# Commonality in Misvaluation, Equity Financing, and the Cross Section of Stock Returns

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Behavioral theories suggest that investor misperceptions and market mispricing will be correlated across firms. This paper uses equity financing to identify comovement in returns and commonality in misvaluation. A zero-investment portfolio (UMO, Undervalued Minus Overvalued) built from repurchase and new issue stocks captures excess comovement in general stock returns relative to a set of multi-factor models. Adding UMO to the 3-factors makes the alphas insignificant for portfolios with extreme size and book-to-market, or based on M&A, convertible bond issuance, and dividend initiation, resumption, and omission. The loadings on UMO incrementally predict the cross-section of returns on portfolios as well as individual stocks. Further evidence is consistent with the UMO loading proxying 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, and 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) establish the 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-factors 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.

Equity financing and payout decisions provide a way to attack 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 shares to take advantage of inefficient stock 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 financing and long-run returns suggests that firms tend to issue equity when their shares are overvalued, and to buy back equity when their shares are undervalued (Loughran and Ritter (1995), Ikenberry, Lakonishok, and Vermaelen (1995)).[4] Furthermore, the aggregate share of equity issuance in new issues is one of the stronger known predictors of future aggregate market returns (Baker and Wurgler (2000)).

Building upon this work, in this paper we use equity financing activities to identify commonality in 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 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 misvaluation of 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

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

[4] Section I.3 discusses evidence of long-run risk-adjusted underperformance after new issues and overperformance after repurchases.

positive variance, even after controlling for the market or other well-known factors. We call this misvaluation factor UMO (Undervalued Minus Overvalued).

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.[5] This hypothesis implies that firms' financing decisions contain information for predicting returns that has not hitherto been exploited.

To see why UMO loadings are proxies for systematic mispricing, 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.

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 repurchase than with the high-tech firms that are engaging in new issue.

Both lines of reasoning—based on investor misvaluation of fundamental factors, or on shifts in sentiment toward investment styles—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 equity financing other than exploiting temporary stock misvaluation. For example, if investment is rationally undertaken in response to low project risk, then high investment will be associated with low subsequent returns. We address rational alterna-

[5] Daniel, Hirshleifer, and Subrahmanyam (2005) provide a model in which loadings on factor portfolios constructed from price-based characteristics such as book-to-market are proxies for misvaluation.

tive hypotheses by controlling for a set of benchmark factors, including the Fama French factors, the momentum factor, the leverage factor (Ferguson and Shockley 2003), the investment factor (Lyandres, Sun, and Zhang 2008), as well as industry effects in our tests.[6]

We show that UMO contains commonality in stock returns beyond that implied by above benchmark factors. First, we examine whether UMO returns can be explained by these benchmark factors. As a well-diversified portfolio, the $R^2$ from regressing UMO on the benchmark factors should be close to 1 unless it captures a distinct incremental source of commonality. In other words, the variance of the residual in such a regression should be substantially greater than that associated with long-short portfolios with randomly-selected stocks. We find that it is indeed the case. In addition, we find that general securities, such as the 25 size and book-to-market portfolios, share return excess comovement with UMO controlling for the benchmark factors.

We provide four types of evidence that UMO can be used to achieve high returns and predict the returns of general stocks. First, in regressions of UMO on a set of benchmark factors, UMO delivers significant abnormal returns of 6-10% per annum. Second, UMO also produces a higher Sharpe ratio than each of the benchmark factors but the investment factor. It increases the Sharpe ratio of the *ex post* tangency portfolio by over 50% relative to the Fama-French factors.[7] 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.

Second, a well-known anomaly is that the 3 or 4-factor models price four corner portfolios with extreme size and book-to-market equity very poorly. We find that adding UMO into standard time-series asset pricing regressions on the 3 or the 4 factors substantially reduces these well-known pricing errors. While the investment or the leverage factor mildly reduces the pricing errors of one or two of the corner portfolios, adding UMO to the 3 or 4 factor models makes the pricing errors of the four corner (not only small growth or large value, but also small value and large growth) portfolios insignificant. In general, including UMO in almost all of the factor models (where other possible factors are included or omitted) causes a failure to reject the null that all 25 size and

[6]We also consider in Section A of the Appendix other controls as robustness checks, including the macro economic factors suggested by Eckbo, Masulis, and Norli (2000) and Fama-French factors purged of new issue firms (see, e.g., Loughran and Ritter (2000)).

[7]This Sharpe ratio represents the maximum Sharpe ratio achievable by investing in these factors.

book-to-market portfolios are properly priced.

Third, prior literature has shown anomalous price drift following a set of selective corporate events in a similar spirit to equity issuances and repurchases; managers take actions to exploit stock market mispricing in order to benefit existing shareholders. Such events include, for example, mergers & acquisition (Loughran and Vijh 1997), convertible bond issuance (Lee and Loughran 1998), dividend initiation, resumption, and omission, (Michaely, Thaler, and Womack 1995; Boehme and Sorescu 2002). We show that adding UMO to the 3-factors essentially eliminates the abnormal return associated with M&A (from $-0.36\%$ per month to 0.05%), and convertible bond issuance (from $-0.39\%$ to $-0.03\%$), and significantly reduces that associated with dividend initiation and resumption (from 0.24% to 0.16%) and dividend omission (from $-0.28\%$ to $-0.21\%$). All statistical significance of these intercepts in a 3-factor model vanishes once UMO is included.

Fourth, 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 composite share issuance measure (Daniel and Titman (2006)).

In the above portfolio approaches, UMO loadings predict the cross-section of portfolio returns after controlling for the loadings on the benchmark factors, with an estimated UMO premium of about 5%–10% per annum. At the firm level, UMO loadings have incremental power to predict returns after controlling for size, book-to-market equity, past short-run and long-run returns, industry dummies, and the 3-factor loadings. This evidence is consistent with the proposition that the equity 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. Furthermore, neither the UMO loadings nor the issuance/repurchase characteristic variable, proxied by the composite share issuance measure (Daniel and Titman (2006)), subsumes the power of the other to forecast stock returns. This finding is consistent with behavioral theories that imply that covariances and characteristics will in general both have incremental power to predict stock returns

(Daniel, Hirshleifer, and Subrahmanyam (2005)). An alternative possibility is that characteristics are proxies for measurement errors in the loadings.

In addition to these four kinds of evidence that the information contained in new issues and repurchases helps predict the returns of other stocks, we also provide evidence that security loadings on the UMO factor are much less stable than the loadings on several well-known proposed fundamental factors. UMO loadings are much less stable than the loadings on the 3 factors, and have a period of stability much shorter than the period usually presumed (3–5 years) in standard asset pricing tests for fundamental risk. 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 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 of individual stocks will shift signs to reflect the shifts in factor or style mispricing. Therefore, we expect UMO loadings to be unstable (see the discussion in Section III.5).

This paper contributes to the growing strand of literature on market inefficiency as a possible source of stock return comovement (Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Wurgler (2005), Goetzmann and Massa (2005), Barber, Odean, and Zhu (2007), Baker and Wurgler (2006, 2007), Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2008), Boyer (2008), and Hirshleifer and Jiang (2009)). Alternatives are possible to our choice of financing decisions to identify commonality in misvaluation, such as valuation-based characteristics such as size or book-to-market (Daniel, Hirshleifer, and Subrahmanyam (2001)) or discretionary accruals (e.g., Teoh, Welch, and Wong (1998), Polk and Sapienza (2009)). A difference is that the decision to issue or repurchase equity, 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. Furthermore, using this proxy we can still control for book-to-market or HML loadings to filter away as the effects of growth opportunities as much as possible.

# I Motivation and Hypotheses

## I.1 Rational Factor Pricing Models

In rational factor pricing models such as the intertemporal CAPM, in the cross section expected returns of different stocks increase linearly with the stocks' loadings on return factors. Only factor covariance is 'priced,' so after controlling for factor loadings no other publicly available information can be used to predict returns. Furthermore, the size of expected returns must be commensurate with risk and the degree of risk aversion. For example, at the aggregate level the excess return on the market is determined by its volatility and by investor risk aversion; the apparent failure of this prediction is the equity premium puzzle (Mehra and Prescott (1985)). Similarly, in the cross section, Hansen and Jagannathan (1997) bounds limit the magnitude of Sharpe ratios on stocks in relation to the variability of intertemporal marginal utilities of substitution, where such variation in marginal utilities is driven by the interaction of risk with risk aversion.

There are several possible reasons why priced risk in a rational asset pricing model may be related to equity financing. First, as discussed in the introduction, equity issuance decreases leverage, which should reduce factor loadings and premia (e.g., Eckbo, Masulis, and Norli (2000)). Also, an implication of this argument is that shifts in leverage changes should explain the returns of new issue firms. Similarly, commonality in return predictability associated with financing should be explained by leverage effects.

Second, a shift in a firm's loadings which decrease its risk premium/discount rate should cause it to increase planned investment (Berk, Green, and Naik 1999). This implies greater need to issue equity to fund investment, so we expect issuers to have lower risk premia. Of course, the proceeds of new issues are not always invested. So an implication of this argument is that the ability of equity issuance to predict returns should be explained by investment. Similarly, comovement among firms involved with financing transactions should derive from comovement among firms with unusual investment levels (Lyandres, Sun, and Zhang 2008). Furthermore, the ability of a financing factor to explain the cross section of returns should be largely subsumed by an investment factor.

In summary, rational factor pricing provides three main predictions for the cross-section of returns: that expected returns increase linearly with factor loadings; that after controlling for factor loadings, expected returns do not vary with any other publicly observable variables, and that the magnitude of the premium for factor risk is not too large relative to the size of the risk. More specific versions of rational factor pricing suggest further possible implications: that the ability of financing decisions to predict returns should be explained by leverage effects, or by investment effects.

### I.2 Behavioral Models

We contrast the rational factor pricing predictions of the preceding subsection with behavioral hypotheses based upon the style investing model of Barberis and Shleifer (2003) and the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (2001).[8] In the model of Barberis and Shleifer (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 between style funds. 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, which we define as

[8] Several other models also imply non-fundamental commonality in asset price movements. For instance, 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.

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.

### I.3 Equity Financing

A motivation for our tests is past evidence suggesting that the post-event long-run performance of new issues and repurchases reflect correction of mispricing as opposed to changes in rational risk premia. There is much evidence that managers tend to issue equity to exploit equity overpricing for the interests of existing shareholders. For example, Loughran and Ritter (1995, 2000) and Spiess and Affleck-Graves (1995) find that firms that engage in IPOs and SEOs on average underperform for three to five years subsequent to the issue.[9] Consistent with the market timing theory, Graham and Harvey (2001) find that a majority of CFOs say that stock mispricing is an important motive to issue equity. Similarly, Lakonishok and Vermaelen (1990) and Ikenberry, Lakonishok, and Vermaelen (1995) show that firms tend to repurchase equity when they perceive undervaluation and repurchase firms on average overperform in the subsequent three years.

Furthermore, there is evidence that the underperformance associated with new issue firms is shared by other firms with similar characteristics (Li and Zhao 2006). It is also shown that 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)). These findings are consistent with equity issuance responding to sector- or market-wide mispricing.

The preponderance of evidence supports misvaluation rather than risk as an explanation for the new issues puzzle (e.g., Loughran and Ritter (2000)). Jegadeesh (2000) documents that the stock market reacts unfavorably to earnings announcements subsequent to new issues, consistent with expectational errors (assuming that betas are not exceptionally low on earnings announcement dates). A rational risk-based explanation for the new issues puzzle seems to require that recent issuers have unusually low risk. However, it has not so far been established that new issue firms

[9] Brav, Geczy, and Gompers (2000) conclude that a modified 3-factor benchmark based on AMEX and NASDAQ stocks captures post-IPO but not post-SEO underperformance. Loughran and Ritter (2000) argue that conclusions for post-IPO performance are sensitive to details of the data selection criteria.

are a good hedge for aggregate consumption.[10]

Finally, a few recent studies show that firm-level measures of corporate equity financing are negatively related to subsequent stock returns in the post-1970 period (e.g., Daniel and Titman (2006), Pontiff and Woodgate (2008)). These studies, however, do not test whether equity financing is associated with systematic mispricing. Hirshleifer and Jiang (2009) test for shifts in comovement of firms that engage in equity financing with previous equity issuers or repurchasers. Our paper differs in focusing on the level of comovement of general stocks with equity-financing firms to show that return covariance with respect to a factor based on equity financing events forecasts portfolio and firm-level stock returns.

