INNOVATIVE EFFICIENCY AND STOCK RETURNS*

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We find that innovative efficiency (IE), patents granted per dollar of R&D capital, is a strong positive return predictor after controlling for firm characteristics and adjusting for the Carhart four-factor model. This finding, other factor model tests, and the high Sharpe ratio of the Efficient Minus Inefficient portfolio suggest that mispricing as well as risk contributes to the IE effect. Further tests based upon attention and uncertainty proxies suggest that limited investor attention contributes to the effect. The high weight of the EMI portfolio return in the tangency portfolio suggests that IE captures incremental pricing effects relative to well-known factors.

Keywords: innovative efficiency, limited attention

JEL Classification: G12, G14, O32

1. Introduction

Recent studies have provided evidence suggesting that owing to limited investor attention, prices do not fully and immediately impound the arrival of relevant public information, especially when such information is less salient or arrives during a period of low investor attention (e.g., Klibanoff, Lamont, and Wizman 1998; Huberman and Regev 2001; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009; Hou, Peng, and Xiong 2009). Several papers have therefore argued that limited attention results in underreaction and return predictability. Several theoretical models also predict that limited investor attention affects stock prices and can cause market underreaction (Merton 1987; Hirshleifer and Teoh 2003; Peng and Xiong 2006).

These studies consider the processing of news about current performance such as earnings announcements. However, we would expect investors to have even greater difficulty processing information that is less tangible, and about firms whose future prospects are highly uncertain. For example, information about the prospects of new technologies or other innovations should be especially hard to process, because the significance of such news depends upon strategic options and other complex considerations. If so, there will on average be price drift after the arrival of non-salient public news about the prospects for firms' innovations. In other words, on average there will be higher abnormal returns after good news than after bad news.

In this study, we examine the relation between innovative efficiency and subsequent stock returns. Lanjouw and Schankerman (2004) suggest that innovative efficiency is an important contributor to a firm's market value. We test whether a measure of innovative efficiency, the ratio of a firm's patents to its R&D expenditure, predicts future abnormal returns after controlling for other standard return predictors.

Innovations are usually officially introduced to the public in the format of approved patents that provide necessary detailed information. Owing to the creation of the Court of Appeals for the Federal Circuit (CAFC) in 1982 and several well-documented patent lawsuits (e.g., the Kodak-Polaroid case), U.S. firms have increasingly recognized the necessity to patent their innovations and hence have been especially active in patenting activities since the early 1980s (Hall and Ziedonis 2001; Hall 2005). Patents are thus the most important measure of contemporary firms' innovative performance (Griliches 1990); they are materialized innovations of business value and are actively traded in intellectual property markets (Lev 2001).

A firm's past innovative efficiency is not necessarily as salient to investors as explicitly forward-looking information about the prospects for the particular R&D projects that the firm is examining. According to Kahneman and Lovallo (1993), people tend to consider the judgment or decision problem they are facing as unique, and in consequence, "neglect the statistics of the past in evaluating current plans." Kahneman and Lovallo call a focus on the uniqueness of the problem the 'inside view,' and a focus on relevant statistical performance data from previous trials the 'outside view.' An excessive focus on the inside view implies that people will tend to be most overoptimistic about prospects for success when they neglect unfavorable non-salient statistical information; and tend to be less optimistic, and perhaps over-pessimistic about the prospects of success, when they neglect favorable statistical information.[1]

[1] Lovallo and Kahneman (2003) emphasize that the inside view tends to promote overoptimism on the part of managers because they are required to weave scenarios, imagine events, or gauge their own levels of ability and control, all of which are susceptible to organizational pressure and cognitive biases such as overoptimism, anchoring, and competitor neglect. The argument for optimism of managers does not necessarily extend to

Furthermore, there is extensive evidence that individuals pay less attention to, and place less weight upon, information that is harder to process (see, e.g., the review of Song and Schwarz 2010). As argued above, information about innovations is hard to process, because it requires developing and applying a theory of how the economic fundamentals of a firm or its industry are changing. It also requires an analysis of the road from patents to final products on the market, the profit of which can be highly uncertain and long deferred. We would expect such hard-to-process to be underweighted unless there is some offsetting effect (such as high salience).

These considerations suggest that investors will underreact to the information content in innovative efficiency because of the difficulty evaluating the economic implications of patents granted. If so, then firms that are more efficient in innovations may be undervalued, whereas firms that are less efficient in innovations may be overvalued. Therefore, we expect a positive relation between innovative efficiency and future stock returns.

