios from July 1972 through December 2008. The dependent variable is the value-weighted monthly excess returns (in percent) of the 25 portfolios. The independent variables are the loadings on a set of return factors, including MKT, HML, SMB, UMO, $\text{UMO}_{\perp\text{SEC}}$, MOM, INV, and LEV, all defined in Table II. The loadings of each portfolio on the factors are estimated from a time-series regression using monthly excess returns over the past 60 months as of the end of June of each year. The estimated loadings are used as independent variables in the cross-sectional regressions in each of the next 12 months from July of year t through June of the year $t+1$. The time-series averages of the cross-sectional regression coefficients are reported. In brackets are the associated robust Newey-West (1987) t-statistics. The ave. R^2s are the time-series averages of the monthly adjusted R-squares across the full sample period.

	MKT	SMB	HML		UMO	Ave. R^2
(1)	−0.12				0.51	30%
	[0.28]				[2.54]	
(2)	−0.92	0.16	0.35			44%
	[3.25]	[0.94]	[1.95]			
(3)	−0.57	0.16	0.33		0.75	45%
	[2.00]	[0.97]	[1.81]		[4.83]	
	MKT	SMB	HML		$\text{UMO}_{\perp\text{SEC}}$	Ave. R2
(4)	−0.62	0.15	0.35		0.66	45%
	[2.39]	[0.90]	[1.93]		[4.07]	
	MKT	SMB	HML	MOM	UMO	Ave. R2
(5)	−0.80	0.16	0.35	0.00		46%
	[2.52]	[0.98]	[1.95]	[0.01]		
(6)	−0.59	0.18	0.34	−0.08	0.73	47%
	[1.90]	[1.07]	[1.85]	[0.25]	[4.46]	
	MKT	SMB	HML	INV	UMO	Ave. R2
(7)	−0.87	0.19	0.36	−0.12		46%
	[3.03]	[1.18]	[1.95]	[0.83]		
(8)	−0.67	0.19	0.33	−0.16	0.74	48%
	[2.44]	[1.16]	[1.83]	[1.13]	[4.60]	
	MKT	SMB	HML	LEV	UMO	Ave. R2
(9)	−1.05	0.17	0.35	0.73		46%
	[3.63]	[1.03]	[1.90]	[2.98]		
(10)	−0.71	0.17	0.33	0.81	0.78	46%
	[2.37]	[1.06]	[1.80]	[3.04]	[4.88]	

Table V: Return performance of deciles based on UMO loadings estimated from past 12-month daily returns

This table reports the average monthly percentage decile returns sorted based on pre-formation conditional UMO loadings, β_u^{pre}, from July 1973 through December 2008. The sorting variable β_u^{pre}, for each stock, is the coefficient β_u in the following regression, which requires at least 100 daily stock returns from month $t-12$ through $t-1$:

$$R - r_f = \alpha + \beta_m \text{MKT} + \beta_s \text{SMB} + \beta_h \text{HML} + \beta_u \text{UMO} + \epsilon.$$

At the end of month $t-1$, stocks are sorted based on β_u^{pre} into deciles and the equal-weighted decile returns of month t are reported. The portfolio H−L is long on the highest β_u^{pre} decile and short on the lowest β_u^{pre} decile. The variable α_{CAPM} is the intercept from the regression of the full sample monthly H−L returns on MKT. The variable α_{FF3} is the intercept from a similar regression with controls for the FF 3 factors. The reported pre-formation UMO loading (β_u^{pre}) is averaged across stocks included in each decile and then averaged across months. The post-formation UMO loading β_u^{post} is estimated using the full sample monthly decile returns from the above regression. Columns 2–4 use all firms and the last three columns exclude firms in UMO of the current year. Robust Newey-West (1987) t-statistics are reported in square bracket.

	All sample firms			Excl. UMO firms		
β_u^{pre} Rank	RET	β_u^{pre}	β_u^{post}	RET	β_u^{pre}	β_u^{post}
L	0.82	−2.16	−0.99	0.84	−2.18	−0.88
2	1.11	−0.98	−0.56	1.01	−1.00	−0.58
3	1.26	−0.57	−0.35	1.16	−0.59	−0.41
4	1.21	−0.31	−0.25	1.09	−0.33	−0.36
5	1.28	−0.11	−0.10	1.25	−0.12	−0.18
6	1.28	0.08	−0.06	1.17	0.06	−0.07
7	1.22	0.27	−0.02	1.15	0.25	−0.09
8	1.35	0.50	0.03	1.26	0.48	−0.06
9	1.23	0.85	0.04	1.15	0.82	0.02
H	1.58	2.00	0.01	1.46	1.91	−0.15
H−L	0.77	4.16	0.99	0.62		0.73
t(H−L)	[3.75]		[9.23]	[3.15]		[10.17]
α_{CAPM}	0.90			0.73		
$t(\alpha_{\text{CAPM}})$	[4.67]			[3.95]		
α_{FF3}	0.63			0.54		
$t(\alpha_{\text{FF3}})$	[3.82]			[3.27]		

Table VI: Fama-MacBeth regressions at the firm level

This table reports the firm-level Fama-MacBeth regression results from July 1975 to December 2008. The dependent variable is monthly percentage returns of individual stocks. Three sorting procedures that involve only prior information are used to estimate firm-level conditional UMO loadings (β^{UMO}). The β^{UMO} coefficient is estimated by first sorting stocks into deciles based on market equity (ME), and then, within each ME decile, further subdividing stocks into deciles based on the external financing variable (EXFIN). The 100 portfolios' equal-weighted monthly returns are computed and the loadings of each portfolio on UMO are estimated in a time-series regression of at least 36 month returns from July of 1972 through month $t-1$ on UMO together with MKT, SMB, and HML. Finally, the portfolio-level UMO loadings are assigned to individual stocks that are included in the portfolios at month $t-1$ to forecast stock returns at month t. The variable EXFIN is the net external financing, defined as the sum of net equity financing and net long-term debt financing, scaled by total assets. The variable IR is the net composite issuance variable. The variable AG is defined as the percentage annual change in total assets. The variable IVA is the investment over assets ratio. The variable NOA is the net operating assets. The variable ACCRUALS is the operating accrual. The variable CI is the abnormal capital investment. Details of the calculation of these variables are presented in the Appendix. All of the above variables are measured at the end of each June using total assets with the fiscal year ending as of December of the previous year. All of the above characteristic variables and the three UMO loadings are normalized to have zero mean and a standard deviation of one at a monthly basis. The variable LOG(BM) is logarithm of book-to-market equity, in which book equity is measured as of December of year $t-1$ and the market cap is measured at the end of December of year $t-1$. The variable LOG(ME) is the logarithm of market cap at the end of June each year. LOG(BM) and LOG(ME) are used from July of year t to June of year $t+1$ and updated annually. The variables $r(t-1)$, $r(t-12, t-2)$, and $r(t-36, t-13)$ are, respectively, the past returns during month $t-1$, from month $t-12$ through $t-2$, and from month $t-36$ through $t-13$, which are designed to capture the short-run, intermediate, and long-run return autocorrelations. These returns are expressed at a monthly basis. IR is the composite issuance variable (Daniel and Titman, 2006) based on market equity and stock returns from month $t-60$ to $t-1$. INDDUMs refer to a collection of industry dummies based on the Fama-French 49 industry classifications. "Yes" under INDDUMs means that the industry dummies are included in monthly cross-sectional regressions. The 3-factor loadings include β_{MKT}, β_{SMB}, and β_{HML}, which are estimated by regressing at least 15 daily stock returns on the 3 factors in month t. "Yes" under 3-Factor Loadings means that the factor loadings are included in monthly cross-sectional regressions. Intercepts are included in all regressions but the coefficients are unreported. Panel A includes all firms and Panel B excludes firms in UMO of the current year. In Panel B, all controls refer to the 5 standard return predictors (LOG(ME), LOG(BM), $r(t-1)$, $r(t-12, t-2)$, and $r(t-36, t-13)$), INDDUMs, and the 3-factor loadings. Robust Newey-West (1987) t-statistics are reported below the coefficients in brackets.