## I.4 Hypotheses

We focus our hypotheses on the predictions of behavioral models, with the predictions of rational factor pricing as the key alternative. Existing behavioral models predict that either misperception of signals about fundamental factors, or investor sentiment about styles can create common mispricing of many assets, and that firms make financing decisions in response to the systematic (as well as the firm-specific) component of their mispricing. As a result, we argue that a security's loading on common movements in mispricing measures the degree to which it inherits general mispricing, so that loadings on the mispricing factor should positively predict security returns. If firms often undertake financing decisions in response to mispricing (including common mispricing), then new issue and repurchase firms will tend to load heavily on mispricing factors. Therefore, to identify commonality in misvaluation empirically, we can make use of corporate financing events such as equity issuances and repurchases.

Specifically, a misvaluation factor (UMO) that is long on repurchase stocks (Undervalued) and short on new issue stocks (Overvalued) should capture comovement associated with mispricing. In testing for commonality in misvaluation, there is a question of what measures of risk to control for, since there are now many factor models in the literature. There is a tradeoff, because it is desirable to control for rational risk effects as much as possible, but there is a danger that factor pricing control is actually a proxy for misvaluation. (In the context of the Fama and French 3-

[10]Indeed, Ritter and Welch (2002) estimate a market beta of 1.73 for an equal-weighted portfolio of IPOs. Intuitively it seems likely that IPO firms, which consist largely of growth opportunities, would be highly sensitive to other factors as well. This does not, however, rule out the possibility that a risk-based explanation exists.

factor model, see Daniel and Titman (1997). In the context of the investment factor, Polk and Sapienza (2009) suggests that investment is related to mispricing.) There is no perfect solution, but for reported tests we focus on the most commonly used 3-factor model (Fama and French 1993), and those augmented by the momentum factor (Carhart 1997), the leverage factor (Ferguson and Shockley 2003), or the investment factor (Lyandres, Sun, and Zhang 2008), and call them the 'benchmark factors' hereafter. Our robustness checks in Section A of the Appendix further consider the macroeconomic factors of Eckbo, Masulis, and Norli (2000), and the 3-factors purged of new issues of Loughran and Ritter (2000).[11]

Based on the abovementioned behavioral models, we formulate the following testable hypotheses about UMO. Section B of the Appendix formally derives these predictions in a model based on the approach of Daniel, Hirshleifer, and Subrahmanyam (2001).[12] 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:** *UMO will have non-negligible positive variance, and in a time-series regression of the misvaluation factor UMO on benchmark factors, the variance of the residual terms will be substantially above that of randomly generated long-short portfolios.*

In general, if we randomly form a zero-investment portfolio with many securities that is well-diversified on both the long and short side, the loadings on underlying factors will on average be close to zero, and idiosyncratic risk diversifies as well, so that portfolio return variance is close to zero. Prediction 1 asserts that forming a long-short portfolio based upon firms' financing decisions causes loading on some underlying factor(s), resulting in substantial positive variance.[13]

Prediction 1 further asserts that financing decisions identify a factor that is not explained by the benchmark factors, i.e., that the existing factors will provide an $R^2$ substantially less than one in explaining its variability, so that there is substantial variation in UMO that cannot be explained by the benchmark factors. To have a reference against which to identify excess comovement, we

[11] Section A of the Appendix provides evidence of additional robustness checks.

[12] Section B of the Appendix shows that the intuitive hypothesis development we provide can be supported by formal analysis.

[13] Prediction 1 with the three or four factors as right hand side variables is not a mere rephrasing of the well-known fact that the three and four factor models do not price the returns on new issue and repurchase portfolios. That well-known fact is a statement about the relation of portfolio *mean* returns to the loadings on the three or four factors. Prediction 1 is a statement about the variation in *realized* returns that these factor models are unable to explain.

compare the variance of the residuals from regressing UMO on a set of benchmark factors with that from regressing a long-short (also equal-weighted) portfolios of randomly selected stocks, where the number of stocks is the same as those on both sides of UMO.

Under the behavioral approach, UMO captures the spread in subsequent returns between currently underpriced versus overpriced firms. Models of inefficient markets such as those of DeLong, Shleifer, Summers, and Waldmann (1990), Daniel, Hirshleifer, and Subrahmanyam (2001), and Barberis and Shleifer (2003) imply that variation in UMO cannot be fully explained by fundamental cash flow factors, because there are common fluctuations in prices owing to sentiment or investor misperceptions of private information signals.[14]

**Prediction 2:** *General stocks will have return comovement with UMO, even after controlling for the benchmark factors.*

While fundamental factors move returns, the UMO misvaluation factor will incrementally move returns since the effects of overconfidence or sentiment are imperfectly correlated with fundamentals. 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 have return comovement on the misvaluation factor, UMO, even after controlling for proxies for possible fundamental factors, which, in our tests, include the Fama French factors, and the momentum, investment and leverage factors. Furthermore, those stocks that load in a similar way to repurchase stocks will positively comove with UMO, while those that load in a way similar to new issue stocks will negatively comove with UMO.

For instance, in the example discussed in the introduction, when investors irrationally believe that the oil price will be low, airlines will be overpriced and tend to issue while the solar product vendor underpriced and repurchase. Accordingly, firms that benefit from low oil prices will load negatively on UMO and those that are hurt will load positively on UMO.

**Prediction 3:**

[14]There has been debate about whether the size and the book-to-market factors are proxies for risk or mispricing. If they reflect mispricing, they may capture part of the irrational fluctuations in stock returns that UMO is designed to capture. Nevertheless, it is interesting to verify whether UMO captures commonality beyond that captured by other well-known factors. There is reason to hope so since managers' information is not limited to the firm's size and book-to-market.

*a. In time series regressions, adding a UMO factor will reduce the pricing errors of the models based on benchmark factors on general stocks or stocks with selective corporate events.*

*b. The loadings on UMO will forecast the cross section of stock returns.*

*c. If there is firm-specific as well as common misvaluation, then the issuance/repurchase characteristic will have incremental ability to predict returns after controlling for the UMO loading.*

Under our prediction that UMO captures common mispricing incrementally to factors such as SMB, HML, and the momentum factor (MOM), adding a UMO factor to the models with benchmark factors reduces the pricing errors in time-series regressions.[15] Such prediction applies not only to general stocks as represented by the 25 size-BM portfolios, but also to portfolios consisting of stocks with recent selective corporate events that can occur to exploit market mispricing.

Since there is a large literature documenting the long-term drift following selective corporate events, we focus on a few notable examples that have been interpreted as reflecting equity over- or underpricing, have been found to generate 3-5 years abnormal performance, and have a relatively large set of observations over a long period of time.[16] Thus, we examine the returns to acquirers in M&A transactions (Loughran and Vijh 1997), to issuers of convertible bonds (Lee and Loughran 1998), and to firms that experience dividend initiation, resumption, or omission (Michaely, Thaler, and Womack 1995; Boehme and Sorescu 2002). The first two and dividend omission have been found to produce long-term underperformance, and dividend initiation/resumption to long-term overperformance. If such abnormal performance is partly caused by systematic mispricing, we expect that adding UMO will subsume at least part of the abnormal returns.

Furthermore, 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. (The detailed argument for why a stock's loading on UMO is a proxy for the common component of the stock's mispricing was provided in the introduction.) Stocks that load positively on UMO will behave like repurchase

[15] Even under a behavioral setting, we do not, however, expect the UMO factor to reduce alphas to zero, because the model pricing errors in general reflect firm-specific mispricing, not just the systematic mispricing captured by UMO.

[16] Some other possible types of selective events, such as stock splits, cause only a short-term (up to 12 months) drift; others, such as spinoffs, have relatively small sample sizes.

firms and outperform while those loaded negatively on UMO will behavior 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 mispricing, not just common mispricing, the amount of issuance or repurchase should be able to predict returns even after controlling for the degree to which the firm partakes of common mispricing. We therefore predict that the issuance/repurchase variable of Daniel and Titman (2006) will predict returns even after controlling for the UMO loading.[17]

In the sections that follow we test these predictions, and provide further evidence regarding the alternative explanation that UMO is a priced fundamental risk factor. The main results are presented using the 3-factors, augmented by the momentum, investment, or the leverage factor as the benchmark factors. The robustness checks that involve alternative benchmark factors are presented in Section A of the Appendix.

## II Data

Our sample includes common stocks traded on NYSE, AMEX, and NASDAQ over the period January 1970 to December 2005. We also exclude utilities and financials 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 2005. 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.[18] The leverage factor (LEV) is the return of high leveraged firms minus that of low leverage firms.[19] The details of constructing the two factors are described in Table 2.

[17]We do not derive this prediction formally. Daniel, Hirshleifer, and Subrahmanyam (2005) provide a model with an analogous prediction about book-to-market and HML loadings.

[18]We use the monthly return series of the investment factor provided by Evgeny Lyandres.

[19]Our findings are similar if we use the leverage factor returns provided by Michael Ferguson that are available up to 2001.

The sample firms that conduct M&A deals are from Thomson Financial's SDC database from 1981–2005 since reliable information about M&A only starts from 1981. We include only completed deals and exclude cross-border deals, deals associated with bankruptcy, and joint ventures. The convertible bond issuer sample is also from SDC over the period 1970–2005. We exclude unit offerings. The sample of firms with dividend initiation and resumption are constructed based on CRSP dividend payment information from 1970–2005. Following Michaely, Thaler, and Womack (1995), we define dividend initiation as the first cash dividend payment for a firm that has traded for at least 24 months. We define the dividend omission date as the expected regular dividend payment date (month) with no payout announcement. Regular dividend payments are defined as at least six consecutive quarterly cash payments, at least three consecutive semi-annual cash payments, or at least two consecutive annual cash payments. Following Boehme and Sorescu (2002), we define dividend resumption as the first cash dividend paid by a firm following a hiatus in payments ranging from 33 to 180 months. The annual number of events is displayed in Section E of the Appendix. We exclude all financials and utilities to make it comparable to UMO. But our results are insensitive to this criterion.

### II.1 Main Sample

Among the sample firms, we identify 7965 initial public offering (IPO) and 6833 seasoned equity offering (SEO) from the SDC Global New Issues dataset among our sample firms, which are cross-checked with the data provided by Jay Ritter. The annual number of firms is reported in Table 1. For SEOs, we exclude unit offerings and pure secondary Offerings. Multiple issues made by the same firm within one year are treated as one single event.

———INSERT TABLE 1 HERE———

Also shown in Table 1, we identify 34,582 firms in our sample with equity repurchases (RP) from COMPUSTAT annual statements, in which the occurrence of RP is defined as a positive difference between the total expenditure on the purchase of common and preferred stocks (Compustat item 115) and the reduction in the value of preferred stock (Compustat item 56).

Our results are in general robust to different data sources or sample selection criteria. For instance, the main findings are similar if we identify IPO events as the first appearance in CRSP, if we obtain repurchase events (both open market and tender offer repurchases) from SDC, or if we restrict in primary offerings in SEOs. The rationale for the robustness, in our approach, is that if equity financing events identify systematic mispricing shared by general stocks, then these factors should be identifiable using any representative sample of new issues and repurchases. Therefore, as long as we obtain a well-diversified UMO portfolio, the comovement of general stocks with respect to UMO should be relatively insensitive to the number of firms included in UMO.

## II.2 Key Variables

At the end of June of each year, we include firms with IPOs or SEOs in the past 24 months but not with repurchases (RPs) in the two most recent fiscal years with the fiscal year end as of last December in the portfolio 'O' (Overpriced). We include firms with RPs in the two most recent fiscal years with the fiscal year end as of last December but not with IPOs or SEOs in the past 24 months in the 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).

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.[20]

As discussed in introduction, the industry/sector-wide fundamental shocks (e.g., Hou (2007)) can influence UMO but are not captured by the 4 factors. Therefore, we also form a sector-neutral

[20] 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.

'$\text{UMO}_{\perp\text{SEC}}$' that accounts for the sector effect. Specifically, we 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 $\text{O}_{\perp\text{SEC}}$. Similar procedures are used for $\text{U}_{\perp\text{SEC}}$. Finally, $\text{UMO}_{\perp\text{SEC}}$ returns are the difference between $\text{U}_{\perp\text{SEC}}$ and $\text{O}_{\perp\text{SEC}}$. By giving each sector's new issues or repurchases the same weight, we minimize the sector influence on $\text{UMO}_{\perp\text{SEC}}$.[21]

———INSERT TABLE 2 HERE———

Table 2 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 July of 1972 through December of 2005. As shown in Table 1, the average number of firms in July of each year is 615 for O and 1147 in U, showing that UMO contains a sizable number of stocks.[22]

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 0.94% per month, or over 11% per year while $\text{UMO}_{\perp\text{SEC}}$ 0.88% per month. The two are highly correlated, with a coefficient of 0.93 as shown in Panel B. Panel B also shows that UMO has strong correlations with MKT, SMB, HML, and LEV. In our subsequent tests, we estimate loadings on UMO by controlling for these factors.