An alternative argument for why innovative efficiency should predict higher future returns derives from the *q*-theories (Cochrane 1991, 1996; Liu, Whited, and Zhang 2009). Firms with higher innovative efficiency tend to be more profitable and have higher return-on-assets. All else equal, the *q*-theories imply that higher profitability predicts higher returns, because a high return on assets indicates that these assets were purchased by the firm at a discount (i.e., that they carry a high risk premium.).

Specifically, suppose that the market for capital being purchased by a firm is competitive and efficient. When a firm makes an R&D expenditure to purchase innovative capital, the

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investors, who have much less of a personal attachment to the firm's projects. (However, a possible example might be an analyst who has chosen to follow or recommend a firm based on a positive analysis, and thereby becomes prone to an optimistic inside view.) In any case, our focus is on how the degree of optimism/pessimism varies with statistical performance information, rather than the overall average degree of optimism.

price it pays will be appropriately discounted for risk. For concreteness, we can think for an example of a firm that acquires a high-tech target at a competitive market price.[2] In this scenario, a firm will on average achieve higher 'return' (large number of patents, resulting in high cash flows) on its innovative expenditures as fair compensation if its purchased innovative capital is highly risky, and will receive low return if capital is relatively low-risk. Past innovative efficiency is therefore a proxy for risk, so firms that have high past innovative efficiency should subsequently be productive in patenting (Dierickx and Cool 1989) and earn higher profits and stock returns.[3]

The evidence we provide supports this basic common prediction of the limited attention and the *q*-theories. To test our key prediction that innovative efficiency predicts stock returns, we define innovative efficiency (IE) as the ratio of the number of patents granted to five-year cumulative R&D expenditures with a two-year application-grant lag (more details are provided in Section 2.1).[4] We find a significantly positive relation between innovative efficiency and future stock returns, which standard risk factor models do not explain. Specifically, the value-weighted return of the high IE portfolio is 38 basis points per month higher than that of the low IE portfolio. The alphas of the high-minus-low IE portfolio estimated from the CAPM, the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model range from 45 to 46 basis points per month. In fact, the high-minus-low IE portfolio loads significantly negatively on the market and size factors, implying high

[2] When firms make acquisitions, under appropriate circumstances it can book part of the expenditure as 'in process R&D.'

[3] There are other possible rational risk arguments consistent with a positive relation between past innovative efficiency and future stock returns. A high level of innovative activity, even if successful in the past, is likely to be associated with greater economic uncertainty and real options, and therefore high risk and expected return. See, e.g., Greenwood and Jovanovic (1999), Berk, Green, and Naik (2004), Hsu (2009), Garleanu, Kogan, and Panageas (2009), Pastor and Veronesi (2009), and Garleanu, Panageas, and Yu (2009).

[4] Although patent citations are another measure of innovation output, they are subject to the forward-looking bias because the number of citations received by a patent is unknown when it is granted. Moreover, we also consider one-year and three-year cumulative R&D expenditures as the innovation input and obtain similar results.

IE firms are less risky than low IE firms from the perspective of these conventional risk factor models.

Adding the financing-based mispricing factor UMO (Undervalued Minus Overvalued, Hirshleifer and Jiang 2010) to the Fama-French three-factor model and the Carhart four-factor model improves their explanatory power. The loadings of the high-minus-low IE portfolio on UMO are significantly positive, suggesting high IE firms are undervalued relative to low IE firms. However, the alphas remain high at 31 basis points per month and are statistically significant at the 5% level.

The alternative three-factor model of Chen, Novy-Marx, and Zhang (2010) is motivated by an investment-based asset pricing model. It also explains a portion of this IE-return relation. The alpha estimated from this model is 24 basis points per month, which is significant at the 10% level. The improvement mainly derives from the significantly positive loading of the high-minus-low IE portfolio on the profitability (ROA) factor. This evidence suggests high IE firms are more profitable than low IE firms. Combining the investment-based three-factor model with the mispricing factor UMO further improves the explanatory power, and reduces the alpha to 20 basis points, which is no longer significant. These findings imply both mispricing and risk associated with profitability play a role in the IE-return relation.

The IE-return relation remains significant even after controlling for industry effects and other known return predictors, such as size, book-to-market, momentum, R&D intensity, investment intensity, ROA, asset growth, net stock issues, and institutional ownership as shown in Fama-MacBeth (1973) cross-sectional regressions.