Table VI: Fama-MacBeth regressions at the firm level (Cont'd)

Panel A: All sample firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β^{UMO}	0.48	0.35	0.26	0.25	0.31	0.33	0.32	0.35	0.33
	[6.87]	[7.80]	[5.39]	[5.65]	[6.93]	[7.41]	[6.96]	[7.57]	[7.19]
EXFIN			−0.18						
			[3.40]						
IR				−0.19					
				[4.22]					
AG					−0.20				
					[5.85]				
IVA						−0.13			
						[0.59]			
NOA							−0.35		
							[2.48]		
ACCRUALS								−0.12	
								[1.96]	
CI									−0.07
									[1.29]
LOGME		−0.06	−0.09	−0.10	−0.08	−0.07	−0.08	−0.07	−0.07
		[1.16]	[1.83]	[2.13]	[1.39]	[1.32]	[1.36]	[1.24]	[1.36]
LOGBM		0.32	0.29	0.18	0.27	0.31	0.33	0.32	0.27
		[4.22]	[4.12]	[2.68]	[3.74]	[4.13]	[4.28]	[4.30]	[3.66]
$\text{RET}_{(t-1)}$		−0.06	−0.06	−0.06	−0.06	−0.06	−0.06	−0.06	−0.05
		[14.17]	[14.27]	[13.65]	[14.34]	[14.30]	[14.26]	[14.07]	[13.44]
$\text{RET}_{(t-12,t-2)}$		0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.05
		[3.48]	[3.37]	[3.31]	[3.48]	[3.43]	[3.39]	[3.06]	[3.49]
$\text{RET}_{(t-36,t-13)}$		−0.02	−0.03	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02
		[1.81]	[1.95]	[1.35]	[1.36]	[1.69]	[1.60]	[1.78]	[1.77]
INDDUM	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-FACTOR LOADINGS	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ave. R^2	0.6%	5.8%	5.9%	6.7%	5.9%	5.8%	5.8%	6.0%	6.1%
Ave. # of Obs	3683	3442	3442	2264	3199	3251	3113	2767	2811

Panel B: Excluding Firms in UMO

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β^{UMO}	0.44	0.33	0.24	0.21	0.29	0.31	0.29	0.33	0.31
	[6.21]	[6.74]	[4.34]	[4.15]	[5.84]	[6.35]	[5.80]	[6.48]	[6.08]
EXFIN			−0.19						
			[3.39]						
IR				−0.19					
				[3.89]					
AG					−0.23				
					[4.51]				
IVA						−0.25			
						[5.06]			
NOA							−0.31		
							[4.49]		
ACCRUALS								−0.09	
								[1.84]	
CI									−0.02
									[0.46]
ALL CONTROLS	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ave. R^2	0.6%	7.1%	7.3%	8.7%	7.5%	7.3%	7.3%	7.8%	7.9%
Ave. # of Obs	1845	1742	1742	1115	1603	1590	1573	1299	1358

Table VII: Comparison of demeaned pre- and post-ranking UMO loadings

This table reports the average demeaned pre and post-ranking UMO loadings for the 100 pre-ranking loading sorted portfolios. At the end of June of each year, individual stocks' excess percentage returns over the previous 60 months (each stock is required to have at least 36 out of 60 monthly returns) are regressed on MKT, SMB, HML, and UMO to obtain the pre-ranking UMO loadings ($b^{\text{UMO}}_{\text{pre}}$). The estimated ($b^{\text{UMO}}_{\text{pre}}$) are used to sort all stocks into 100 portfolios. The 100 portfolios are held from July of year t through June of year $t+1$. The equal-weight monthly percentage returns are computed. Finally, for each of the 100 portfolios, the full sample post-ranking UMO loadings ($b^{\text{UMO}}_{\text{post}}$) are estimated using a multifactor time-series regression that includes MKT, SMB, HML, and UMO. The demeaned $b^{\text{UMO}}_{\text{pre}}$ is the deviation of individual stocks' pre-ranking loadings from the mean loading of all available stocks in a given month. The demeaned $b^{\text{UMO}}_{\text{post}}$ is the deviation of portfolios' post-ranking loadings from their mean. The average demeaned $b^{\text{UMO}}_{\text{pre}}$ and $b^{\text{UMO}}_{\text{post}}$ are reported for the 100 portfolios in Panels A and B. The same procedure is used to estimate the demeaned market beta, SMB loadings, and HML loadings from the Fama-French 3 factor model. UMO (All) refers to the results using all available firms while UMO (Excl. U & O) refers to the results that exclude firms in UMO. Post-ranking loadings that are significant at the 5% level are in bold font. The Pearson correlations between the average demeaned portfolio pre- and the demeaned post-ranking loadings are reported in square bracket.

Panel A: Average demeaned pre-ranking loadings $b^{\text{UMO}}_{\text{pre}}$

Pre-Ranking	0	1	2	3	4	5	6	7	8	9
0+	−6.12	−3.80	−3.14	−2.74	−2.45	−2.23	−2.04	−1.89	−1.75	−1.64
10+	−1.53	−1.44	−1.35	−1.28	−1.20	−1.14	−1.08	−1.02	−0.97	−0.92
20+	−0.87	−0.83	−0.79	−0.75	−0.71	−0.67	−0.64	−0.60	−0.57	−0.54
30+	−0.50	−0.47	−0.44	−0.41	−0.39	−0.36	−0.33	−0.30	−0.28	−0.25
40+	−0.23	−0.20	−0.18	−0.15	−0.13	−0.10	−0.08	−0.05	−0.03	0.00
50+	0.02	0.04	0.07	0.09	0.12	0.14	0.16	0.19	0.21	0.24
60+	0.26	0.29	0.32	0.34	0.37	0.40	0.43	0.46	0.49	0.52
70+	0.55	0.58	0.61	0.64	0.68	0.72	0.76	0.80	0.84	0.88
80+	0.93	0.98	1.03	1.08	1.14	1.20	1.27	1.34	1.42	1.52
90+	1.62	1.73	1.86	2.01	2.18	2.40	2.70	3.11	3.78	6.08

Panel B: Demeaned post-ranking loadings $b^{\text{UMO}}_{\text{post}}$

Pre-Ranking	0	1	2	3	4	5	6	7	8	9
0+	**−0.57**	**−0.22**	−0.09	0.03	−0.05	**−0.18**	**−0.15**	−0.07	−0.03	**−0.18**
10+	**−0.10**	**−0.12**	−0.06	−0.04	**−0.08**	−0.07	0.04	−0.03	**−0.12**	−0.07
20+	0.00	**−0.12**	−0.06	**−0.11**	−0.03	**−0.10**	0.07	**−0.06**	−0.01	0.04
30+	0.02	0.00	**−0.14**	0.06	0.06	**−0.06**	0.11	**−0.06**	0.06	0.11
40+	0.05	0.00	**0.19**	**−0.19**	−0.02	0.07	0.10	**0.19**	0.01	0.09
50+	0.16	**0.23**	0.14	0.05	−0.05	0.12	0.06	0.07	0.07	0.07
60+	0.16	0.07	0.13	0.16	0.14	0.10	0.14	**0.19**	0.01	**0.19**
70+	0.10	0.01	0.08	0.06	0.14	0.09	0.18	0.08	0.14	0.05
80+	0.00	0.11	−0.05	−0.01	0.11	0.00	0.08	**−0.11**	0.12	−0.01
90+	−0.09	−0.09	0.00	−0.09	0.01	−0.14	**−0.16**	**−0.44**	**−0.21**	**−0.27**