UMO and $\text{UMO}_{\perp\text{SEC}}$ provide Sharpe ratios 0.25 and 0.29, respectively, which are greater than those of MKT (0.11), SMB (0.05), HML (0.16), MOM (0.21), and LEV (0.14), but smaller than INV (0.36). In Panel C, we report the summary statistics of the *ex post* tangency portfolio calculated following MacKinlay (1995). The tangency portfolio generates the highest Sharpe ratio by optimally combining the subset of factors. It is shown that adding UMO to the 3 factors increases the maximum Sharpe ratio from 0.27 to 0.41, adding UMO to the 3 factors plus the momentum factor

[21] By forcing the equal weight on sectors, however, we also reduce the sector-wide mispricing captured by UMO. Thus, we expect $\text{UMO}_{\perp\text{SEC}}$ to contain less common mispricing than UMO.

[22] 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 (IPO+SEO) or repurchase firms. This is due to at least three effects. First, some IPO firms conduct SEOs in the subsequent two-year period after IPOs and thus are counted in O as one stock. Second, multiple SEOs (repurchases) in a two-year period by one firm are counted in O (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.

increases this Sharpe ratio from 0.37 to 0.44, adding UMO to the 3 factors plus the investment factor from 0.50 to 0.55, and adding UMO to the 3 factors plus the leverage factor from 0.27 to 0.42. The highest Sharpe ratio (0.55) is achieved by combining the 3 factors with both LEV and UMO. Neither the momentum nor the leverage factor has incremental contribution to improve the maximum Sharpe ratio. Overall, the results suggest that UMO is an important contributor to high Sharpe ratios.

# III Empirical Tests

In this section, we test whether, as hypothesized, UMO captures commonality in returns and help predict the cross section of returns.

## III.1 UMO and Other Factors

Prediction 1 asserts that UMO is a source of comovement in returns. Specifically, despite being a zero-investment portfolio, it is predicted to have a non-negligible variance, even after regressing on the benchmark factors. Thus, the variance of the residual terms from regressing UMO on the benchmark factors is predicted to be greater than that would be ordinarily 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 1000 times to generate a variance of the residual terms to compare the variance of residuals associated with UMO for the given set of benchmark factors.

Consistent with Prediction 1, we find $R^2$s on the order of roughly 50–60%, and the variances of the residual terms are about 4.1–5.6, which are statistically significantly greater than that based on randomly selected portfolios:

$$\underset{(6.47)}{\text{UMO} = 0.73} - \underset{(-4.66)}{0.18}\ \text{MKT} - \underset{(-4.34)}{0.22}\ \text{SMB} + \underset{(8.11)}{0.67}\ \text{HML} \qquad R^2 = 59\% \quad \underset{[0.958,1.483]}{\sigma^2(\epsilon) = 5.635};$$

$$\underset{(4.11)}{\text{UMO} = 0.54} - \underset{(-4.43)}{0.15}\ \text{MKT} - \underset{(-4.93)}{0.23}\ \text{SMB} + \underset{(9.12)}{0.71}\ \text{HML} + \underset{(2.92)}{0.18}\ \text{MOM} \qquad R^2 = 63\% \quad \underset{[0.949,1.477]}{\sigma^2(\epsilon) = 5.070};$$

$$\underset{(4.18)}{\text{UMO} = 0.52} - \underset{(-3.77)}{0.14}\ \text{MKT} - \underset{(-4.78)}{0.22}\ \text{SMB} + \underset{(8.57)}{0.66}\ \text{HML} + \underset{(3.08)}{0.32}\ \text{INV} \qquad R^2 = 61\% \quad \underset{[0.950,1.477]}{\sigma^2(\epsilon) = 5.380};$$

$$\underset{(6.85)}{\text{UMO} = 0.73} - \underset{(-5.81)}{0.21}\ \text{MKT} - \underset{(-3.71)}{0.20}\ \text{SMB} + \underset{(4.04)}{0.35}\ \text{HML} + \underset{(3.60)}{0.33}\ \text{LEV} \qquad R^2 = 63\% \quad \underset{[0.952,1.479]}{\sigma^2(\epsilon) = 4.109},$$

where the robust Newey-West (Newey and West (1987)) $t$-statistics of the coefficients are reported in parentheses, $\sigma^2(\epsilon)$ is the variance of the residual terms with the 1% confidence interval of the residual terms reported in square brackets based on randomly selected portfolios.

The positive alphas show that UMO offers abnormally high returns that are not fully explained by the set of benchmark factors. This evidence confirms the findings of previous research that documents significant long-run overperformance associated with repurchases and underperformance associated with new issues. The mainly low $R^2$s and high residual variances 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, it is also consistent with the possibility that markets are efficient and that the commonality comes from fundamental sources not captured by the 4 factors.

As will be discussed further in Section I.1, it is possible that the returns on firms with financing events are related to a common factor in growth/investment opportunities. This is to large extent is controlled for by HML. However, to further test for this possibility, in Section A of the Appendix, we consider other sets of benchmark factors, including, the Fama-French factors purged of new issues (e.g., Loughran and Ritter (2000)), and the macroeconomic factors of Eckbo, Masulis, and Norli (2000). Even after controlling for models containing these additional factors, the $R^2$ of UMO is still below 65%, significantly lower than the simulated $R^2$s based on random, long-only portfolios over the same sample period.

### III.2 Return Comovement

Prediction 2 pertains to the incremental return comovement of general stocks with UMO. We predict such comovement based upon the fact that at any given time overpriced or underpriced general stocks should load on some of the same mispriced fundamental factors that new issues and repurchase stocks load upon, and the fact that mispriced general stocks should share some of the same style characteristics causes mispricing in new issue and repurchase stocks.

In the example discussed in the introduction, when investors irrationally believe that the oil price will be low, airlines will be overpriced and tend to issue while the solar product vendor will be underpriced and will 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, new issue and repurchase firms will flip, so do the loadings of other firms on UMO. That is, UMO loadings of individual stocks are transitory. Similarly, as sentiment shifts, different styles will be associated with over/underpricing and new issue versus repurchase, so the loadings of stocks with different styles on UMO will be transitory.[23] 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.

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 portfolios are periodically rebalanced, stocks enter or exit the portfolios according to their degree of mispricing to ensure the stable 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 and the composite issuance variable of Daniel and Titman (2006) (which we describe in detail later). These portfolios are rebalanced once every year to make sure each continues to include similar levels of the characteristics, implying similar degrees of under- or overpricing, and therefore similar loadings on UMO over time.

Specifically, we regress value-weighted monthly returns on each of the 25 size-BM portfolios on UMO together with the benchmark factors and test whether UMO loadings ($\beta_u$) are jointly different from zero.

———INSERT TABLE 3 HERE———

[23]This prediction is not driven by investors regarding issuance and repurchase as styles, it is driven by firms responding with issuance or repurchase to underpricing or overpricing that is induced by sentiment shifts between other styles such as size or value versus growth.

Table 3 reports the UMO loadings and associated Newey-West $t$-statistics of the 25 size-BM portfolios. Results based on $\text{UMO}_{\perp\text{SEC}}$ are similar unless otherwise mentioned. Controlling for the benchmark factors, 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. In other words, 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. Most of the 25 UMO loadings are statistically significant. The patterns are similar with respect to different sets of benchmark factors. All $F$-tests strongly reject the null that all UMO loadings are jointly equal to zero.

In unreported analyses, we find similar patterns using other sets of portfolios that are sorted based on size, book-to-market (BM), and the composite issuance measure (IR) (Daniel and Titman (2006)), where IR is defined as

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

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.[24] Thus, consistent with Prediction 2, the results show that general stocks tend to comove with UMO beyond that implied by the benchmark factor models.

### III.3 Pricing the 25 Size and Book-to-Market Portfolios

If UMO captures common variation in mispricing, Prediction 3.a asserts that UMO will reduce the pricing errors of the standard asset pricing models in time-series regressions. Thus, we examine the alphas before and after adding UMO to the benchmark factor models in pricing the 25 size-BM portfolios.

———INSERT TABLE 4 HERE———

The alphas and corresponding $t$-statistics are reported in Table 4. When the 3-factor model is used, all but a few portfolios are properly priced, as indicated by the fact that a majority of alphas

[24] Pontiff and Woodgate (2008) provide an alternative measure designed to capture corporate financing activities. For brevity, we only use IR in this paper.

indistinguishable from zero. This is not surprising since SMB and HML are designed to capture return commonality in the size-BM portfolios.

However, there are significant pricing errors among the four corner portfolios, positive for the small-value and large-growth portfolios, and negative for the small-growth and large-value portfolios. Adding the momentum factor, the investment factor, or the leverage factor slightly reduces the pricing errors of one or two corner portfolios, but the $F$-statistics that test whether all alphas are jointly equal to zero remain significantly at the 5% or 1% levels. Interestingly, the signs of the pricing errors of the four corner portfolios correspond to the signs of their UMO loadings reported in Table 3, suggesting that UMO is a possible missing common factor for returns on these portfolios.

Indeed, when UMO is additionally included, these pricing errors are substantially reduced and become mostly insignificant. After adding UMO to four sets of benchmark factors (the 3-factor, the 3 factors plus MOM, INV, or LEV), the alphas of the four corner portfolios shrink towards zero and become statistically insignificant in all but one case. Furthermore, the $F$-statistics for the joint test of whether the alphas are all zero are reduced to 1.82, 1.47, 1.00 and 1.67, respectively, with the first significant at the 10% level and the other three insignificant. In other words, the null hypothesis that all alphas are jointly equal to zero is generally no longer rejected. Overall, this evidence indicates that UMO is important for pricing general stocks, including stocks with extreme size and book-to-market equity. This evidence suggests that the anomalous returns on the corner portfolios results from commonality in mispricing that is captured by the UMO factor.

### III.4 The Pricing of Portfolios Based upon Selective Corporate Events

We now test whether UMO helps capture mispricing of stocks with recent selective corporate events. Based on the criteria discussed earlier, we focus on M&A, convertible bond issuance, dividend initiation/resumption, and omission. For these four types of events, we form three equal-weighted portfolios that include firms that have undertaken the corresponding type of activity in the most recent 36 months. The event portfolios capture the long-run performance of event firms from month $t+1$ to $t+36$. Prediction 3.a asserts that UMO will help to reduce the abnormal returns associated with these portfolios relative to conventional factor models.

———INSERT TABLE 5 HERE———

We run time-series regressions of the event portfolio excess returns first on either the 3 factors, or on both the 3 factors and UMO. The results are reported in Table 5. It is evident that UMO makes the significant alphas in the 3-factor model insignificant. For M&A, the alpha changes from $-0.38$ to 0.04, which is essentially identical to zero. For convertible bond issuers, the alpha changes from $-0.39$ to $-0.03$, which is also essentially identical to zero. For dividend initiation and resumption, the alpha decreases from 0.24 to 0.16, a 30% drop, and for dividend omission, the alpha drops by 25%. All alphas switch from statistically significant to insignificant. These findings support the idea that, like equity financing, these selective corporate events, occur in response to common mispricing across firms.

### III.5 UMO Loadings and the Cross Section of Portfolio Returns

Having established the ability of UMO to reduce pricing errors in time-series regressions, we now exploit the information in UMO loadings to predict the cross section of future portfolio returns, our Prediction 3.b. As discussed previously, behavioral models predict that UMO loadings are proxies for systematic undervaluation, and therefore will predict higher excess returns.

Also, UMO loadings for individual stocks tend to be unstable over time. Intuitively, different style 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.[25] 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 Newey-West $t$-statistics are reported in Table 6.

———INSERT TABLE 6 HERE———

[25] Section B of the Appendix contains a proof for this assertion (see Proposition 3).

Table 6 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 0.57% per month ($t = 2.54$) with controls for MKT, 0.80% per month ($t = 3.47$) in regression (3) with controls for the 3 factors, and 0.81% per month ($t = 3.63$) in regression (6) with controls for the 4 factors. Similar results are obtained after additionally controlling for INV or LEV. Replacing UMO with $\text{UMO}_{\perp\text{SEC}}$ in regression (4) makes little difference: yielding an estimated premium of 0.75% per month ($t = 3.77$).