To test whether constraints on investor attention affect the IE-return relation, we use size, analyst coverage, and advertising expenses as proxies for attention to a stock (Hong, Lim, and Stein 2000; Hirshleifer and Teoh 2003; Grullon Kanatas, and Weston 2004).[5] In Fama-MacBeth subsample regressions, we find higher average IE slopes in small stocks, stocks with low analyst coverage, and stocks with low advertising expenses, after controlling for other return predictors. For example, after controlling for R&D-to-sales in Fama-MacBeth regressions, the average IE slopes are 0.08% and 0.04% in small and big subsamples, respectively; 0.09% and 0.06% in low and high analyst coverage subsamples, respectively; and 0.13% and 0.07% in low and high advertising expenses subsamples, respectively. Although the cross-subsample differences in average IE slopes (small vs. big, low vs. high analyst coverage, or low vs. high advertising expenses) are not statistically significant, their magnitudes are economically substantial.

Moreover, we double-sort firms independently into three IE groups (low "L", middle "M", or high "H") and two investor attention groups based on size, analyst coverage, or advertising expenses. The returns and alphas on the high-minus-low IE portfolio are much higher among firms with small size. The monthly returns to the high-minus-low IE portfolio in the small and large subsamples are 61 and 33 basis points, respectively. The alphas estimated from the CAPM, the Fama-French three-factor model, and the Carhart four-factor model range from 55 to 66 basis points in the small subsample and from 39 to 42 basis points in the large subsample. However, the cross-subsample differences in returns and alphas are not always statistically significant.

Further analysis suggests different sources for the predictability of returns among large versus small firms. The investment-based three-factor model augmented by UMO fully

[5] Other measures of investor attention are related to these variables. For example, Fang and Peress (2009) report that media coverage increases in firm size and analyst coverage.

explains the IE-return relation in the large subsample, with its explanatory power mainly derived from the ROA (profitability) factor. However, none of the models can fully explain this relation in the small subsample, as the alpha of the high-minus-low IE portfolio estimated from the investment-based three-factor model augmented by UMO is 39 basis points per month and is 3.46 standard errors from zero. The explanatory power in this model mainly derives from UMO; the loading on the ROA factor is no longer significant. This factor model evidence suggests that among large firms the profitability factor contributes substantially to the ability of IE to predict returns, while among small firms mispricing contributes to the ability of IE to predict returns.

The mean hedge returns and alphas based on IE are also much higher among firms with low analyst coverage and low advertising expenses. Although the cross-subsample differences in the high-minus-low IE portfolio's returns and alphas are not always significantly positive, their magnitude is economically substantial and further confirms that limited attention leads to return predictability associated with innovative efficiency.

If the IE-return relation represents a market inefficiency driven by psychological constraints such as limited attention, we expect to observe greater return predictability among hard-to-value stocks. Following Kumar (2009), we use firm age, turnover, and idiosyncratic volatility as proxies of valuation uncertainty. Consistent with misvaluation effects, Fama-MacBeth regressions show that the average IE slopes are much higher among firms with younger age, higher turnover, and higher idiosyncratic volatility. For example, the IE slope in the young age subsample is 0.13 and significant at the 1% level. In contrast, the slope in the old age subsample is only 0.02 and insignificant.

To further examine if the IE-based return predictability is driven by risk, mispricing, or both, we construct a factor-mimicking portfolio for innovative efficiency, EMI (Efficient Minus Inefficient), following the procedure of Fama and French (1993). By combining long positions on firms with high innovative efficiency and short positions on stocks with low innovative inefficiency within different size categories, we form a portfolio that captures any incremental return comovement associated with innovative efficiency. We find that the EMI factor is negatively correlated with the market (–0.18) and size (–0.25) factors and positively correlated with ROA (0.33), UMO (0.31), the investment (0.11) factor, and the value (0.20) factor.

The EMI factor offers an ex post Sharpe ratio, 0.25, which is much higher than that of the market, size, value, momentum, and investment-related factors. The high level of the equity premium is a well-known puzzle for rational asset pricing theory (Mehra and Prescott 1985). So on the face of it, the high Sharpe ratio associated with the EMI factor also suggests the IE-return relation may be too strong to be entirely explained by rational risk premia.

Adding EMI to the Fama-French three factors increases the Sharpe ratio of the ex post tangency portfolio to 0.40 with a weight of 0.42 on EMI. Even when all the factors are included, the weight on EMI in the ex post tangency portfolio is 23%, which is substantially higher than that of any of the other factors except UMO and the market factor. These findings imply the IE-return relation captures return predictability effects above and beyond those captured by the other well-known factors.