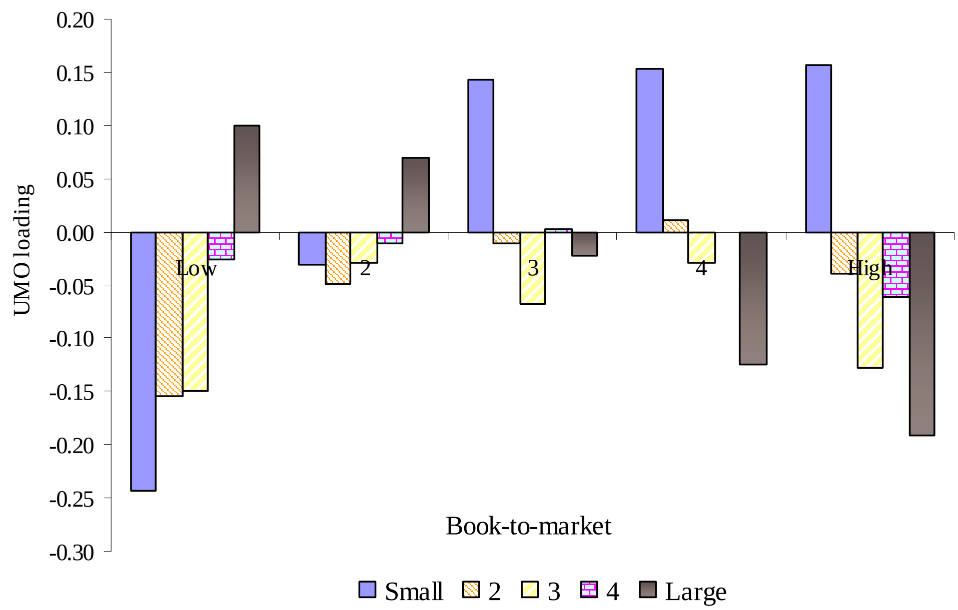
Panel C: Comparison of pre- and post-ranking loadings

	UMO	UMO	MKT	SMB	HML
	All	Excl. U & O	All	All	All
Out of 20 extreme portfolios with demeaned loadings that flip signs	10	10	0	1	0
Post-ranking loadings indistinguishable from zero	73	73	0	0	7
Correlation of pre- and post-ranking demeaned loadings	(0.20)	(0.18)	(0.89)	(0.89)	(0.88)

Figure 1: UMO loadings and Fama-French three-factor alphas of the Fama-French 25 size-BM portfolios

Panel A plots the slope coefficient on UMO of regressions of excess monthly returns of the 25 value-weighted size-BM portfolios on the misvaluation factor UMO and the Fama-French three factors (MKT, SMB, and HML). Panel B plots the intercept (alphas) of regressions of excess monthly returns of the 25 size-BM portfolios on the Fama-French three factors. The two panels show strong similarity between UMO loadings and abnormal returns of the 25 portfolios relative to the 3 factors, suggesting that UMO is a source of 3-factor model pricing errors of the 25 portfolios. The factors are defined in Table II.

Panel A: UMO Loadings



Panel B: Fama-French Three-Factor Alphas

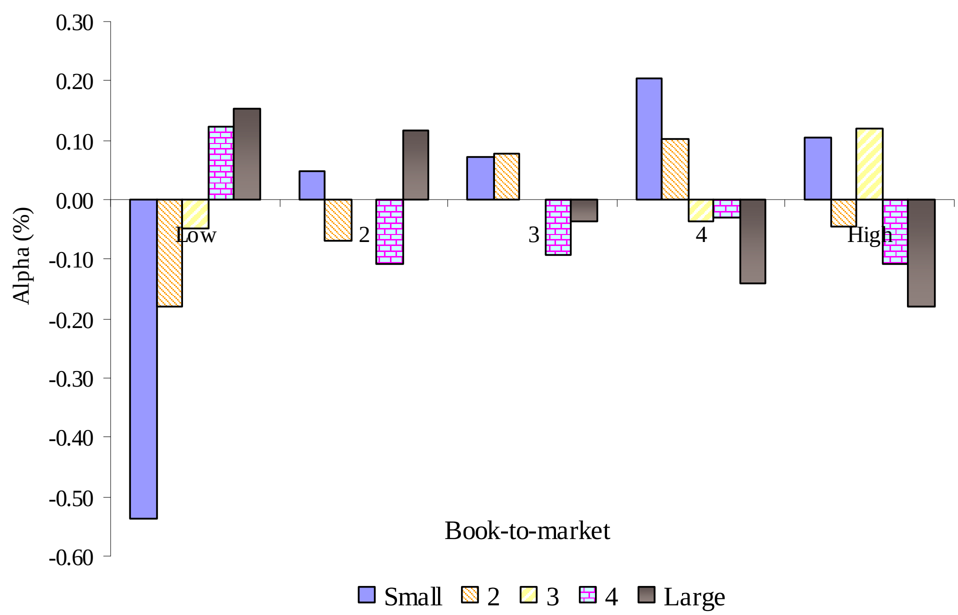
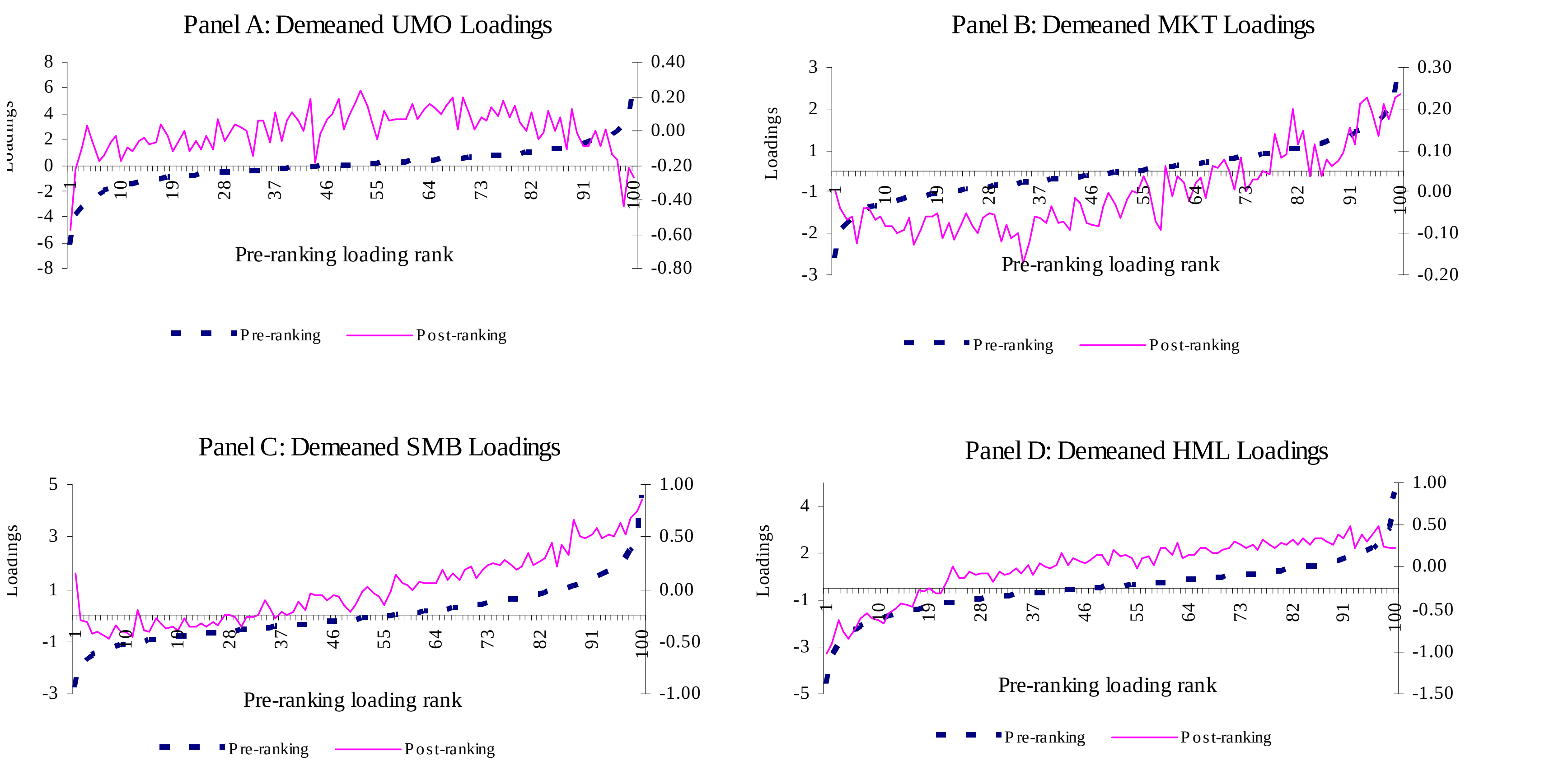