Lewellen, Nagel, and Shanken (2008) and Daniel and Titman (2008) 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 Appendix, 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.

Similar results also obtain for the 25 BM-IR portfolios, the 25 BM portfolios, the 100 size-BM portfolios, or the 25 IR portfolios. For each set of them, we all find that high UMO loadings on average positively forecast future portfolio returns. For brevity, these results are not reported here.

### III.6 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 misvaluation and have stronger return reversal when mispricing is corrected.

As discussed previously in Section III.5 estimating UMO loadings on individual stocks is challenging due to the (theoretically predicted) instability of these loadings.[26] We therefore adopt two different approaches to estimate UMO loadings.

[26]The higher stability of the loadings on the Fama-French factors suggests that these loadings do not solely reflect sensitivity to mispriced factors. The greater the extent to which a set of loadings capture relatively persistent fundamental risks as well as mispriced factors, the more stable we expect these loadings to be. Thus, the relative instability of our UMO loadings suggest that UMO is a purer proxies for misvaluation than the Fama/French factors.

#### III.6.1 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 on UMO together with the 3 factors. We call the estimated UMO loading the pre-formation loading, denoted as $\beta_u^{\text{pre}}$.[27]

———INSERT TABLE 7 HERE———

After obtaining $\beta_u^{\text{pre}}$, we sort stocks based on $\beta_u^{\text{pre}}$ into deciles and calculate both the equal-weighted decile returns in the following month. As shown in Table 7, the decile returns tend to increase with $\beta_u^{\text{pre}}$. The return differentials between the highest and the lowest $\beta_u^{\text{pre}}$ deciles is 0.75% per month ($t = 2.64$), or 9% per annum. The alphas from the CAPM and the 3 factor model remain sizable and statistically significant. After excluding firms in UMO, also shown in Table 7, we observe results that are equally strong. 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 equity financing or repurchase.

#### III.6.2 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

[27] Shortening the estimation period to 3 months yields similar results.

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, we first sort all stocks into 100 portfolios according to two of the firm characteristics that proxy for misvaluation, involving firm size (ME) of the most recent June, BM as of the most recent December, and IR calculated based on market equity and stock returns from month $t-60$ through $t-1$. 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. Finally, each individual stock assumes the portfolio loading according to which portfolio it belongs in month $t-1$.

We denote these conditional UMO loadings as $\beta^{\mathrm{UMO}}$ 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.[28] The past return measures are expressed at a monthly basis. The estimated coefficients are averaged across time and reported in Table 8. 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 8 HERE———

Consistent with Prediction 3.b, as shown in Table 8, the average coefficients of $\beta^{\mathrm{UMO}}$ are all positive and statistically significant, regardless of the firm characteristics that are used to sort stocks. For instance, with the full cross section of stock returns, after controlling for the other firm characteristics, the coefficient of $\beta^{\mathrm{UMO}}$ that is estimated from ME and IR sorted portfolios is 0.27% per month ($t = 4.69$). The coefficient of $\beta^{\mathrm{UMO}}$ is 0.16% per month ($t = 2.87$) when BM and IR are used to sort portfolios, and 0.14% per month ($t = 3.02$) when ME and BM are used.

[28] 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.

In Panel B, we report results after excluding stocks used to form UMO of the current year. The results change little. Therefore, our 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 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.

### III.7 Characteristics versus Covariances

In order to distinguish risk versus mispricing more sharply as explanations for the return predictability, following Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001), we run a horse race between covariance and characteristics associated with equity financing as return predictors. Specifically, we test whether or not the conditional UMO loading $\beta^{\mathrm{UMO}}$ dominates the composite issuance variable IR in explaining the cross section of stock returns. Under traditional rational factor pricing, stock returns should be determined solely by covariance, not characteristics. In contrast, 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.[29]

To test between the predictions of alternative theories, in Regression (5) of Table 8, we report the Fama-MacBeth regression results that include both the characteristic variable IR and the covariance variable $\beta^{\mathrm{UMO}}$, as well as five standard controls used previously.[30] We find that both IR and $\beta^{\mathrm{UMO}}$ have significant coefficients in the expected directions: negative for IR and positive for $\beta^{\mathrm{UMO}}$. Thus, $\beta^{\mathrm{UMO}}$ does not fully subsume the predictive power of IR. This opposes the prediction

[29] In their model, when both factor and firm-specific cash flow components are mispriced, characteristics are proxies for both factor mispricing and 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.

[30] The UMO loadings used in Regression (5) are estimated from portfolios sorted based on firm size and IR. Among the sorting combinations used in Table 8 the loadings estimated based on ME-IR portfolios have the largest dispersion and carry a larger premium than those based upon other combinations of characteristics. This suggests that the ME-IR portfolios are likely to provide the most accurate estimates of the UMO loadings. To maximize the power in our tests in Regression (5), we use those loadings as UMO conditional loadings.

of rational pricing of UMO. Of course, as always with characteristics versus covariance tests, the possibility of measurement error of covariances raises the possibility that more accurately estimated covariances would predict returns more effectively.

In regression (10), we estimate the Fama-MacBeth regressions as in specification (5) except that we exclude the new issue and repurchase stocks in UMO. The results remain similar. Therefore, our findings show that both covariance and characteristics based on equity issuance and repurchases contain some distinct incremental information for predicting future returns. This finding opposes rational factor pricing theories, which predict that only covariances matter. It supports the hypothesis that UMO loadings contain information about firms' systematic mispricing.

An alternative explanation for these findings is that markets are efficient, but that UMO is a poor proxy for the underlying factor that drives the returns on new issue and repurchase stocks. 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 evidence that characteristics have incremental power beyond covariances to predict returns implies that an even higher Sharpe ratio than that of UMO can be achieved by combining UMO with IR characteristic-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. We do not rule out this possibility.

### III.8 Are UMO Loading 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 so unstable. The usual presumption for tests of rational asset pricing has been stability of loadings for periods of 3-5 years.

To estimate the systematic risk of stocks, it is 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 large dispersion in post-ranking loadings. In contrast, if UMO loadings reflect mispricing, they are likely to be unstable over periods as long as 5 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 of post-ranking loadings.

Following Fama and French (1992), we estimate UMO pre-ranking loadings ($b^{\mathrm{UMO}}_{\mathrm{pre}}$) 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 $b^{\mathrm{UMO}}_{\mathrm{pre}}$. Using the full sample equal-weighted returns of the 100 portfolios, we estimate the post-ranking UMO loadings ($b^{\mathrm{UMO}}_{\mathrm{post}}$) in a multi-factor regression for each portfolio. We report the average $b^{\mathrm{UMO}}_{\mathrm{pre}}$ and the estimated $b^{\mathrm{UMO}}_{\mathrm{post}}$ for the 100 portfolios in Table 9.

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 50 extreme loadings portfolios which include the top and the bottom 25. If firms have relatively persistent sensitivity to UMO as a stable risk factor, we expect these loadings to retain their signs 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 9 AND FIGURE 1 HERE———

In Panel A of Table 9, 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. Not surprisingly are the top 25 portfolio pre-ranking loadings positive and the bottom 25 negative. Contrary to the hypothesis that factor loadings are persistent for substantial periods, 6 out of the 50 extreme portfolios switch the signs of their $b^{\text{UMO}}_{\text{pre}}$'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 50 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. 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.[31]

Overall, there are a total of 38 out of 100 UMO loading portfolios with essentially zero post-ranking loadings, suggesting that sorting stocks based on $b^{\text{UMO}}_{\text{pre}}$'s creates little dispersion in $b^{\text{UMO}}_{\text{post}}$'s.[32] 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 10 HML loading portfolios, carry post-ranking loadings that are insignificantly different from zero.[33] These patterns are also evidenced in Figure 1, which plots the pre- and post-ranking loadings associated with UMO and the 3 factors.

[31] The inferences remain similar if we use raw, rather than demeaned, loadings. In addition, as shown in Table 9, most of the sign-flipping comes from stocks with positive pre-ranking loadings. These stocks comove positively with repurchase stocks, whose overperformance tends to be concentrated in the first 3 years (Ikenberry, Lakonishok, and Vermaelen (1995)). In contrast, stocks with negative post-ranking loadings, which comove positively with new issue stocks, appear to maintain the sign of their loadings, which, however, tend to shrink toward to zero. This pattern is consistent with prior findings that new issue stocks tend to underperform for 3-5 years (e.g., Loughran and Ritter (1995) and Ritter (2003)).

[32] If we exclude firms in UMO of the current year, there are 33 portfolios that have post-ranking UMO loadings indistinguishable from zero.

[33] 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 5 years.

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 0.93 to 0.97 for the 3 factors but merely 0.56 for UMO. 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.

## IV 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 1972–2005, 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 repurchase in response to underpricing. These selective 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 financing factor, and firms that engage in other selective corporate events such as M&A, convertible debt issuance, or dividend initiation/resumption and omission.

We also show that UMO helps to reduce pricing errors associated with extreme size-BM portfolios and stocks recently involved in the other selective corporate events, and that UMO loadings are useful predictors of the cross section of portfolio and stock returns. Although it is hard to rule out rational factor pricing explanations 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 based upon market frictions. Although our evidence casts some doubt upon UMO as a fundamental risk factor in a frictionless market, it is possible that market frictions such as illiquidity make it hard to realize the high Sharpe ratios achievable based upon financing-based portfolios. If this is the explanation, then markets are inefficient, but investors may be rational.

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Table 1: 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), and stock repurchases (RP) for each year over the period 1970–2004, and the number of firms in the event portfolios O, N, and U in the beginning of July of each year from 1972 through 2005. At the end of June of each year, firms issuing IPOs or/and SEOs in the last 24 months but not involving in stock repurchases during the most recent two fiscal years with the fiscal year end as of last December are included in the portfolio O (Overpriced). Firms with stock repurchases made during the most recent two fiscal years with the fiscal year end as of last December but not issuing IPOs or SEOs in the last 24 months are included portfolio U (Underpriced). Firms that involve both equity offerings and stock repurchases or neither are included portfolio N (Neutral).

| Year | IPO | SEO | RP | O | N | U | Year | IPO | SEO | RP | O | N | U |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1970 | 9 | 39 | | | | | 1989 | 157 | 139 | 981 | 393 | 2510 | 1462 |
| 1971 | 22 | 123 | 196 | | | | 1990 | 140 | 128 | 1059 | 438 | 2550 | 1290 |
| 1972 | 330 | 87 | 255 | 206 | 1699 | 184 | 1991 | 307 | 246 | 986 | 506 | 2524 | 1206 |
| 1973 | 42 | 37 | 708 | 490 | 3484 | 320 | 1992 | 415 | 311 | 884 | 848 | 2347 | 1182 |
| 1974 | 5 | 19 | 804 | 206 | 2986 | 748 | 1993 | 518 | 437 | 954 | 1053 | 2490 | 1065 |
| 1975 | 11 | 48 | 749 | 61 | 2679 | 1048 | 1994 | 455 | 291 | 1043 | 1269 | 2769 | 1066 |
| 1976 | 30 | 72 | 657 | 108 | 2712 | 1019 | 1995 | 467 | 421 | 1184 | 1161 | 2917 | 1124 |
| 1977 | 19 | 41 | 714 | 145 | 2743 | 922 | 1996 | 677 | 505 | 1368 | 1319 | 3035 | 1251 |
| 1978 | 34 | 74 | 689 | 91 | 2683 | 883 | 1997 | 438 | 364 | 1484 | 1431 | 3034 | 1329 |
| 1979 | 55 | 75 | 712 | 146 | 2612 | 873 | 1998 | 253 | 231 | 1803 | 1153 | 3031 | 1530 |
| 1980 | 124 | 225 | 656 | 242 | 2539 | 867 | 1999 | 437 | 285 | 1896 | 796 | 2685 | 1758 |
| 1981 | 296 | 220 | 718 | 578 | 2573 | 817 | 2000 | 330 | 287 | 1725 | 805 | 2438 | 1921 |
| 1982 | 87 | 170 | 803 | 631 | 2611 | 786 | 2001 | 61 | 156 | 1567 | 652 | 2165 | 1838 |
| 1983 | 552 | 481 | 817 | 692 | 2598 | 891 | 2002 | 54 | 143 | 1363 | 382 | 2082 | 1771 |
| 1984 | 255 | 95 | 953 | 1097 | 2622 | 873 | 2003 | 56 | 172 | 1229 | 211 | 1961 | 1650 |
| 1985 | 233 | 191 | 974 | 787 | 2632 | 1030 | 2004 | 137 | 208 | 1133 | 309 | 1957 | 1451 |
| 1986 | 444 | 225 | 1013 | 687 | 2685 | 1123 | 2005 | | | | 392 | 1936 | 1355 |
| 1987 | 360 | 203 | 1249 | 939 | 2663 | 1098 | All | 7965 | 6833 | 34582 | 20918 | 87576 | 39004 |
| 1988 | 155 | 84 | 1256 | 694 | 2624 | 1273 | Mean | 228 | 195 | 1017 | 615 | 2576 | 1147 |

Table 2: 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 2005. The event portfolios U, N, O are defined in Table 1. UMO (Underpricing Minus Overpricing) is the misvaluation factor that is long on U and short on O. MKT is the return of the value-weighted CRSP index in excess of the one-month T-bill rate. SMB is the size factor. HML is the book-to-market factor. MOM is the momentum factor. INV is the investment factor. It is defined as the return on the 30% firms with the lowest investment-to-asset ratios minus that on the highest 30% firms, controlling for size and book-to-market. LEV is the leverage factor. It is defined as the return on the 30% firms with the highest book debt-to-market equity ratios minus that on the lowest 30% firms, controlling for the size in the end of the most recent June. $\text{UMO}_{\perp\text{SEC}}$ 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. 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, and O. Panel B reports the correlations among the factor portfolios. Panel C reports the summary statistics of the *ex post* tangency portfolio, which delivers the maximum Sharpe ratios by optimally combining the factors. The portfolio weights are calculated as $(\iota' V^{-1}\mu)^{-1}V^{-1}\mu$, where $\iota$ is a k×1 vector of ones, $V$ is the covariance matrix of the factor returns, and $\mu$ is the mean factor returns.