Existing empirical literature on return predictability based upon innovation measures primarily focuses on the positive relation between R&D intensity or innovations in R&D spending and subsequent stock returns (Lev and Sougiannis 1996; Chan, Lakonishok, and Sougiannis 2001; Li 2010; Lin 2010; Li and Liu 2010; Eberhart, Maxwell, and Siddique

2004).[6] In contrast, our focus here is on predictability based upon innovative efficiency, a measure of innovative *output* (patents) relative to innovation input (R&D expenditures). Since there is a great deal of variation in the amount of innovative output generated per unit of R&D expenditure, innovative efficiency contains distinct value-relevant information.

2. The Data, the Innovative Efficiency Measure, and the Innovative Efficiency Portfolio

2.1. The Data and the Innovative Efficiency Measure

Our sample consists of firms in the intersection of Compustat, CRSP (Center for Research in Security Prices), and the NBER patent database. We obtain accounting data from Compustat and stock returns data from CRSP. All domestic common shares trading on NYSE, AMEX, and NASDAQ with accounting and returns data available are included except financial firms, which have four-digit standard industrial classification (SIC) codes between 6000 and 6999 (finance, insurance, and real estate sectors). Following Fama and French (1993), we exclude closed-end funds, trusts, American Depository Receipts, Real Estate Investment Trusts, units of beneficial interest, and firms with negative book value of equity. To mitigate backfilling bias, we require firms to be listed on Compustat for two years before

[6] Lev and Sougiannis (1996) document a positive relation between R&D capital scaled by market equity and stock returns, suggesting either a systematic mispricing of the shares of R&D-intensive companies, or a compensation for an extra-market risk factor associated with R&D. Chan, Lakonishok, and Sougiannis (2001) find R&D scaled by market equity predicts returns, but R&D scaled by sales does not. Li (2010) shows the R&D-return relation mainly exists in financially constrained firms and is robust to different measures of R&D intensity. Furthermore, this R&D-return relation can be fully explained by CAPM in many cases, suggesting R&D-intensive firms carry higher systematic risk when they are financially constrained. Lin (2010) and Li and Liu (2010) develop *q*-theory models consisting of intangible capital and tangible capital, and argue that intangible investment raises firm productivity and leads to higher expected stock returns. Eberhart, Maxwell, and Siddique (2004) document significantly positive long-term stock returns for firms that unexpectedly increase their R&D expenditures by a significant amount. They suggest R&D increases are beneficial investments, and that the market is slow to recognize the extent of this benefit.

including them in our sample. For some of our tests, we also obtain analyst coverage data from the Institutional Brokers Estimate System (IBES) and institutional ownership data from the Thomson Reuters Institutional (13f) Holdings dataset.

Patent-related data are from the updated NBER patent database originally developed by Hall, Jaffe, and Trajtenberg (2001). The database contains detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006:[7] patent assignee names, firms' Compustat-matched identifiers, the number of citations received by each patent, the number of citations excluding self-citations received by each patent, application dates, grant dates, and other details. Patents are included in the database only if they are eventually granted by the USPTO by the end of 2006. It is noted that the NBER patent database contains two time placers for each patent: its application date and grant date. To prevent any potential look-ahead bias, we choose the grant date as the effective date of each patent, and measure firm *i*'s innovation output in year *t* as the number of patents granted to firm *i* in year *t* ("patent counts").

We measure firm *i*'s innovative efficiency of year *t* as the ratio of firm *i*'s patent counts in year *t* to its R&D capital in fiscal year ending in year *t* – 2. Following Chan, Lakonishok, and Sougiannis (2001), we compute R&D capital as the five-year cumulative R&D expenditures assuming an annual depreciation rate of 20%. Specifically, R&D capital for firm *i* in year *t* is a weighted average of annual R&D expenditures over the last five years:

$$R\&D\ Capital_{i,t} = R\&D_{i,t} + 0.8*R\&D_{i,t-1} + 0.6*R\&D_{i,t-2} + 0.4*R\&D_{i,t-3} + 0.2*R\&D_{i,t-4}.$$

We allow a two-year gap between the innovation input and output as it takes, on average, two years for the USPTO to grant a patent application (Hall, Jaffe, and Trajtenberg

[7] The updated NBER patent database is available at https://sites.google.com/site/patentdataproject/Home/downloads.

2001).Therefore, the higher this ratio is, the more efficient a firm is in innovation. This is, of course, a measure of one type of innovative efficiency.