Figure 2: Pre- and post-ranking demeaned loadings of UMO and of the Fama-French 3 factors

This figure plots the average pre-ranking loadings and the post-ranking loadings of the 100 portfolios sorted based on pre-ranking loadings with respect to the misvaluation factor (UMO), and the Fama-French 3 factors (MKT, SMB, and HML). UMO is defined in Table II. The pre-ranking UMO loadings of individual stocks are estimated by regressing up to 60 available (and at least 36, if 60 are not available) most recent monthly percentage returns as of June of each year on UMO together with the 3 factors. Then stocks are sorted into 100 portfolios based on the pre-ranking UMO loadings and the equal-weighted percentage returns from July of year t through June of year $t+1$ are calculated. The post-ranking UMO loadings are estimated from regressing the full-sample monthly returns of each of the 100 portfolios on UMO together with the 3 factors. The pre-ranking and post-ranking loadings on MKT, SMB, and HML are estimated using the same method except that stock returns are regressed only on the 3 factors. To facilitate the comparison across different factors, we subtract the means from the pre- and post-ranking loadings. For pre-ranking loadings, the monthly mean loadings are used. The average pre-ranking loadings are plotted in dotted blue line while the post-ranking loadings in solid purple line.



Addendum

The addendum is provided to report additional robustness checks and show that the intuitive hypothesis development of the main text can be supported by formal analysis. Section A of this addendum shows that the main results of this paper hold for alternative benchmark multi-factor models and orthogonalized misvaluation factors. Section B shows that portfolios with extreme UMO loadings consist of hard-to-value and difficult-to-arbitrage stocks. Section C shows that the intuitive hypothesis development of the main text can be supported by formal modeling. Proofs of the Section C model propositions are provided in Sections D and E.

A. Robustness of main results: Alternative benchmark factors and orthogonalized misvaluation factor

This section shows that our main results hold after controlling for alternative benchmark factors, including the macroeconomic factors of Eckbo, Masulis, and Norli (2000), the new three-factor model of Chen and Zhang (2010), and the size and book-to-market factors purged of new issues of Loughran and Ritter (2000). We also show that our main results remain if we orthogonalize UMO to the 3- or 4-factors before adding it to the Fama-MacBeth regressions. This is to address a possible concern that UMO can spuriously price the 25 size-BM portfolios in the cross section if it is simply correlated with SMB and HML (Lewellen, Nagel, and Shanken 2010).

Eckbo, Masulis, and Norli (2000) suggest that equity financing changes firm leverage, thus altering firm's exposure to macroeconomic factors and leading to long-run abnormal returns relative to standard models. The six macroeconomic variables are constructed similar to Eckbo, Masulis, and Norli (2000) based on the St. Louis Fed Economic Data (FRED) and CRSP data. The market factor (MKT) is the excess return on the CRSP value-weighted market portfolio. Term premium (TERM) is defined as the yield spread between the 10-year and 1-year treasury constant maturity bonds. Default spread (DEF) is defined as the yield spread between Moody's seasoned Baa and Aaa corporate bonds.[1] TBILL spread (TBsp) is defined as the spread between the 90-day and the 30-day TBill rates, expressed at a monthly level. The percentage change in real per capita consumption of nondurable goods is denoted as ΔRPC. Unanticipated inflation (UI) is estimated using a model for expected inflation that regresses real returns (returns of 30-day TBills less inflation) on a constant and 12 of its lagged values. Similar to Eckbo et al., we form factor mimicking portfolios for the five

[1] Our data differs from Eckbo, Masulis, and Norli (2000) in that we use the yield spread, not the bond return spread, due to data availability. In addition, we measure the term premium between the 10-year and 1-year Treasury bonds (not between the 20-year and 1-year due to a break in this series from January 1987 through September 1993).

economic factors (except for MKT) through regressions of the Fama-French 25 size-BM portfolios on these factors. In our tests, we use the factor mimicking portfolio returns as the realized factor returns.[2]

Chen and Zhang (2010) show that a three-factor model including the market factor, an investment factor (IA), and a return-on-assets factor (ROA) helps explain a set of market anomalies including the anomaly based on net stock issues. We obtain the investment factor and ROA factor series from the authors' website for the period 1972–2008.

Loughran and Ritter (2000) and Brav, Geczy, and Gompers (2000) suggest replacing the Fama-French size and book-to-market factors with purged factors for more accurate assessment of the long-term performance of new issue firms. Specifically, the purged size and book-to-market factors exclude firms that engaged in new issue firms during the prior five years. We obtain the purged Fama-French factor returns (SMB_p and HML_p) from Jay Ritter from 1970–2003.

The orthogonalized UMO factors ($\text{UMO}_{\perp 3}$ and $\text{UMO}_{\perp 4}$) are defined as the sum of the intercept and residuals from regressing of UMO on the 3- or 4-factors. By construction, $\text{UMO}_{\perp 3}$ and $\text{UMO}_{\perp 4}$ have zero correlation with the 3- or 4-factors. If the orthogonalized factors remain significant in the Fama-MacBeth regressions of the 25 size-BM portfolios, we can safely conclude that the pricing power of the UMO is not due to correlations with SMB or HML.

Table A-1 presents the results of the time-series regressions of UMO on these three alternative sets of benchmark factors. The results show that the variation of UMO cannot be fully explained by these benchmark factors. Regressing UMO on the benchmark factors in time series regressions yields R-squares of 48% to 56%. The standard deviation of the regression residuals is way above the right end of 1% confidence interval based on long-short portfolios with randomly-selected stocks. This suggests that a significant portion of UMO variations is independent of the benchmark factors. The intercept remains economically and statistically significant, suggesting abnormal returns exist in UMO relative to these benchmark factors. Therefore, UMO contains incremental commonality in returns of equity financing firms beyond that captured by these existing factors.

Table A-2 presents the Fama-MacBeth regression results using the 25 size-BM portfolios. Panel A shows that, after controlling for the three alternative sets of benchmark factors, UMO loadings remain significant. In other words, asset exposure to these new benchmark factors does not fully

[2]Following Eckbo et al. (2000), to construct these factor mimicking portfolios, we first regress each of the 25 size-BM portfolios on the six factors separately to estimate the slope coefficient matrix B (25×6). Then we calculate the weights (ω) on the mimicking portfolios as $\omega = (B'V^{-1}B)^{-1}B'V^{-1}$, where V is the (25×25) covariance matrix of error terms for these regressions. For each factor, the return series is the sum of the products of the corresponding weights of the factor on the corresponding 25 portfolios.