Panel A: Portfolio returns

| | Mean | Stdev | $t$-stat | SR | ME | BM |
|---|---|---|---|---|---|---|
| U | 1.58 | 5.65 | 5.60 | 0.19 | 1,564 | 1.01 |
| N | 1.38 | 6.79 | 4.06 | 0.13 | 538 | 0.94 |
| O | 0.63 | 8.14 | 1.56 | 0.02 | 489 | 0.53 |
| UMO | 0.94 | 3.73 | 5.08 | 0.25 | | |
| $\text{UMO}_{\perp\text{SEC}}$ | 0.88 | 2.99 | 5.88 | 0.29 | | |
| MKT | 0.49 | 4.59 | 2.13 | 0.11 | | |
| SMB | 0.18 | 3.30 | 1.09 | 0.05 | | |
| HML | 0.51 | 3.10 | 3.29 | 0.16 | | |
| MOM | 0.88 | 4.27 | 4.13 | 0.21 | | |
| INV | 0.60 | 1.68 | 7.21 | 0.36 | | |
| LEV | 0.54 | 3.70 | 2.90 | 0.14 | | |

Panel B: Correlation matrix of factor mimicking portfolios

| | UMO | $\text{UMO}_{\perp\text{SEC}}$ | MKT | SMB | HML | MOM | INV |
|---|---|---|---|---|---|---|---|
| $\text{UMO}_{\perp\text{IND}}$ | 0.93 | | | | | | |
| MKT | −0.52 | −0.48 | | | | | |
| SMB | −0.42 | −0.37 | 0.26 | | | | |
| HML | 0.71 | 0.66 | −0.46 | −0.30 | | | |
| MOM | 0.15 | 0.12 | −0.07 | 0.02 | −0.11 | | |
| INV | 0.33 | 0.30 | −0.34 | −0.14 | 0.19 | 0.27 | |
| LEV | 0.67 | 0.60 | −0.28 | −0.28 | 0.78 | −0.26 | 0.06 |

Table 2: Summary statistics of event and factor portfolios

| Panel C: Ex post tangency portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Portfolio Weights | | | | | | | Tangency Portfolio | | |
| | MKT | SMB | HML | MOM | INV | LEV | UMO | Mean | Std | SR |
| (1) | 0.28 | 0.15 | 0.56 | | | | | 0.45 | 1.66 | 0.27 |
| (2) | 0.22 | 0.10 | 0.43 | 0.24 | | | | 0.56 | 1.50 | 0.37 |
| (3) | 0.17 | 0.07 | 0.19 | | 0.57 | | | 0.54 | 1.08 | 0.50 |
| (4) | 0.28 | 0.16 | 0.54 | | | 0.02 | | 0.45 | 1.66 | 0.27 |
| (5) | 0.27 | 0.21 | 0.02 | | | | 0.50 | 0.65 | 1.58 | 0.41 |
| (6) | 0.24 | 0.16 | 0.11 | 0.14 | | | 0.35 | 0.66 | 1.47 | 0.44 |
| (7) | 0.18 | 0.11 | 0.05 | | 0.47 | | 0.20 | 0.60 | 1.10 | 0.55 |
| (8) | 0.28 | 0.20 | 0.15 | | | −0.16 | 0.53 | 0.66 | 1.57 | 0.42 |
| (9) | 0.18 | 0.10 | 0.07 | 0.05 | 0.43 | | 0.17 | 0.60 | 1.09 | 0.55 |

Table 3: Comovement of the 25 size and book-to-market portfolios with UMO

This table reports the estimated UMO loadings of the 25 size-BM portfolios from July 1972 through December 2005. The dependent variables are the value-weighted 25 portfolio excess returns. The UMO loadings ($\beta_u$) are estimated from time-series regressions of portfolio excess returns on UMO after controlling for the Fama-French 3 factors (FF3), the 3 factors plus the momentum factor (FF3+MOM), or plus the investment factor (FF3+INV), or plus the leverage factor (FF3+LEV). Robust Newey-West (1987) $t$-statistics for the UMO loadings are reported in the right panel. $F$-stat tests whether the 25 $\beta_u$'s are jointly equal to zero. The corresponding $p$-values are reported.

Panel A: Controls: FF3

| | $\beta_u$ | | | | | $t$-stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BM | | | | | | BM | | | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.44 | −0.13 | 0.07 | 0.10 | 0.05 | S | −6.76 | −2.86 | 1.88 | 2.45 | 0.87 |
| 2 | −0.11 | 0.06 | 0.10 | 0.11 | 0.01 | 2 | −2.18 | 1.06 | 2.47 | 3.71 | 0.23 |
| 3 | −0.08 | 0.09 | 0.07 | 0.11 | −0.02 | 3 | −2.53 | 2.21 | 1.63 | 1.89 | −0.31 |
| 4 | 0.01 | 0.12 | 0.12 | 0.05 | 0.02 | 4 | 0.36 | 1.91 | 2.06 | 0.92 | 0.47 |
| B | 0.11 | 0.12 | 0.00 | −0.07 | −0.20 | B | 5.08 | 3.32 | 0.05 | −1.83 | −2.46 |
| | | | | | | $F$-stat | | *11.52* | $p$-value | | *0.0001* |

Panel B: Controls: FF3+MOM

| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S | −0.46 | −0.14 | 0.07 | 0.11 | 0.08 | S | −7.23 | −3.36 | 1.93 | 2.88 | 1.76 |
| 2 | −0.08 | 0.09 | 0.13 | 0.13 | 0.02 | 2 | −1.44 | 1.68 | 3.08 | 3.88 | 0.50 |
| 3 | −0.06 | 0.13 | 0.11 | 0.14 | 0.03 | 3 | −1.52 | 2.75 | 2.37 | 2.59 | 0.53 |
| 4 | 0.02 | 0.16 | 0.17 | 0.09 | 0.06 | 4 | 0.46 | 2.35 | 2.69 | 1.61 | 1.20 |
| B | 0.14 | 0.13 | −0.02 | −0.04 | −0.19 | B | 5.25 | 3.26 | −0.27 | −1.07 | −2.30 |
| | | | | | | $F$-stat | | *13.62* | $p$-value | | *0.0001* |

Panel C: Controls: FF3+INV

| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S | −0.47 | −0.15 | 0.07 | 0.09 | 0.05 | S | −7.48 | −3.66 | 1.80 | 2.33 | 0.89 |
| 2 | −0.10 | 0.08 | 0.12 | 0.12 | 0.01 | 2 | −1.93 | 1.58 | 2.84 | 4.39 | 0.39 |
| 3 | −0.08 | 0.12 | 0.10 | 0.12 | −0.01 | 3 | −2.17 | 2.90 | 2.13 | 2.18 | −0.11 |
| 4 | 0.00 | 0.15 | 0.13 | 0.05 | 0.03 | 4 | 0.10 | 2.33 | 2.29 | 0.84 | 0.53 |
| B | 0.11 | 0.13 | 0.02 | −0.06 | −0.21 | B | 4.71 | 3.48 | 0.40 | −1.39 | −2.64 |
| | | | | | | $F$-stat | | *13.03* | $p$-value | | *0.0001* |

Panel D: Controls: FF3+LEV

| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S | −0.37 | −0.10 | 0.06 | 0.09 | 0.02 | S | −4.95 | −1.99 | 1.62 | 2.17 | 0.28 |
| 2 | −0.11 | 0.01 | 0.06 | 0.07 | −0.02 | 2 | −2.20 | 0.21 | 1.32 | 2.18 | −0.69 |
| 3 | −0.09 | 0.05 | 0.02 | 0.08 | −0.05 | 3 | −2.85 | 1.12 | 0.43 | 1.37 | −0.89 |
| 4 | 0.03 | 0.08 | 0.07 | 0.05 | 0.00 | 4 | 0.62 | 1.25 | 1.26 | 0.91 | 0.08 |
| B | 0.08 | 0.09 | 0.00 | −0.09 | −0.21 | B | 3.11 | 2.35 | 0.00 | −2.08 | −2.73 |
| | | | | | | $F$-stat | | *6.97* | $p$-value | | *0.0001* |

Table 4: Alphas of the 25 size and book-to-market portfolios

This table reports the alphas, or abnormal returns, from regressing the excess returns of the 25 size-BM portfolios on multiple factors from July 1972 through December 2005. The dependent variables are the value-weighted 25 portfolio excess returns in percent. The independent variables are a set of common factors that include the Fama-French 3 factors (FF3), the 3 factors plus the momentum factor (FF3+MOM), or plus the investment factor (FF3+INV), or plus the leverage factor (FF3+LEV). The left panels report the alphas (in percent) and the right panels report the robust Newey-West (1987) $t$-statistics of the alphas. $F$-stat tests whether the 25 intercepts are jointly equal to zero. The corresponding $p$-value is bootstrapped and refers to the probability that an $F$ value drawn from the bootstrapped distribution under the null that all alphas are zero is greater than the empirical estimate.

| | $\alpha_{\text{FF3}}$ | | | | | | $t$-stat | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | BM | | | | | | BM | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.51 | 0.08 | 0.12 | 0.24 | 0.15 | S | −4.03 | 0.88 | 1.82 | 3.22 | 1.98 |
| 2 | −0.21 | −0.12 | 0.03 | 0.10 | −0.07 | 2 | −2.46 | −1.55 | 0.48 | 1.26 | −0.99 |
| 3 | −0.04 | −0.03 | −0.10 | −0.07 | 0.01 | 3 | −0.54 | −0.38 | −1.24 | −0.93 | 0.12 |
| 4 | 0.13 | −0.15 | −0.05 | −0.02 | −0.11 | 4 | 1.41 | −1.52 | −0.54 | −0.26 | −1.11 |
| B | 0.17 | 0.06 | −0.02 | −0.12 | −0.24 | B | 2.54 | 0.75 | −0.21 | −1.64 | −2.14 |
| | | | | | | $F$-stat | | *2.88* | $p$-value | | *0.01* |

| | $\alpha_{\text{FF3+UMO}}$ | | | | | | $t$-stat | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | BM | | | | | | BM | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.19 | 0.16 | 0.07 | 0.16 | 0.05 | S | −1.50 | 2.00 | 1.02 | 2.05 | 0.59 |
| 2 | −0.12 | −0.14 | −0.02 | 0.05 | −0.08 | 2 | −1.46 | −1.84 | −0.24 | 0.66 | −1.13 |
| 3 | 0.02 | −0.09 | −0.13 | −0.18 | −0.01 | 3 | 0.22 | −1.07 | −1.62 | −1.92 | −0.13 |
| 4 | 0.12 | −0.19 | −0.11 | −0.09 | −0.11 | 4 | 1.36 | −1.87 | −1.12 | −0.96 | −1.08 |
| B | 0.11 | −0.01 | −0.05 | −0.06 | −0.10 | B | 1.56 | −0.09 | −0.49 | −0.80 | −0.96 |
| | | | | | | $F$-stat | | *1.82* | $p$-value | | *0.08* |