The IE measure is premised on R&D expenditures over the preceding five years contributing to successful patent applications. We recognize that the length of the lags between R&D expenditures and patent applications is hard to identify precisely and, thus, consider alternative measures of innovation input to scale the patents granted in year t: R&D expenditure in fiscal year ending in year $t-2$, and three-year cumulative R&D expenditures in fiscal year ending in year $t-2$. In unreported results, we find similar predictability.

We construct the IE measure for each year from 1981 to 2006. The sample period starts in 1981 to ensure the quality of R&D expenditure data. Since the accounting treatment of R&D expenses reporting is standardized in 1975 (Financial Accounting Standards Board Statement No. 2), the estimate of R&D capital starts in 1979 to allow for a full five-year period with reliable R&D expenditure data. Furthermore, the two-year application-grant lag makes 1981 the first year for the IE measure.

The patent database also records the number of citations received by the patents from the year granted till 2006. Patent citations reflect the technology or economic significance of patents (e.g., Trajtenberg 1990; Harhoff, Narin, Scherer, and Vopel 1999), but given the long time span in which they occur in the years after a patent is granted, citations are a less obvious candidate for predicting stock returns. Although patent citations are another measure of innovation output, they are subject to the forward-looking bias because the number of citations to be received by a patent through 2006 is unknown when it is granted. Nevertheless, we find the Pearson correlation between patent counts scaled by R&D capital and patent citations scaled by R&D capital is 0.85. This high correlation suggests that patent counts are likely to capture much of the valuation-relevant information contained in patent citations.

2.2. The Innovative Efficiency Portfolio

To examine the return predictability of IE, we sort firms into three groups (low, middle, and high) at the end of February of year *t* based on the 33th and 66th percentiles of IE measured in year $t - 1$. The two-month lag between the granted year end and the time of portfolio formation is imposed to ensure patent information known to the public. We hold the portfolios over the next twelve months (March of year *t* to February of year $t + 1$) and rebalance them every year.

Table 1 reports the time-series average of cross-sectional mean characteristics for the three IE groups and the group of firms with missing IE. IE is missing if either patent counts are missing or R&D capital is missing or is zero. All characteristics are for the year prior to the ranking year except market capitalization and momentum, which are measured at the end of February of the ranking year. On average, there are 1351 firms with non-missing IE and 3376 firms with missing IE each year. The distribution of the IE measure is skewed with the low, middle, and high IE groups containing 669, 232, and 450 firms, respectively. Firms with non-missing IE cover 55% of total U.S. market capitalization. This is therefore an economically interesting set of firms to study. The average market capitalizations of the middle and high IE groups are $4.81 billion and $2.76 billion, respectively. In contrast, the average market capitalizations of the low and missing IE groups are only $1.29 billion and $0.80 billion, respectively.

For every million dollars invested in R&D, the high IE group produces 2.54 patents, 48.34 citations including self-citations, and 45.11 citations excluding self-citations. On the other hand, the low IE group receives nearly zero patents, 0.01 citations including self-citations, and 0.01 citations excluding self-citations per million dollars of R&D capital. This pattern is consistent with the high correlation between patent counts and citations discussed before.

Table 1 also reports other characteristics that have been found to predict stock returns: R&D expenditure, R&D expenditure to market equity, R&D expenditure to sales, book-to-market ratio, net stock issues, return on assets (ROA), asset growth, capital expenditure scaled by total assets (CapEx/Assets), momentum, and institutional ownership. Book-to-market ratio is book equity over market capitalization. Net stock issues is the change in the natural log of split-adjusted shares outstanding. ROA is income before extraordinary items divided by lagged total assets. Asset growth is the change in total assets divided by lagged total assets. CapEx/Assets is capital expenditure divided by lagged total assets. Momentum is the prior six-month returns (with one-month gap between the holding period and the current month). Institutional ownership is the fraction of a firm's shares outstanding owned by institutional investors.

The high IE group has the lowest R&D intensity, suggesting that IE is distinct from R&D intensity. In general, the high IE group has lower book-to-market ratio, higher ROA, lower CapEx/Assets, higher institutional ownership, and issues less equity than the low IE group.

3. Predictability of Returns Based upon Innovative Efficiency

3.1. Single Sort Tests

Table 2 shows that average excess return, measured as the difference between monthly portfolio returns and the one-month Treasury bill rate, increases monotonically with IE. The value-weighted monthly excess returns on the low, middle, and high IE portfolios are 41 basis points (t = 2.54), 62 basis points (t = 2.35), and 79 basis points (t = 2.79), respectively. The difference between the high and low IE portfolio returns is 38 basis points per month (t = 2.54), which is statistically and economically significant.