Table A-1: Time-series regression of UMO on benchmark factors

Panel A reports the time series regression results of UMO on alternative benchmark factors from July 1972 through December 2008 (2003 when the purged size and book-to-market factors are used). The dependent variable is the percentage return of UMO that is long repurchase firms and short new issue firms. The market factor (MKT) refers to the excess returns of CRSP value-weighted portfolio. TERM is the term premium factor mimicking portfolio. DEF is the default premium factor mimicking portfolio. TBSP is the T-Bill spread factor mimicking portfolio. ΔRPC is the change in consumption of nondurable goods factor mimicking portfolio. UI is the unexpected inflation factor mimicking portfolio. The return-on-asset (ROA) factor is the difference between the return on a portfolio of stocks with high returns on assets and the return on a portfolio of stocks with low returns on assets. The investment factor (IA) is the difference between the return on a portfolio of low-investment stocks and the return on a portfolio of high-investment stocks. The purged size factor (SMB_p) and book-to-market factor (HML_p) exclude firms involved in equity issuance during the prior five years. Robust Newey-West *t*-statistics of the intercepts and independent variables are reported in brackets. $\sigma(\epsilon)$ is the standard deviation of the residual terms with the 1% confidence interval of the residual terms reported in brackets, based on long-short portfolios with randomly selected stocks.

	Intercept	MKT	TERM	DEF	TBSP	ΔRPC	UI	R^2	$\sigma(\epsilon)$
(1)	0.54	-0.37	0.18	0.22	-2.29	2.58	*-0.22*	55%	2.05
	[4.86]	[8.64]	[8.41]	[3.01]	[4.83]	[0.40]	[1.77]		[0.974, 1.211]
	Intercept	MKT	ROA	IA				R^2	$\sigma(\epsilon)$
(2)	0.53	−0.23	0.24	0.62				51%	2.15
	[3.89]	[6.35]	[4.36]	[7.79]					[0.976, 1.223]
	Intercept	MKT	SMB_p	HML_p	MOM			R^2	$\sigma(\epsilon)$
(3)	0.92	−0.25	0.03	0.55				48%	2.33
	[7.69]	[6.36]	[0.55]	[6.91]					[0.964,1.247]
(4)	0.70	-0.22	0.03	0.61	0.21			56%	2.05
	[5.86]	[6.60]	[0.64]	[9.40]	[4.26]				[0.961,1.244]

account for the positive premium associated with high UMO loadings. We see no visible reduction in the magnitude of coefficients for these alternative specifications. In Panel B, we add $\text{UMO}_{\perp 3}$ and $\text{UMO}_{\perp 4}$ to the 3- or 4-factors in the Fama-MacBeth regression. Both UMO factors continue to be priced cross-sectionally. The portfolio loadings on $\text{UMO}_{\perp 3}$ and $\text{UMO}_{\perp 4}$ are significantly correlated with future portfolio returns. In an unreported test, we further consider a factor based on the asset growth variable of Cooper, Gulen, and Schill (2008). We find no evidence that the asset growth factor subsumes the power of UMO loadings to forecast the cross section of portfolio returns. Taken together, the results suggest that existing common factors do not fully account for the variation and pricing power of UMO.

B. Characteristics of the UMO loading portfolios

Behavioral finance theory suggests that mispricing should be greatest for stocks that are hard-to-value and difficult-to-arbitrage (see e.g., Daniel, Hirshleifer, and Subrahmanyam (2001) and the evidence of Baker and Wurgler (2006)). In this section, we explore whether stocks with extreme UMO loadings, which we hypothesize are mispriced, are hard to value and to arbitrage.

We study several firm characteristics that were used as proxies for the difficulty to value or to arbitrage by Baker and Wurgler (2006). These characteristics include firm size, age, return volatility, fixed assets, R&D, book-to-market equity, and sales growth. The mean annual characteristics are reported in Table A-3. Consistent with the idea that growth potential is a source of the overpricing of the low UMO loadings stocks, the lowest quintile has low book-to-market equity and high past sales growth. Supporting the notion that the more mispriced stocks are harder to value, firms in the top or bottom loading quintiles are smaller, younger, and have higher return volatility than firms in the middle groups. Relative to the highest quintile, the lowest quintile of stocks has smaller fixed assets but greater R&D investments, suggesting that firms with more intangible investments are more likely to be overpriced. In sumary, this evidence suggests that stocks with extreme UMO loadings are difficult to value and to arbitrage, which may explain why mispricing can persist for such stocks.

Table A-2: Fama-MacBeth regression at the portfolio level

This table reports the Fama-MacBeth regression results using the 25 size and book-to-market portfolios from July 1972 through December 2008 (2003 when the purged size and book-to-market factors are used). The 4-factors, MKT, SMB, HML, and MOM are the market, size, book-to-market, and momentum factors. Other factors are defined in Table A-1. The dependent variable is percentage monthly returns of the 25 size and book-to-market portfolios from July of year t through June of year $t+1$. The independent variables are factor loadings estimated from a multi-factor time-series regression using monthly excess returns from July of year $t-5$ through June of year t. The time-series averages of the cross-sectional coefficients, which measure the estimated percentage premia, are reported, below which are the associated robust Newey-West (1987) t-statistics in brackets. The average R^2s are the time-series averages of the monthly adjusted R-squares across the entire sample period.

Panel A: Alternative benchmark factors								
	UMO	MKT	TERM	DEF	TBSP	ΔRPC	UI	Ave. R^2
(1)	0.58	−0.58	0.93	−0.24	−0.01	0.00	0.04	53%
	[3.39]	[2.12]	[2.24]	[1.57]	[0.42]	[2.03]	[0.65]	
	UMO	MKT	ROA	IA				Ave. R^2
(2)	0.79	−0.21	0.52	0.09				42%
	[4.01]	[0.63]	[1.95]	[0.56]				
	UMO	MKT	SMB_p	HML_p				Ave. R^2
(3)	0.78	−0.48	0.21	0.25				44%
	[4.79]	[1.63]	[1.32]	[1.55]				
Panel B: Orthogonalized UMO								
	$\text{UMO}_{\perp 3}$	MKT	SMB	HML				Ave. R^2
(4)	0.45	−0.57	0.16	0.33				45%
	[3.76]	[2.00]	[0.97]	[1.81]				
	$\text{UMO}_{\perp 4}$	MKT	SMB	HML	MOM			Ave. R^2
(5)	0.44	−0.59	0.18	0.34	−0.08			47%
	[3.40]	[1.90]	[1.07]	[1.85]	[0.25]			

Table A-3: Characteristics of portfolios sorted based on conditional UMO loadings

This table reports the mean characteristics of the portfolios sorted based on conditional UMO loadings from July 1972 through December 2008. The UMO loadings (β^{UMO}) in Panel A are estimated using daily returns over the past 12 months, as used in Table V. Those in Panel B are estimated using characteristic portfolios sorted based on market size and the external financing variable, as used in Table VI. At the end of each June, we sort stocks into quintiles based on the estimated β^{UMO} and calculate the mean characteristics, including log size (LOGME), firm age (AGE), return volatility (σ), fixed assets (PPE/A), research and development (RD/A), book-to-market ratio (B/M), and sales growth (GS). Return volatility is measured as the standard deviation of the monthly returns during the most recent 12 months. Robust Newey-West t-statistics are reported in brackets.