| | $\alpha_{\text{FF3+MOM}}$ | | | | | | $t$-stat | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | BM | | | | | | BM | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.46 | 0.09 | 0.10 | 0.23 | 0.19 | S | −3.28 | 1.06 | 1.44 | 3.07 | 2.42 |
| 2 | −0.14 | −0.06 | 0.06 | 0.11 | −0.06 | 2 | −1.71 | −0.85 | 0.93 | 1.50 | −0.76 |
| 3 | 0.02 | 0.01 | −0.05 | −0.03 | 0.10 | 3 | 0.19 | 0.12 | −0.59 | −0.32 | 0.99 |
| 4 | 0.13 | −0.10 | 0.02 | 0.03 | −0.05 | 4 | 1.48 | −1.05 | 0.23 | 0.36 | −0.52 |
| B | 0.19 | 0.06 | −0.05 | −0.06 | −0.19 | B | 2.76 | 0.85 | −0.55 | −0.81 | −1.65 |
| | | | | | | $F$-stat | | *2.29* | $p$-value | | *0.02* |

| | $\alpha_{\text{FF3+MOM+UMO}}$ | | | | | | $t$-stat | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | BM | | | | | | BM | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.21 | 0.16 | 0.06 | 0.17 | 0.15 | S | −1.61 | 2.00 | 0.85 | 2.13 | 1.66 |
| 2 | −0.09 | −0.12 | −0.01 | 0.04 | −0.07 | 2 | −1.13 | −1.50 | −0.11 | 0.54 | −0.91 |
| 3 | 0.05 | −0.06 | −0.11 | −0.11 | 0.08 | 3 | 0.63 | −0.64 | −1.24 | −1.02 | 0.77 |
| 4 | 0.12 | −0.19 | −0.07 | −0.01 | −0.08 | 4 | 1.37 | −1.86 | −0.70 | −0.14 | −0.79 |
| B | 0.11 | −0.01 | −0.04 | −0.04 | −0.09 | B | 1.70 | −0.10 | −0.41 | −0.45 | −0.73 |
| | | | | | | $F$-stat | | *1.47* | $p$-value | | *0.17* |

Table 4: Alphas of the 25 size and book-to-market portfolios: Cont'd

| | $\alpha_{\text{FF3+INV}}$ | | | | | $t$-stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BM | | | | | | BM | | | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.55 | 0.01 | 0.08 | 0.18 | 0.14 | S | −4.37 | 0.13 | 1.13 | 2.58 | 1.79 |
| 2 | −0.14 | −0.01 | 0.07 | 0.14 | −0.05 | 2 | −1.71 | −0.07 | 1.04 | 2.02 | −0.69 |
| 3 | 0.01 | 0.07 | −0.01 | −0.02 | 0.07 | 3 | 0.09 | 0.84 | −0.19 | −0.28 | 0.60 |
| 4 | 0.09 | −0.05 | 0.01 | −0.05 | −0.09 | 4 | 0.99 | −0.47 | 0.13 | −0.55 | −0.86 |
| B | 0.12 | 0.08 | 0.06 | −0.03 | −0.26 | B | 1.72 | 0.95 | 0.54 | −0.38 | −2.29 |
| | | | | | | $F$-stat | | *1.88* | $p$-value | | *0.05* |

| | $\alpha_{\text{FF3+INV+UMO}}$ | | | | | $t$-stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BM | | | | | | BM | | | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.31 | 0.09 | 0.05 | 0.14 | 0.11 | S | −2.42 | 1.10 | 0.61 | 1.75 | 1.24 |
| 2 | −0.09 | −0.05 | 0.01 | 0.07 | −0.06 | 2 | −1.12 | −0.68 | 0.14 | 1.05 | −0.79 |
| 3 | 0.05 | 0.01 | −0.07 | −0.09 | 0.07 | 3 | 0.60 | 0.12 | −0.80 | −0.93 | 0.59 |
| 4 | 0.08 | −0.12 | −0.06 | −0.07 | −0.11 | 4 | 0.94 | −1.20 | −0.63 | −0.75 | −0.99 |
| B | 0.07 | 0.02 | 0.05 | 0.00 | −0.15 | B | 0.91 | 0.18 | 0.41 | −0.02 | −1.26 |
| | | | | | | $F$-stat | | *1.00* | $p$-value | | *0.49* |

| | $\alpha_{\text{FF3+LEV}}$ | | | | | $t$-stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BM | | | | | | BM | | | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.51 | 0.08 | 0.12 | 0.24 | 0.14 | S | −4.81 | 0.98 | 1.80 | 3.24 | 2.02 |
| 2 | −0.21 | −0.12 | 0.03 | 0.09 | −0.07 | 2 | −2.46 | −1.65 | 0.46 | 1.28 | −1.02 |
| 3 | −0.04 | −0.04 | −0.10 | −0.07 | 0.01 | 3 | −0.54 | −0.44 | −1.41 | −0.97 | 0.10 |
| 4 | 0.13 | −0.16 | −0.05 | −0.02 | −0.11 | 4 | 1.44 | −1.62 | −0.59 | −0.26 | −1.11 |
| B | 0.17 | 0.06 | −0.02 | −0.12 | −0.24 | B | 2.59 | 0.74 | −0.21 | −1.65 | −2.15 |
| | | | | | | $F$-stat | | *3.01* | $p$-value | | *0.01* |

| | $\alpha_{\text{FF3+LEV+UMO}}$ | | | | | $t$-stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | BM | | | | | | BM | | | | |
| Size | L | 2 | 3 | 4 | H | Size | L | 2 | 3 | 4 | H |
| S | −0.24 | 0.16 | 0.07 | 0.17 | 0.13 | S | −2.00 | 1.92 | 1.05 | 2.21 | 1.52 |
| 2 | −0.12 | −0.13 | −0.01 | 0.04 | −0.06 | 2 | −1.58 | −1.80 | −0.20 | 0.56 | −0.81 |
| 3 | 0.03 | −0.07 | −0.12 | −0.13 | 0.05 | 3 | 0.35 | −0.84 | −1.47 | −1.41 | 0.47 |
| 4 | 0.11 | −0.21 | −0.10 | −0.06 | −0.11 | 4 | 1.25 | −2.07 | −1.06 | −0.64 | −1.10 |
| B | 0.11 | −0.01 | −0.02 | −0.06 | −0.09 | B | 1.62 | −0.07 | −0.19 | −0.79 | −0.87 |
| | | | | | | $F$-stat | | *1.67* | $p$-value | | *0.11* |

Table 5: Alphas of event portfolios based on M&A, convertible bond issuance, dividend initiation and resumption

This table reports results of time-series regressions of the excess returns of four event portfolios on the Fama-French 3 factors with and without UMO. In Panel A, the dependent variable is the monthly excess returns of acquirers in M&A deals in the most recent 36 months from 1980-2005. In Panel B, the dependent variable is the monthly excess returns of firms that issue convertible bonds in the most recent 36 months from 1972-2005. In Panel C, the dependent variable is the monthly excess returns of firms that initiate or resume cash dividend payments from 1972-2005. In Panel D, the dependent variable is the monthly excess returns of firms with omissions of regular or irregular quarterly, semi-annual, or annual dividend payouts. In all panels, the event portfolios include event stocks from month $t+1$ through $t+36$, where $t$ refers to the effective date in M&A in Panel A, the bond issuing date in Panel B, the dividend payment date in Panel C, and the dividend omission date (the expected payment date with omission based on regular payout frequency) in Panel D. In all panels, equal-weighted portfolio returns are used. Robust Newey-West (1987) $t$-statistics are reported in italics.

| | Panel A: M&A | | | | | |
|---|---|---|---|---|---|---|
| | Intercept | MKT | SMB | HML | UMO | Adj. $R^2$ |
| (1) | −0.38 | 1.20 | 0.70 | −0.05 | | 88% |
| | *−2.83* | *24.18* | *6.86* | *−0.60* | | |
| (2) | 0.04 | 1.07 | 0.56 | 0.29 | −0.51 | 91% |
| | *0.27* | *24.91* | *6.30* | *3.36* | *−4.95* | |
| | **Panel B: Convertible Debt** | | | | | |
| | Intercept | MKT | SMB | HML | UMO | Adj. $R^2$ |
| (3) | −0.39 | 1.31 | 0.67 | −0.12 | | 84% |
| | *−2.46* | *24.08* | *5.93* | *−1.28* | | |
| (4) | −0.03 | 1.22 | 0.56 | 0.21 | −0.49 | 86% |
| | *−0.18* | *29.41* | *5.18* | *1.91* | *−4.34* | |
| | **Panel C: Dividend Initiation and Resumption** | | | | | |
| | Intercept | MKT | SMB | HML | UMO | Adj. $R^2$ |
| (5) | 0.24 | 1.01 | 0.90 | 0.37 | | 89% |
| | *2.40* | *27.34* | *10.27* | *5.57* | | |
| (6) | 0.16 | 1.03 | 0.93 | 0.29 | 0.11 | 89% |
| | *1.45* | *28.05* | *9.80* | *3.47* | *1.64* | |
| | **Panel D: Dividend Omission** | | | | | |
| | Intercept | MKT | SMB | HML | UMO | Ave. R2 |
| (7) | −0.28 | 1.09 | 1.00 | 0.76 | | 84% |
| | *−2.39* | *25.36* | *9.21* | *8.01* | | |
| (8) | −0.21 | 1.07 | 0.97 | 0.82 | −0.10 | 84% |
| | *−1.29* | *22.93* | *8.91* | *7.03* | *−0.82* | |

Table 6: 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 2005. 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 common factors, including MKT, HML, SMB, UMO, $\text{UMO}_{\text{SEC}}$, MOM, INV, and LEV, which are all defined in Table 2. Monthly portfolio returns from July of year $t$ through June of year $t+1$ are regressed on portfolio factor loadings that are estimated from a multi-factor time-series regression 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 premium, are reported, below which are the associated robust Newey-West (1987) $t$-statistics in italics. The ave. $R^2$s are the time-series averages of the monthly adjusted R-squares across the full sample period.

| | MKT | SMB | HML | | UMO | Ave. $R^2$ |
|---|---|---|---|---|---|---|
| (1) | 0.11 | | | | 0.57 | 37% |
| | *0.27* | | | | *2.54* | |
| (2) | −0.85 | 0.20 | 0.41 | | | 46% |
| | *3.47* | *1.23* | *2.16* | | | |
| (3) | −0.65 | 0.25 | 0.39 | | 0.80 | 50% |
| | *−2.18* | *1.55* | *2.11* | | *3.47* | |
| | MKT | SMB | HML | | $\text{UMO}_{\perp\text{SEC}}$ | Ave. $R^2$ |
| (4) | −0.68 | 0.24 | 0.40 | | 0.75 | 49% |
| | *−2.27* | *1.46* | *2.14* | | *3.77* | |
| | MKT | SMB | HML | MOM | UMO | Ave. $R^2$ |
| (5) | −0.74 | 0.21 | 0.41 | −0.29 | | 47% |
| | *−2.43* | *1.20* | *2.14* | *−1.03* | | |
| (6) | −0.56 | 0.24 | 0.39 | −0.29 | 0.81 | 51% |
| | *−1.93* | *1.46* | *2.10* | *−0.99* | *3.63* | |
| | MKT | SMB | HML | INV | UMO | Ave. $R^2$ |
| (7) | −0.71 | 0.24 | 0.40 | 0.02 | | 48% |
| | *−2.50* | *1.39* | *2.10* | *0.14* | | |
| (8) | −0.63 | 0.25 | 0.39 | 0.06 | 0.71 | 51% |
| | *−2.20* | *1.49* | *2.10* | *0.41* | *3.13* | |
| | MKT | SMB | HML | LEV | UMO | Ave. $R^2$ |
| (9) | −0.60 | 0.24 | 0.38 | 0.93 | | 49% |
| | *−1.96* | *1.42* | *2.04* | *3.35* | | |
| (10) | −0.58 | 0.26 | 0.38 | 0.77 | 0.73 | 51% |
| | *−1.85* | *1.53* | *2.02* | *2.96* | *3.29* | |

Table 7: 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, $\beta_u^{\text{pre}}$, from July 1973 through December 2005. The sorting variable $\beta_u^{\text{pre}}$, for each stock, is the coefficient $\beta_u$ on UMO in the following regression with at least 100 daily stock returns from month $t-12$ to $t-1$:

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

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

| | All sample firms | | Excl. UMO firms | |
|---|---|---|---|---|
| $\beta_u^{\text{pre}}$ Rank | $\beta_u^{\text{pre}}$ | RET | $\beta_u^{\text{pre}}$ | RET |
| L | −2.37 | 1.09 | −2.42 | 1.25 |
| 2 | −1.12 | 1.32 | −1.15 | 1.43 |
| 3 | −0.67 | 1.40 | −0.70 | 1.43 |
| 4 | −0.38 | 1.44 | −0.41 | 1.51 |
| 5 | −0.16 | 1.41 | −0.18 | 1.46 |
| 6 | 0.02 | 1.51 | 0.01 | 1.48 |
| 7 | 0.21 | 1.52 | 0.21 | 1.57 |
| 8 | 0.43 | 1.48 | 0.44 | 1.44 |
| 9 | 0.75 | 1.54 | 0.78 | 1.56 |
| H | 1.76 | 1.84 | 1.83 | 1.96 |
| H−L | 4.13 | 0.75 | 4.25 | 0.70 |
| $t$(H−L) | | *2.64* | | *2.73* |
| $\alpha_{\text{CAPM}}$ | | 0.97 | | 0.89 |
| $t(\alpha_{\text{CAPM}})$ | | *3.58* | | *3.56* |
| $\alpha_{\text{FF3}}$ | | 0.52 | | 0.53 |
| $t(\alpha_{\text{FF3}})$ | | *2.32* | | *2.46* |

Table 8: Fama-MacBeth regressions at the firm level

This table reports the firm-level Fama-MacBeth regression results from July 1975 to December 2005. 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 ($\beta^{\mathrm{UMO}}$). The $\beta^{\mathrm{UMO}}_{\mathrm{ME+IR}}$ is estimated by first sorting stocks into deciles based on market equity (ME), then within each ME decile, further subdividing stocks into deciles based on the composite issuance variable (IR) (Daniel and Titman 2006), which is calculated based on the market equity and stock returns from month $t-60$ to $t-1$. 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 which are included in the portfolios at month $t-1$ to forecast stock returns at month $t$. The $\beta^{\mathrm{UMO}}_{\mathrm{BM+IR}}$ is estimated from portfolios sorted sequentially by book-to-market equity (BM) and IR. The $\beta^{\mathrm{UMO}}_{\mathrm{ME+BM}}$ is estimated from portfolios independently sorted based on ME and BM. All 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 $\beta_{\mathrm{MKT}}$, $\beta_{\mathrm{SMB}}$, and $\beta_{\mathrm{HML}}$, 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 reported in all regressions but the coefficients are unreported. Panel A includes all firms and Panel B excludes firms in UMO of the current year. Robust Newey-West (1987) $t$-statistics are reported below the coefficients in italics.

Table 8: Fama-MacBeth regressions at the firm level (Cont'd)

| | LOG(ME) | LOG(BM) | $r(t-1)$ | $r(t-12,t-2)$ | $r(t-36,t-13)$ | $\beta^{\mathrm{UMO}}_{\mathrm{ME+IR}}$ | $\beta^{\mathrm{UMO}}_{\mathrm{BM+IR}}$ | $\beta^{\mathrm{UMO}}_{\mathrm{ME+BM}}$ | IR | INDDUMs | 3-Factor Loadings |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: All sample firms | | | | | | | | | | | |
| (1) | −0.15 | 0.44 | −0.07 | 0.05 | −0.05 | | | | | Yes | Yes |
| | *−2.62* | *4.96* | *−14.27* | *2.84* | *−3.05* | | | | | | |
| (2) | −0.17 | 0.23 | −0.06 | 0.04 | −0.03 | 0.27 | | | | Yes | Yes |
| | *−3.25* | *2.71* | *−15.06* | *2.61* | *−2.23* | *4.69* | | | | | |
| (3) | −0.19 | 0.18 | −0.06 | 0.04 | −0.03 | | 0.16 | | | Yes | Yes |
| | *−3.47* | *2.40* | *−14.90* | *2.64* | *−2.20* | | *2.87* | | | | |
| (4) | −0.20 | 0.30 | −0.06 | 0.04 | −0.04 | | | 0.14 | | Yes | Yes |
| | *−3.47* | *3.54* | *−15.12* | *2.71* | *−3.02* | | | *3.02* | | | |
| (5) | *−0.18* | *0.19* | *−0.06* | *0.04* | *−0.04* | *0.22* | | | *−0.32* | Yes | Yes |
| | *−3.57* | *2.39* | *−14.68* | *2.55* | *−2.55* | *4.34* | | | *−2.82* | | |
| Panel B: Excluding firms in UMO of the current year | | | | | | | | | | | |
| | LOG(ME) | LOG(BM) | $r(t-1)$ | $r(t-12,t-2)$ | $r(t-36,t-13)$ | $\beta^{\mathrm{UMO}}_{\mathrm{ME+IR}}$ | $\beta^{\mathrm{UMO}}_{\mathrm{BM+IR}}$ | $\beta^{\mathrm{UMO}}_{\mathrm{ME+BM}}$ | IR | INDDUMs | 3-Factor Loadings |
| (6) | −0.19 | 0.46 | −0.07 | 0.04 | −0.05 | | | | | Yes | Yes |
| | *−2.98* | *5.21* | *−14.49* | *2.10* | *−2.78* | | | | | | |
| (7) | −0.19 | 0.24 | −0.06 | 0.03 | −0.04 | 0.30 | | | | Yes | Yes |
| | *−3.32* | *2.68* | *−14.02* | *1.95* | *−2.45* | *4.85* | | | | | |
| (8) | −0.22 | 0.19 | −0.06 | 0.03 | −0.04 | | 0.18 | | | Yes | Yes |
| | *−3.61* | *2.31* | *−13.90* | *2.00* | *−2.36* | | *2.81* | | | | |
| (9) | −0.23 | 0.32 | −0.06 | 0.03 | −0.04 | | | 0.15 | | Yes | Yes |
| | *−3.64* | *3.36* | *−14.71* | *1.87* | *−2.79* | | | *2.69* | | | |
| (10) | −0.21 | 0.20 | −0.06 | 0.03 | −0.04 | 0.16 | | | −0.54 | Yes | Yes |
| | *−3.71* | *2.25* | *−14.07* | *1.82* | *−2.77* | *2.56* | | | *−4.44* | | |

Table 9: 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 ($b_{\text{pre}}^{\text{UMO}}$). The estimated ($b_{\text{pre}}^{\text{UMO}}$) 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 ($b_{\text{post}}^{\text{UMO}}$) are estimated using a multifactor time-series regression that includes MKT, SMB, HML, and UMO. The demeaned $b_{\text{pre}}^{\text{UMO}}$ is the deviation of individual stocks' pre-ranking loadings from the mean loading of all available stocks in a given month. The demeaned $b_{\text{post}}^{\text{UMO}}$ is the deviation of portfolios' post-ranking loadings from their mean. The average demeaned $b_{\text{pre}}^{\text{UMO}}$ and $b_{\text{post}}^{\text{UMO}}$ 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 Spearman rank correlations between the average demeaned portfolio pre- and post-ranking loadings are reported in italics.

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

| Pre-Ranking | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0+ | −6.96 | −4.34 | −3.56 | −3.12 | −2.77 | −2.52 | −2.32 | −2.14 | −1.99 | −1.86 |
| 10+ | −1.75 | −1.63 | −1.53 | −1.44 | −1.35 | −1.27 | −1.20 | −1.13 | −1.06 | −0.99 |
| 20+ | −0.94 | −0.88 | −0.83 | −0.78 | −0.73 | −0.68 | −0.64 | −0.59 | −0.55 | −0.50 |
| 30+ | −0.46 | −0.42 | −0.39 | −0.35 | −0.32 | −0.28 | −0.25 | −0.21 | −0.18 | −0.15 |
| 40+ | −0.12 | −0.09 | −0.06 | −0.03 | 0.00 | 0.03 | 0.06 | 0.09 | 0.11 | 0.14 |
| 50+ | 0.17 | 0.19 | 0.22 | 0.25 | 0.28 | 0.31 | 0.33 | 0.36 | 0.39 | 0.41 |
| 60+ | 0.44 | 0.47 | 0.49 | 0.52 | 0.55 | 0.58 | 0.61 | 0.63 | 0.66 | 0.69 |
| 70+ | 0.72 | 0.75 | 0.79 | 0.82 | 0.85 | 0.89 | 0.92 | 0.96 | 0.99 | 1.03 |
| 80+ | 1.07 | 1.11 | 1.15 | 1.20 | 1.25 | 1.30 | 1.35 | 1.41 | 1.48 | 1.55 |
| 90+ | 1.63 | 1.71 | 1.81 | 1.92 | 2.05 | 2.21 | 2.43 | 2.74 | 3.24 | 5.03 |

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

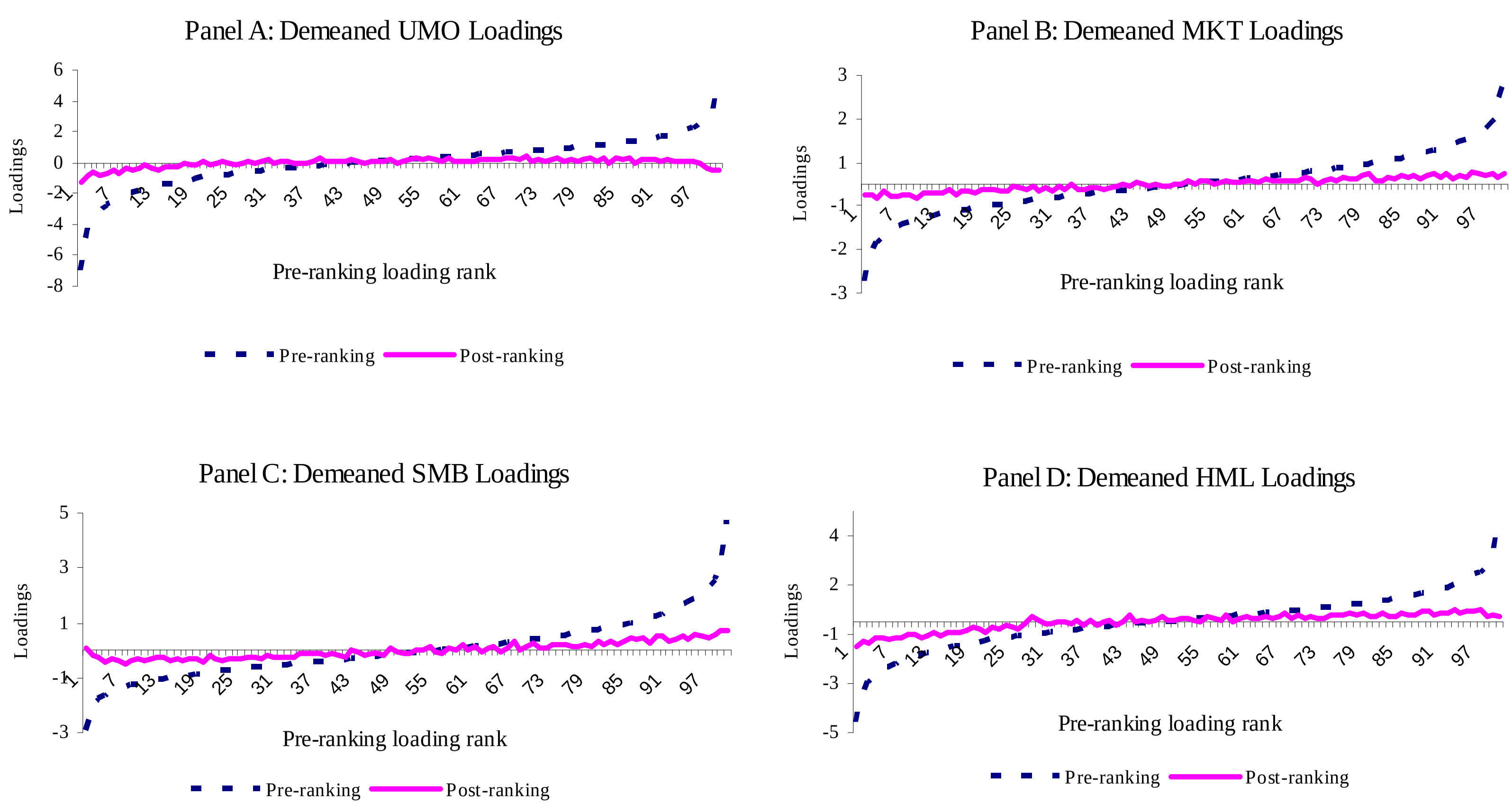
| Pre-Ranking | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0+ | **−1.31** | **−0.85** | **−0.55** | **−0.83** | **−0.68** | **−0.45** | **−0.67** | **−0.36** | **−0.46** | **−0.39** |
| 10+ | **−0.12** | **−0.43** | **−0.51** | **−0.29** | **−0.22** | **−0.24** | **−0.05** | **−0.12** | **−0.20** | 0.11 |
| 20+ | **−0.14** | **−0.05** | 0.12 | **0.00** | **−0.12** | **0.02** | **0.03** | **−0.06** | **0.03** | 0.21 |
| 30+ | **−0.04** | **0.10** | 0.06 | **0.01** | **−0.03** | **−0.01** | 0.14 | 0.28 | **0.07** | **0.11** |
| 40+ | 0.14 | **0.11** | 0.24 | **0.09** | **0.00** | **0.07** | **0.09** | **0.11** | 0.23 | **−0.03** |
| 50+ | **0.03** | **0.14** | 0.26 | 0.21 | 0.26 | 0.23 | **0.14** | 0.35 | **0.11** | **0.12** |
| 60+ | **0.07** | **0.09** | 0.15 | 0.20 | 0.16 | 0.20 | 0.27 | 0.30 | 0.21 | 0.38 |
| 70+ | **0.13** | 0.25 | **0.09** | 0.17 | 0.28 | **0.12** | 0.21 | **0.04** | 0.22 | 0.29 |
| 80+ | 0.13 | 0.31 | **0.02** | 0.35 | 0.17 | 0.28 | **−0.01** | 0.18 | 0.20 | 0.20 |
| 90+ | **0.05** | 0.25 | 0.11 | **0.08** | **0.08** | **0.03** | **0.02** | **−0.37** | **−0.46** | **−0.45** |