We also examine whether the significant return spread between the high and low IE portfolios is explained by standard risk factor models, such as the CAPM, the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model, by regressing the time-series of portfolio excess returns on corresponding risk factor(s) returns. The CAPM contains only the market factor (MKT), which is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. In addition to the market factor, the Fama-French three-factor model contains the size factor (SMB) and the value factor (HML), which are the returns on two factor-mimicking portfolios associated with the size effect and the value effect, respectively. The Carhart four-factor model adds a momentum factor, which is the return on the winner-minus-loser portfolio, to the Fama-French three-factor model.[8] Table 2 shows these models do not explain the return spread between the low and high IE portfolios. In fact, the risk adjustment increases rather than decreases the return spread. The monthly alphas (intercepts) estimated from the CAPM, the Fama-French three-factor model, and the Carhart four-factor model for the high-minus-low IE portfolio are 45, 45, and 46 basis points, respectively. All alphas are larger than the return spread of 38 basis points and are close to or more than three standard errors from zero. A

[8] We obtain four-factor returns and the one-month Treasury bill rate from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

more interesting finding is that, if we interpret the slopes on the factors as risk exposures, the high IE firms are actually less risky than low IE firms; they have lower loadings on the market, size, value, and momentum factors in all three models. The differences between the loadings for high versus low IE firms on the market and size factors are statistically significant at the 1% level, while the differences between the loadings on the value and momentum factors are statistically insignificant.

If the IE-return relation is caused by limited investor attention, it reflects market mispricing. Several authors have suggested that there is commonality in mispricing (e.g., Daniel, Hirshleifer, and Subrahmanyam 2001 and Barberis and Shleifer 2003). For example, if investors do not fully impound information about common movements in innovative efficiency (arising, e.g., from technological change), we would expect a degree of commonality in the mispricing of innovative efficiency. To examine whether commonality in mispricing helps capture the IE effect, we augment the Fama-French model and the Carhart model by adding the mispricing factor (UMO, Undervalued Minus Overvalued) from Hirshleifer and Jiang (2010).[9] The UMO factor is the returns to a zero-investment portfolio that goes long on firms with debt repurchases or equity repurchases and short on firms with IPOs, SEOs, and debt issuances over the past 24 months. The authors interpret the new issue/repurchase activities as managers' response to overvaluation/undervaluation of their firms and provide evidence suggesting the UMO loadings proxy for the common component of a stock's mispricing.

Table 3 shows the addition of the UMO factor is a substantial improvement as it reduces the Fama-French alpha and the Carhart alpha of the high-minus-low IE portfolio by 14 and 15 basis points per month, respectively. Furthermore, the high-minus-low IE portfolio loads

[9] We obtain UMO factor returns from Danling Jiang's website: http://mailer.fsu.edu/~djiang/.

significantly positively on the UMO factor in both augmented models: 0.16 with a *t* statistic of 2.40 for the augmented Fama-French model and 0.24 with a *t* statistic of 3.54 for the augmented Carhart model. This pattern suggests that the high IE firms are undervalued relative to the low IE firms. Nevertheless, these augmented models do not fully explain this IE-return relation as their alphas remain substantial (31 basis points per month) and statistically significant.

These findings are consistent with the innovative efficiency effect being a consequence of market mispricing. Alternatively, innovative efficiency may load on other risk factors. We therefore study whether the investment-based three-factor model of Chen, Novy-Marx, and Zhang (2010) can explain the IE-return relation. This model is motivated by investment-based asset pricing models. The investment-based three-factor model consists of the market factor, an investment factor (INV), and a return on assets factor (ROA). The INV factor is the difference between the return to a portfolio of low-investment stocks and the return to a portfolio of high-investment stocks. The ROA factor is the difference between the return to a portfolio of stocks with high ROA and the return to a portfolio of stocks with low ROA.[10] We construct the INV and ROA factors following the methodology detailed in Chen, Novy-Marx, and Zhang (2010).