Panel A: UMO loadings estimated from daily returns

Rank	β^{UMO}	LOGME	AGE	σ	PPE/A	RD/A	B/M	GS
L	−1.47	3.95	10.20	19.01	0.48	0.10	0.88	1.75
2	−0.39	4.78	15.46	13.10	0.54	0.06	0.89	0.50
3	0.00	5.01	17.76	11.33	0.58	0.05	0.92	0.79
4	0.38	4.76	16.67	12.34	0.55	0.06	0.93	0.46
H	1.41	3.68	12.74	17.75	0.53	0.07	1.08	0.89
H−L		−0.27	2.54	−1.26	0.05	−0.03	0.19	−0.85
		[2.67]	[4.48]	[1.73]	[3.65]	[3.62]	[6.44]	[1.96]

Panel B: UMO loadings estimated from characteristic-sorted portfolios

Rank	β^{UMO}	LOGME	AGE	σ	PPE/A	RD/A	B/M	GS
L	−0.38	5.19	11.96	15.08	0.48	0.10	0.67	1.58
2	−0.13	5.32	17.15	13.32	0.56	0.07	0.84	0.61
3	−0.01	5.06	17.23	12.97	0.55	0.06	0.85	1.20
4	0.13	4.14	15.00	14.61	0.54	0.06	1.01	0.42
H	0.38	2.46	11.49	17.52	0.55	0.06	1.35	0.56
H−L		−2.73	−0.47	2.44	0.07	−0.04	0.68	−1.03
		[15.11]	[0.35]	[2.80]	[1.99]	[4.77]	[9.56]	[2.54]

C. A model with commonality in misvaluation

In this section, we present a behavioral model built upon that of Daniel, Hirshleifer, and Subrahmanyam (2001) to formally derive the empirical predictions in Section 2.This model shows how equity financing helps identify factor-related mispricing and why loadings on the misvaluation factor UMO is positively related to expected returns. In Subsection 1, we briefly review the settings and the relevant results of the DHS (2001) model. In Subsection 2 we extend the analysis to obtain empirical predictions about equity financing and excess comovement of stocks with respect to a misvaluation factor. Though this model is based on investor overconfidence, similar qualitative conclusions could be derived from the setting of the style investing model of Barberis and Shleifer (2003).

1 The Daniel, Hirshleifer, and Subrahmanyam (2001) model

In the model of Daniel, Hirshleifer, and Subrahmanyam (2001), a set of identical risk-averse individuals are each endowed with shares of $N+K$ risky securities and a risk-free consumption claim with terminal (date 2) payoff of 1. The prior distribution of security payoffs at date 2 is:

$$\theta_i = \bar{\theta}_i + \sum_{k=1}^{K} \beta_{ik} f_k + \epsilon_i, \tag{A-1}$$

where β_{ik} is the loading of the ith security on the kth factors, f_k is the realization of the kth factor, and ϵ_i is the ith residual, and where factors are nomralized such that. $E[f_k]=0$, $E[f_k^2]=1$, $E[f_j f_k]=0$ for all $j \neq k$, $E[\epsilon_i]=0$, E[$\epsilon_i f_k$]=0 for all i,k. The values of $\bar{\theta}_i$ and β_{ik} are common knowledge, but the realizations of f_k and ϵ_i are not revealed until date 2.

At date 1, a subset of individuals receives signals about the K factors and N residuals. The noisy signals about the payoff of the kth factor portfolio and ith residual portfolio take the form

$$s_k^f = f_k + e_k^f \quad \text{and} \quad s_i^\epsilon = \epsilon_i + e_i^\epsilon.$$

The precisions (the inverse of variance) of the signals noise terms e_k^f and e_i^ϵ are denoted as ν_k^{Rf} and $\nu_i^{R\epsilon}$, respectively. However, since investors are overconfident about their private signals, they mistakenly think the precisions are higher (C for overconfident), $\nu_k^{Cf} > \nu_k^{Rf}$, and $\nu_i^{C\epsilon} > \nu_i^{R\epsilon}$.

For each security, a proportion of investors ϕ_i, $i=1,2,...,N+K$ receives noisy private signals about the payoff of the common risk factors and idiosyncratic risks. Since individuals are overconfident about the private signals, the equilibrium price of individual security reflects both the covariance risk with the market portfolio and the mispricing component due to the overreaction to private signals,

$$P_i = \bar{\theta}_i - \alpha\beta_{iM} + (1+\omega_i^{\epsilon})S_i^{\epsilon} + \sum_{k=1}^{K} \beta_{ik}(1+\omega_k^f)S_k^f, \tag{A-2}$$

$$E^R[R_i] = \alpha\beta_{iM} - \omega_i^{\epsilon}S_i^{\epsilon} - \sum_{k=1}^{K} \beta_{ik}\omega_k^f S_k^f, \tag{A-3}$$

for all $i = 1, ..., N+K$, where

$$\beta_{iM} = \frac{cov(R_i, R_M)}{var(R_M)}, \qquad \alpha = E[R_M],$$
$$S_i = \lambda_i^R s_i, \qquad \omega_i = \frac{\lambda_i - \lambda_i^R}{\lambda_i^R},$$
$$\lambda_i = \frac{\nu_i^A}{\nu_i + \nu_i^A}, \qquad \lambda_i^R = \frac{\nu_i^R}{\nu_i + \nu_i^R}, \qquad \lambda_i > \lambda_i^R, \qquad \text{and}$$
$$\nu_i^A = \phi_i \nu_i^C + (1-\phi_i)\nu_i^R$$

and where S_i^{ϵ} and S_k^f are the posterior expected payoffs of the factor i and residual k conditional on signals about the factor and residual payoff, respectively. $E[R_M]$ is the rational expected return on an adjusted market portfolio.

Equation (A-3) describes the equilibrium return. The first term is the product of market beta and the unconditional expected market returns, reflecting the compensation for undertaking systematic risk. The second term is the mispricing component due to the overreaction to the residual signal. The last term is the mispricing component due to the overreaction to the factor signals. The overconfidence parameters, ω_i^{ϵ} and ω_k^f, are positive if there are overconfident and rational investors.[3] For each risk factor k, there is a corresponding mispricing term $\omega_k^f S_k^f$ induced by overconfidence, measured by ω_k^f, about the factor signal S_k^f.[4]

2 A model of factor mispricing, new issues, and repurchases

In this subsection we generalize the DHS approach to allow for new issues and repurchases, in order to derive implications about how to identify factor misvaluation using new issue and repurchase portfolios.

[3]The overconfidence parameters are negative if there is underconfidence, and zero if the investors are on average rational.

[4]Since overconfidence parameters ω^fs are not necessarily the same across all factors, the linear combination of the terms for the mispriced factors are not perfect correlated with the market portfolio. The overall mispricing of a security is the sum of the mispricing of factor and residual payoffs.

2.1 Management's assessment of mispricing

We now examine management's assessment of the extent of mispricing, and how this affects new issue and repurchase policy. Let the price of security i that would apply if all investors are rational be P_i^R, and let the equilibrium price in the model conditional on the signals be P_i. The mispricing magnitude, η_i, the difference between the actual price and the rational price, is determined by the mispricing components,

$$P_i^R = \bar{\theta}_i - \alpha\beta_{iM} + S_i^\epsilon + \sum_{k=1}^{K} \beta_{ik} S_k^f \tag{A-4}$$

$$\eta_i = P_i - P_i^R = \omega_i^\epsilon S_i^\epsilon + \sum_{k=1}^{K} \beta_{ik} \omega_k^f S_k^f \, . \tag{A-5}$$

Apart from the assumptions of the DHS model, we now assume that managers are fully rational. In other words, managers can correctly perceive the misvaluation about firm payoffs.[5] We also assume that managers act in the interest of existing shareholders and that exploiting misvaluation is the sole motive for equity issuances or repurchases.