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

| | UMO | UMO | MKT | SMB | HML |
|---|---|---|---|---|---|
| | All | Excl. U & O | All | All | All |
| Portfolios with demeaned loadings that flip signs | | | | | |
| Out of all 100 | 22 | 26 | 6 | 8 | 10 |
| Out of the 50 (the top and bottom 25) | 6 | 10 | 0 | 1 | 0 |
| Post-ranking loadings indistinguishable from zero | 38 | 33 | 0 | 0 | 10 |
| Correlation of pre- and post-ranking demeaned loadings | *0.56* | *0.43* | *0.97* | *0.93* | *0.93* |

Figure 1: 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 2. The pre-ranking UMO loadings of individual stocks are estimated by regressing 36 to 60 most recent monthly percentage returns on UMO together with the 3 factors as of June of each year. 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.



# Appendix

Section A of this appendix shows that the main results of this paper hold for alternative benchmark multi-factor models and orthogonalized misvaluation factors. Section B shows that the intuitive hypothesis development of the main text can be supported by formal analysis. Sections C and D provide supplementary proof to the model in Section B. Section E reports the sample of selective corporate events.

## 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 size and book-to-market factors purged of new issues of Loughran and Ritter (2000) and the macro economic factors of Eckbo, Masulis, and Norli (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 the 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 2008; Daniel and Titman 2008).

Loughran and Ritter (2000) suggest to replace the Fama-French size and book-to-market factors with the purged factors for more accurate assessment of the long-term performance of equity financing firms. Specifically, the purged size and book-to-market factors exclude new issue firms in the prior five years. We obtain the purged Fama-French factor returns ($\mathrm{SMB_p}$ and $\mathrm{HML_p}$) from Jay Ritter from 1970–2003.

Eckbo, Masulis, and Norli (2000) suggest that equity financing changes firms' leverage, thus altering their exposure to macroeconomic factors and leading to long-run abnormal returns relative to standard models. The six macro economic 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. The term premium (TERM) is defined as the yield spread between the 10-year and 1-year treasury constant maturity bonds. The default spread (DEF) is defined as the yield spread between Moody's seasoned Baa and Aaa corporate bonds.[1] The 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

[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. Also, 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.

per capita consumption of nondurable goods is denoted as $\Delta RPC$. The 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 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 these factors.[2]

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-2 presents the results of the time-series regressions of UMO on these two 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 53% to 64%. The variance of the regression residuals is way above the right end of 1% confidence interval based on long-short portfolios with randomly-selected stocks, suggesting significant amount of UMO variation that 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-3 presents the Fama-MacBeth regression results using the 25 size-BM portfolios. In Panel A, 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. Panel B shows that, after controlling for the two alternative sets of benchmark factors, UMO loadings remain significant. In other words, assets' exposure to these new benchmark factors do not fully account for the positive premium associated with high UMO loadings. We see no visible reduction in the magnitude of coefficients for these alternative specifications. Taken together, the results suggest that existing rational explanations for equity financing do not fully account for the variation and pricing power

[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 ($\omega$) 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 are the sum of the products of the corresponding weights of the factor on the corresponding 25 portfolios.

of UMO.

## B. 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 $\beta_{ik}$ is the loading of the $i$th security on the $k$th factors, $f_k$ is the realization of the $k$th factor, and $\epsilon_i$ is the $i$th 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 $\beta_{ik}$ are common knowledge, but the realizations of $f_k$ and $\epsilon_i$ 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 $k$th factor portfolio and $i$th 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 $e_i^\epsilon$ are denoted as $\nu_k^{Rf}$ 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 $\phi_i$, $i = 1, 2, ..., N+K$ 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 $S_i^{\epsilon}$ 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, $\omega_i^{\epsilon}$ and $\omega_k^f$, 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 $\omega_k^f$, 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 $\omega^f$s 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, $\eta_i$, 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 $\eta_o^*$ and the repurchase threshold for underpricing as $\eta_u^*$ ($\eta_o^* > 0$ 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-1: The Relation between Stocks' Misvaluation with Factor Signals and Factor Loadings

| | | Factor Signal $S_k$ | |
|---|---|---|---|
| | | $+$ | $-$ |
| Factor Loading $\beta_{ik}$ | $+$ | 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-1). 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 $\beta_{iM}$ and $\beta_{ik}$, 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 $\omega_k^f$ and the factor loading $\beta_{ik}$. 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 $\beta$s 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 Appendix Section C., 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 $\beta_{ik}$'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 $\beta$ 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 $\beta_{UMO}$ 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 $\lambda_{UMO}$, which is the expected return on the zero-investment portfolio UMO, is positive,*

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

The proof is in Appendix Section D..

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.

## C. Proof of footnote 6 in Appendix Section B.

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, $\beta_{K_oM}$ and $\beta_{K_uM}$, are correlated with the factor loadings, $\beta_{K_ok}$ and $\beta_{K_uk}$, 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 $\Sigma_{XX}$ 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 $\Sigma_{XX}$ and $\Sigma_{XY}$ 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.

## D. Proof of Proposition 4

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.

## E. Sample of Selective Corporate Events

In Table A-4, we report the annual number of events of four types: M&A, convertible bond issuance, dividend initiation/resumption, and dividend omission.

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Table A-2: 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 2005 (2003 when the purged size and book-to-market factors are used). The dependent variable is the percentage returns of UMO that is long the repurchase firms and short the new issue firms. The market factor (MKT) refers to the excess returns of CRSP value-weighted portfolio. The purged size factor, $SMB_p$, and book-to-market factor, $HML_p$, exclude firms that are involved in equity issuance during the prior five years. 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. $\Delta$RPC is the change in consumption of nondurable goods factor mimicking portfolio. UI is the unexpected inflation factor mimicking portfolio. Robust Newey-West $t$-statistics of the intercepts and independent variables are reported in italics. $\sigma^2(\epsilon)$ is the variance of the residual terms with the 1% confidence interval of the residual terms reported in square brackets based on long-short portfolios with randomly selected stocks.

| | Intercept | MKT | $SMB_p$ | $HML_p$ | | | | $R^2$ | $\sigma^2(\epsilon)$ |
|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.91 | −0.22 | −0.24 | 0.71 | | | | 53% | 6.844 |
| | *6.89* | *−5.24* | *−4.25* | *7.04* | | | | | [0.954, 1.517] |
| | Intercept | MKT | TERM | DEF | TBSP | $\Delta$RPC | UI | $R^2$ | $\sigma^2(\epsilon)$ |
| (2) | 0.50 | −0.43 | 0.15 | 0.18 | −4.49 | −12.79 | *0.20* | 64% | 4.967 |
| | *4.54* | *−8.58* | *6.45* | *2.25* | *−8.51* | *−1.95* | *0.99* | | [0.937, 1.455] |

Table A-3: 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 2005 (2004 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-2. 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 that are 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 premium, are reported, below which are the associated robust Newey-West (1987) $t$-statistics in italics. The ave. $R^2$s are the time-series averages of the monthly adjusted R-squares across the full sample period.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Panel A: Alternative benchmark factors | | | | | | | |
| | UMO | MKT | $SMB_p$ | $HML_p$ | | | | Ave. $R^2$ |
| (1) | 0.85 | −0.80 | 0.34 | 0.25 | | | | 50% |
| | *3.56* | *−2.53* | *2.07* | *1.51* | | | | |
| | UMO | MKT | TERM | DEF | TBSP | ΔRPC | UI | Ave. $R^2$ |
| (2) | 0.92 | −0.51 | 1.19 | −0.19 | −0.02 | 0.00 | −0.01 | 55% |
| | *4.17* | *−1.92* | *3.07* | *−1.15* | *−0.68* | *1.73* | *−0.14* | |
| | Panel B: Orthogonalized UMO | | | | | | | |
| | $UMO_{\perp 3}$ | MKT | SMB | HML | | | | Ave. $R^2$ |
| (3) | 0.47 | −0.65 | 0.25 | 0.39 | | | | 50% |
| | *3.26* | *−2.29* | *1.48* | *2.10* | | | | |
| | $UMO_{\perp 4}$ | MKT | SMB | HML | MOM | | | Ave. $R^2$ |
| (4) | 0.55 | −0.56 | 0.24 | 0.39 | −0.29 | | | 51% |
| | *3.96* | *−1.93* | *1.46* | *2.10* | *−0.99* | | | |

Table A-4: Annual Number of Selective Corporate Events

This table reports the annual number of events of mergers & acquisitions (M&A) during 1981–2005, convertible bond issuance, dividend initiation/resumption, and dividend omission during 1972–2005. Dividend initiation as the first cash dividend payment for a firm that has traded for at least 24 months. Dividend resumption is defined as the first cash dividend paid by a firm following a hiatus in payments ranging from 33 to 180 months. Dividend omission is defined as omission of at least six consecutive quarterly cash payments, at least three consecutive semi-annual cash payments, or at least two consecutive annual cash payments.

| year | M&A | Convertible Bonds | Dividend InitiationResumption | Dividend Omission |
|---|---|---|---|---|
| 1972 | - | 27 | 31 | 116 |
| 1973 | - | 30 | 78 | 74 |
| 1974 | - | 6 | 89 | 96 |
| 1975 | - | 11 | 179 | 190 |
| 1976 | - | 18 | 190 | 124 |
| 1977 | - | 10 | 176 | 134 |
| 1978 | - | 12 | 112 | 162 |
| 1979 | - | 11 | 68 | 166 |
| 1980 | - | 71 | 50 | 212 |
| 1981 | 236 | 58 | 32 | 159 |
| 1982 | 427 | 51 | 35 | 246 |
| 1983 | 622 | 87 | 26 | 172 |
| 1984 | 644 | 45 | 48 | 136 |
| 1985 | 185 | 88 | 38 | 158 |
| 1986 | 172 | 156 | 36 | 202 |
| 1987 | 203 | 126 | 53 | 154 |
| 1988 | 185 | 29 | 72 | 153 |
| 1989 | 213 | 50 | 76 | 124 |
| 1990 | 222 | 25 | 66 | 139 |
| 1991 | 254 | 42 | 37 | 162 |
| 1992 | 382 | 43 | 50 | 109 |
| 1993 | 433 | 65 | 37 | 126 |
| 1994 | 536 | 19 | 45 | 84 |
| 1995 | 638 | 18 | 57 | 112 |
| 1996 | 767 | 37 | 41 | 90 |
| 1997 | 775 | 31 | 35 | 79 |
| 1998 | 855 | 16 | 33 | 82 |
| 1999 | 731 | 22 | 31 | 116 |
| 2000 | 776 | 26 | 28 | 127 |
| 2001 | 485 | 31 | 21 | 133 |
| 2002 | 299 | 7 | 23 | 92 |
| 2003 | 267 | 11 | 119 | 54 |
| 2004 | 351 | 12 | 96 | 30 |
| 2005 | 384 | 5 | 65 | 52 |
| Sum | 11042 | 1171 | 1250 | 3303 |