Table 4 shows the investment-based three-factor model helps reduce the monthly return spread between the high and low IE portfolios from 38 basis points (t = 2.54) to 24 basis points (t = 1.69), which is significant at the 10% level. So the model explains a substantial

[10] As the authors explain, investment predicts returns because given expected cash flows, high costs of capital imply low net present values of new capital and low investment. ROA predicts returns because high expected ROA relative to low investment implies high discount rates. The high discount rates are necessary to offset the high expected ROA and induce low net present values of new capital and low investment. If the discount rates were not high enough to offset the high expected ROA, firms would observe high net present values of new capital and invest more. Balakrishnan, Bartov, and Faurel (2010) report that the level of profits predicts individual stock returns (even after controlling for earnings surprise). Hirshleifer, Lim, and Teoh (2009) provide a model in which profitability predicts returns because of imperfect rationality.

portion of the return spread, but more than half of it remains. The improvement mainly results from better explanation of the low IE portfolio's return. For example, the Fama-French alpha is –24 basis points (t = –2.10), whereas the investment-based alpha is only –1 basis point (t = –0.14) for the low IE portfolio. Furthermore, the high-minus-low IE portfolio loads significantly positively on the ROA factor (loading 0.17, t = 3.62), but insignificantly on the INV factor. This suggests high IE firms are more profitable than low IE firms, which is intuitive as we would expect IE to be correlated with the profitability of a firm's intangible investment, and thereby with its overall profitability. In untabulated results, we also find that high IE firms continue to have higher ROA than low IE firms after the portfolio formation date.

Adding the UMO factor to the investment-based three-factor model further reduces the return spread to 20 basis points (t = 1.22), which is no longer statistically significant. The high-minus-low IE portfolio still loads significantly positively on the ROA factor (loading 0.15, with t = 3.14). The point estimate also indicates a positive but insignificant loading on the UMO factor.

Overall, the fact that none of the Fama-French three-factor model, the Carhart four-factor model, nor the investment-based three-factor model eliminate the innovative efficiency effect, but that the investment-based three-factor model together with the mispricing factor does capture the IE-return relation suggests that both rational risk premia and mispricing contribute to the relation.

3.2. Fama-MacBeth Regression Results

In order to control for other characteristics that can predict returns and make sure this IE-return relation does not simply reflect familiar effects or industry characteristics, we conduct Fama-MacBeth (1973) cross-sectional regressions. This provides a robustness check on earlier portfolio tests documenting the IE-return relation. For each month from July of year *t* to June of year *t* + 1, we regress monthly returns of individual stocks on innovative efficiency of year *t* – 1 and other control variables. The control variables include size, book-to-market ratio, momentum, R&D intensity, CapEx/Assets, ROA, asset growth, net stock issues, institutional ownership, and industry dummies.[11] All control variables are measured in the fiscal year ending in year *t* – 1 except size and momentum. Size is the market capitalization at the end of June of year *t*. Momentum is the prior six-month returns (with the standard one-month gap between the holding period and the current month; see, e.g., Hou, Peng, and Xiong 2009). The definitions of the other control variables are detailed in Section 2. The minimum six-month lag between stock returns and the other independent variables ensures the accounting variables are fully observable. To control for any industry effect, we also include industry dummies based on the 48 industry classification defined in Fama and French (1997) in all multivariate regressions. Nevertheless, similar results are obtained in the Fama-MacBeth regressions without industry dummies.

As the distribution of the IE measure is highly skewed and the measure is often zero, we use ln(1+IE) in the regression.[12] Since R&D intensity is sometimes zero as well, we also use ln(1+R&D intensity) in the regression. In unreported results, we find similar results when we simply include IE and R&D intensity in the regressions. We winsorize all independent variables at the 1% and 99%, and after winsorization we standardize all independent variables

[11] On the capital investment effect, see, e.g., Lyandres, Sun, and Zhang (2008) and Polk and Sapienza (2009). On the asset growth effect, see, e.g., Cooper, Gulen, and Schill (2008). On the net stock issuance effect, see, e.g., Daniel and Titman (2006), Fama and French (2008), and Pontiff and Woodgate (2008).
[12] The logarithmic linearization follows Lerner (1994), in which the logarithmic number of patent counts plus one is used as the main explanatory variable for biotechnology firm value.

to zero mean and one standard deviation to facilitate the comparison of the economic magnitudes of effects.

Table 5 reports the average slopes and their time-series *t*-statistics from the monthly cross-sectional regressions. There is a significantly positive relation between IE and stock returns which is robust to the inclusion of different sets of control variables. The slopes on ln(1+IE) are always positive and significant, regardless of the model specifications. For the univariate regression in Model (1), the slope on ln(1+IE) is 0.10% with a *t*-statistic of 3.38. In other words, a one standard deviation of increase in ln(1+IE) leads to an increase of 1.2% in compounded annual return. Models (2) and (4) add size, book-to-market ratio, momentum, and R&D intensity to the regression, and the slope on ln(1+IE) drops slightly to 0.09% but its *t*-statistics are even higher: 4.24 and 4.34 in Models (2) and (4), respectively. Models (3) and (5) additionally include the following regressors: CapEx/assets, ROA, asset growth, net stock issues, and institutional ownership. In these tests, the slope on ln(1+IE) further drops to 0.08% but the *t*-statistics remain high: 4.09 in Model (3) and 4.10 in Model (5).