In addition, we assume that there is a fixed cost associated with equity issuance or repurchases, which can vary across firms. The fixed cost could, for example, take the form of underwriting fees, the negative market reaction to share issuance, or the positive market reaction to share repurchase. It implies a threshold for exploiting overpricing through new issue, or underpricing through repurchase. Let us denote the issuance threshold for overpricing as η_o^* and the repurchase threshold for underpricing as η_u^* ($\eta_o^* > 0$ and $\eta_u^* < 0$). For firm i, market timing of overvaluation (equity issuance) takes place when

$$\eta_i = P_i - P_i^R = \omega_i^\epsilon S_i^\epsilon + \sum_{k=1}^{K} \beta_{ik} \omega_k^f S_k^f > \eta_o^* \, ,$$

and market timing of undervaluation (equity repurchase) takes place when

$$\eta_i = P_i - P_i^R = \omega_i^\epsilon S_i^\epsilon + \sum_{k=1}^{K} \beta_{ik} \omega_k^f S_k^f < \eta_u^* \, .$$

Given a favorable signal about factor k (i.e. $S_k^f > 0$), when investors are overconfident about factor k (i.e. $\omega_k^f > 0$), factor k is overpriced and so is security i that has a positive loading on

[5] An alternative approach would be to assume that managers receive different signals from outsiders. Their signals are more precise about the factor payoff and the residual payoff. For example, managers may have more precise information about the sales or earnings of their firms than outsiders. Both sales and earnings contain information about aggregate market and individual firms. Under this assumption, even if some or all managers were overconfident, they might still be able to recognize mispricing of their firms.

Table A-4: The Relation between Stocks' Misvaluation with Factor Signals and Factor Loadings

		Factor Signal S_k	
		+	−
Factor Loading β_{ik}	+	Overpricing	Underpricing
	−	Underpricing	Overpricing

factor k ($\beta_{ik} > 0$). In other words, factor underpricing generates underpricing of firms that load positively on this factor, and overpricing of those that load negatively. Therefore, a given factor mispricing can produce both overpriced and underpriced firms (see Table A-4). An extreme factor signal and/or a high level of overconfidence can produce both large underpricing and overpricing of different securities. Thus, mispricing is more dispersed across firms when factor mispricing is large. Of course, even if all loadings on the factor are positive, so long as the loadings are unequal factor misvaluation induces different degrees of misvaluation in different securities.

2.2 Excess return comovement

Given an observed equity issue or repurchase, two different inferences are possible: that the security price overreacted to the firm-specific signal, or that the security loads heavily on currently mispriced factors. Only the second case, however, generates comovement of the stock with the UMO factor.

Proposition 1. *Conditional on β_{iM} and β_{ik}, the ex ante covariance between any two securities is the sum of the covariances through the market portfolio and through the mispriced factors,*

$$cov(R_i, R_j) = \beta_{iM}\beta_{jM}\, var(R_M) + \sum_{k=1}^{K} \beta_{ik}\beta_{jk}\, var(\omega_k^f S_k^f) \quad \text{for all} \quad i \neq j.$$

The first term is the covariance through the market portfolio, and the second term is the covariance through mispriced factors. The above covariance implies that, after controlling for the covariance through the market (or more generally through a given set of standard factors such as the Fama/French factors), two securities' excess comovement is due to the covariation induced by the common misvaluation.

2.3 A Zero-Investment Portfolio that Captures Common Misvaluation

Since misvaluation of firm-specific payoff does not generate covariances among securities, without loss of generality we now assume that there are no private signals about firm-specific payoffs for all securities, $s_i^\epsilon = 0$ for all i. Under this assumption, the level of mispricing then depends on three components: the factor signal realization S_k^f, the overconfidence parameter ω_k^f and the factor loading β_{ik}. Given the the factor signals and overconfidence parameters, to generate a large mispricing a firm needs to load heavily on mispriced factors. Therefore, firms with market timing events will tend to have extreme loadings on the mispriced factors.

In the spirit of Fama and French (1993), we form a zero-investment portfolio to capture the common misvaluation. Consider the two portfolios O and U, where O consists of K_o firms that issue equity, and U consists of K_u firms that repurchase shares. The expected returns of the two portfolios, conditional on the signals, can be written as (where the set of securities I_1, I_2 are mutually exclusive):

$$E^R[R_O] = \alpha\beta_{K_oM} - \sum_{k=1}^{K} \beta_{K_ok}\omega_k^f S_k^f \tag{A-6}$$

$$E^R[R_U] = \alpha\beta_{K_uM} - \sum_{k=1}^{K} \beta_{K_uk}\omega_k^f S_k^f, \tag{A-7}$$

where

$$\beta_{K_oM} = \frac{1}{K_o}\sum_{i=1, i\in I_1}^{K_o} \beta_{iM}, \qquad \beta_{K_ok} = \frac{1}{K_o}\sum_{i=1, i\in I_1}^{K_o} \beta_{ik}, \tag{A-8}$$

$$\beta_{K_uM} = \frac{1}{K_u}\sum_{i=1, i\in I_2}^{K_u} \beta_{iM}, \qquad \beta_{K_uk} = \frac{1}{K_u}\sum_{i=1, i\in I_2}^{K_u} \beta_{ik}\,. \tag{A-9}$$

According to Fama and French (1993), the zero-investment portfolio that goes long on stocks with high loadings on the mispriced factors and short on stocks with low loadings should be largely free from other factor risks. In other words, we can assume that the average βs are equal for the two portfolios, i.e., $\beta_{K_oM} = \beta_{K_uM}$.[6]

Proposition 2. *If there are no private signals about residual cash flow components, then the zero-investment portfolio, UMO, that invests one dollar in the portfolio U and sells one dollar in the portfolio O has the conditional expected return*

$$E^R[R_{UMO}] = \sum_{k=1}^{K}(-\beta_{UMO,k}\omega_k^f S_k^f) > 0,$$

where $\beta_{UMO,k} = \beta_{K_u,k} - \beta_{K_o,k}$.

[6] Empirically, it is possible that average betas of the two groups of stocks are not equal. Thus, UMO that is long on U and short on O will contain a component of the market returns. In this case, we can estimate the UMO loadings in a regression that includes both UMO and the market factor. In Addendum Section D., we show that the estimated UMO loadings from a multifactor regression are equal to the true UMO loadings.

When factor mispricing is corrected, UMO earns positive expected returns. Hence, given positive signals about factor payoffs, $\beta_{UMO,k}$ should be positive. In contrast, given negative signals, $\beta_{UMO,k}$ should be negative.

2.4 The correlation of security returns with UMO

Each security's comovement with UMO can be measured by its loadings with respect to UMO. We characterize these loadings as follows.

Proposition 3. *Conditional on the security fundamental loadings (the β_{ik}'s), the loadings on UMO in the regression $R_i = a + b_{i,UMO}R_{UMO} + \varepsilon_i$ are*

$$b_{i,UMO} = \frac{cov(R_i, R_{UMO})}{var(R_{UMO})} = \frac{\sum_{k=1}^{K} \beta_{ik}\beta_{UMO,k}\, var(\omega_k^f S_k^f)}{\sum_{k=1}^{K} \beta_{UMO,k}^2\, var(\omega_k^f S_k^f)} . \tag{A-10}$$

If we assume the overconfidence parameters are the same across different factors, i.e., $\omega_k^f = \omega_{k'}^f$, and that the variance of the factors are the same, i.e., $var(S_k^f) = var(S_{k'}^f)$ for $k \neq k'$, then the estimated β is

$$b_{i,UMO} = \frac{\sum_{k=1}^{K} \beta_{ik}\beta_{UMO,k}}{\sum_{k=1}^{K} \beta_{UMO,k}^2} . \tag{A-11}$$

In the simplest case, only one dimension of risk, $K = 1$, exists, the estimated loading can be written as

$$b_{i,UMO} = \frac{\beta_i}{\beta_{UMO}} . \tag{A-12}$$

Equation (A-11) shows that firms that load heavily on UMO, on average, tend to load heavily in the common factors. Equation (A-12) implies that, empirically, the UMO loading of individual stocks can be very unstable. For example, suppose that the factor is the price of oil, and that investors at one time overconfidently forecast high oil prices, and at a later time overconfidently forecast low oil prices. Then β_{UMO} will firstly be positive and later become negative. Accordingly, a car company that benefits from low oil prices will first be undervalued and load positively on UMO, and later will be overvalued and load negatively on UMO. Thus, depending on the realization of the signals, the UMO loadings can vary and even frequently flip signs.

When there are multiple factors UMO loadings can flip even if the mispricing of factors does not actually reverse (from under- to overpricing or vice versa). Intuitively, suppose that a stock loads positively on the oil factor but negatively on a new economy factor. Then it should load positively on UMO when an oil factor is underpriced but negatively on UMO when, instead, the new economy factor underpriced. This reinforces the point that we do not expect a given stock to have a consistently high or low UMO loading, or even a consistent sign of its UMO loading over long periods of time.

2.5 The cross section of stock returns

Proposition 4. *If there are $K > 1$ risk factors, the overconfidence parameters are the same across different factors, i.e., $\omega_k^f = \omega_{k'}^f$ for all $k \neq k'$, the variance of the risk factors are the same, i.e., $var(S_k^f) = var(S_{k'}^f)$ for all $k \neq k'$, and the cross-security dispersion in factor loadings is the same across factors, $var(\beta_{ik}) = var(\beta_{ik'})$ for all $k \neq k'$, then in the cross-sectional regression $R_i = \lambda_0 + \lambda_{UMO} b_{i,UMO} + u_i$, the estimated premium λ_{UMO}, which is the expected return on the zero-investment portfolio UMO, is positive,*

$$\lambda_{UMO} = -\sum_{k=1}^{K} \beta_{UMO,k} \omega_k^f S_k^f > 0.$$

The proof is in Addendum Section E..

Propositions 3 and 4 show that high UMO loadings should be positively correlated with high stock returns. UMO loadings capture the mispricing derived from factor overreaction. The greater the loading, the larger the inherited factor underpricing. Therefore, when subsequent conclusive factor arrives, factor mispricing is corrected and stocks that partake more factor underpricing earn higher returns.

D. Proof of footnote 6 in Addendum Section C.

We describe how even when the average market betas in portfolios O and U are not equal, so that UMO is correlated with MKT, we can still estimate a UMO loading that captures the covariance with respect to the mispricing factor conditional on the market by running a multi-factor regression on both UMO and MKT.

In the portfolio O and U, if the market loadings, β_{K_oM} and β_{K_uM}, are correlated with the factor loadings, β_{K_ok} and β_{K_uk}, the portfolio UMO is not a pure proxy for mispricing. By longing one dollar of U and shorting one dollar of O, we obtain the following return

$$E^R[R_{UMO}] = \beta_{UMO,M} E(R_M) - \sum_{k=1}^{K} \beta_{UMO,k} \omega_k^f S_k^f,$$

where $\beta_{UMO,M} = \beta_{K_u,M} - \beta_{K_o,M}$ and $\beta_{UMO,k} = \beta_{K_u,k} - \beta_{K_o,k}$.

To estimate the factor loadings on UMO after controlling for the market return, we can run a time-series regression $R_i = a + b_{i,UMO} R_{UMO} + b_{i,M} R_M$. Let the vector $X = [R_{UMO}, R_M]$ and define

$$\Sigma_{XY} = [cov(R_{UMO}, R_i), cov(R_M, R_i)].$$

Further, let Σ_{XX} denote the variance-covariance matrix of the vector X. Then the OLS estimator of $b_{i,UMO}$, $b_{i,M}$ can be written as

$$[b_{i,UMO}, b_{i,M}] = \Sigma_{XX}^{-1}\Sigma_{XY}.$$

Let us denote $var(R_M) = V_M$. The covariances and variances required to calculate Σ_{XX} and Σ_{XY} are

$$\begin{aligned}
cov(R_{UMO}, R_M) &= \beta_{UMO,M}V_M, \\
cov(R_{UMO}, R_i) &= \beta_{iM}\beta_{UMO,M}V_M + \sum_{k=1}^{K}\beta_{ik}\beta_{UMO,k}\, var(\omega_k^f S_k^f), \\
cov(R_M, R_i) &= \beta_{iM}\beta_{UMO,M}V_M.
\end{aligned}$$

The coefficient $b_{i,UMO}$ can be calculated as

$$\begin{aligned}
b_{i,UMO} &= \frac{var(R_M)\, cov(R_{UMO}, R_i) - cov(R_{UMO}, R_M)\, cov(R_M, R_i)}{var(R_{UMO})\, var(R_M) - cov^2(R_{UMO}, R_M)} \\
&= \frac{\sum_{k=1}^{K}\beta_{ik}\beta_{UMO,k}\, var(\omega_k^f S_k^f)}{\sum_{k=1}^{K}\beta_{UMO,k}^2\, var(\omega_k^f S_k^f)}.
\end{aligned}$$

Hence, after controlling for the market portfolio, the time-series regression still generates the same coefficient as in Proposition 3. Q.E.D.

E. Proof of Proposition 4 in Addendum Section C.

We will now prove that under mild regularity conditions the estimated UMO premium from a cross-sectional regression is equal to the expected return on UMO. Therefore, higher UMO loadings should be associated with higher expected stock returns.

We have shown when there are no private signals about the residual payoff, the expected return of security i and mispricing factor loading $b_{i,UMO}$ are, respectively,

$$E^R[R_i] = \alpha\beta_{iM} - \sum_{k=1}^{K}\beta_{ik}\omega_k^f S_k^f,$$

$$\text{and} \quad b_{i,UMO} = \frac{cov(R_i, R_{UMO})}{var(R_{UMO})} = \frac{\sum_{k=1}^{K}\beta_{ik}\beta_{UMO,k}\, var(\omega_k^f S_k^f)}{\sum_{k=1}^{K}\beta_{UMO,k}^2\, var(\omega_k^f S_k^f)}.$$

Therefore, the covariance and variance are

$$cov(R_i, b_{i,UMO}) = -\frac{\sum_{k=1}^{K} \beta_{UMO,k}\omega_k^f S_k^f \, var(\omega_k^f S_k^f) \, var(\beta_{ik})}{\sum_{k=1}^{K} \beta_{UMO,k}^2 \, var(\omega_k^f S_k^f)},$$

$$\text{and} \quad var(b_{i,UMO}) = \frac{\sum_{k=1}^{K} \beta_{UMO,K}^2 var^2(\omega_k^f S_k^f) \, var(\beta_{ik})}{\left[\sum_{k=1}^{K} \beta_{UMO,k}^2 \, var(\omega_k^f S_k^f)\right]^2}.$$

The regression $R_i = \lambda_0 + \lambda_{UMO} b_{i,UMO} + u_i$ estimates the coefficient

$$\lambda_{UMO} = -\frac{\sum_{k=1}^{K} \beta_{UMO}\omega_k^f S_k^f \, var(\omega_k^f S_k^f) \, var(\beta_{ik}) \sum_{k=1}^{K} \beta_{UMO,k}^2 \, var(\omega_k^f S_k^f)}{\sum_{k=1}^{K} \beta_{UMO,K}^2 var^2(\omega_k^f S_k^f) \, var(\beta_{ik})}$$

If $var(\omega_k^f S_k^f) = var(\omega_{k'}^f S_{k'}^f)$ and $var(\beta_{ik}) = var(\beta_{ik'})$ for $k \neq k'$, the above coefficient can be simplified as $\lambda_{UMO} = -\sum_{k=1}^{K} \beta_{UMO,k}\omega_k^f S_k^f$. Q.E.D.

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