The slopes on the control variables are consistent with the literature. Firms with smaller size, higher book-to-market ratio, higher R&D intensity, lower capital investment, higher ROA, lower asset growth, lower net stock issues, and higher institutional ownership provide higher stock returns. In unreported tables, we find that alternative measures of R&D intensity based on total assets, CapEx, and number of employees generate similar coefficients and statistical significance associated with IE. This evidence therefore indicates that the explanatory power of IE is robust and is distinct from that of the other control variables.

4. Limited Attention, Valuation Uncertainty, and the Strength of Return

Predictability

4.1. Fama-MacBeth Regressions within Attention and Valuation Uncertainty Subsamples

To test the proposed hypothesis that limited investor attention leads to a positive IE-return relation, we conduct Fama-MacBeth regressions within subsamples split by size, analyst coverage, and advertising expenses as proxies for investor attention to a stock.[13] Size is market capitalization. Analyst coverage is the average monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous year. We expect firms with smaller size, lower analyst coverage, and lower advertising expenses to receive less attention from investors, and therefore potentially to have more sluggish short-term stock price reactions to the information contained in innovative efficiency, and therefore greater predictability of future returns. Hong, Lim, and Stein (2000) test the information-diffusion model of Hong and Stein (1999) and report that the profitability of momentum strategies decreases with size and analyst coverage. In their theoretical paper on limited attention and stock prices, Hirshleifer and Teoh (2003) propose both size and analyst coverage measures as proxies for investor attention. Evidence on stock return lead-lags suggests that information diffuses gradually across between large and small firms, and between firms that are followed by different numbers of analysts (Brennan, Jegadeesh, and Swaminathan 1993; Hong, Torous, and Valkanov 2007; Hou 2007; Cohen and Frazzini 2008). Moreover, Grullon, Kanatas, and Weston (2004) argue that investors' familiarity with a stock increases with the amount of

[13] The Pearson and Spearman correlation coefficients between size and analyst coverage are 0.37 and 0.75, respectively. The Pearson and Spearman correlation coefficients between size and advertising expenses are 0.65 and 0.73, respectively. The Pearson and Spearman correlation coefficients between analyst coverage and advertising expenses are 0.41 and 0.61, respectively.

advertising, and report that stock issuers with higher advertising expenses attract a larger number of institutional and individual investors.

Also, consistent with size being a proxy for investor attention, Chambers and Penman (1984) and Bernard and Thomas (1989) find that post-earning announcement drift, an anomaly in which market prices underreact to earnings surprises, is strongest among small firms. Furthermore, the accrual anomaly, wherein market prices do not seem to fully reflect the information contained in cash flows versus accruals, is also stronger among small firms (Mashruwala, Rajgopal, and Shevlin 2006).

Several other papers also use measures of analyst stock coverage as proxies for analyst and/or investor attention. Irvine (2003) documents a rise in liquidity following initiation of analyst coverage of a stock. Bushee and Miller (2007) document that small firms that hire an investor relations firm subsequently experience increased analyst following, suggesting that investor relations expenditures succeed in increasing investor attention. Koester, Lundholm, and Soliman (2010) find that positive extreme earnings surprises are associated with low analyst following, and that the analysts who are following such firms are busier following a greater number of other firms. They further suggest that managers engineer such surprises to attract attention, and document that after such surprises analyst following increases. Andrade, Bian and Burch (2010) propose that information dissemination mitigates equity bubbles, and find that lower analyst coverage leads to greater price drop in reaction to the securities transaction tax increase in China in 2007.

We construct two size subsamples based on the NYSE median size breakpoint at the end of February of year t, two analyst coverage subsamples based on the median of analyst coverage calculated at the end of year $t - 1$, and two advertising expenses subsamples divided based on the median of the annual advertising expenses in the fiscal year ending in year t – 1.[14] Within each subsample, we then regress monthly returns of individual stocks in each month from July of year t to June of year t + 1 on standardized innovative efficiency and standardized control variables, including size, book-to-market ratio, momentum, R&D intensity, investment intensity, ROA, asset growth, net stock issues, institutional ownership, and industry dummies.

Panel A of Table 6 shows that the IE-return relation is stronger among firms of smaller size, lower analyst coverage, and lower advertising expenses. For example, when R&D intensity is measured by R&D expenditures scaled by sales, the average slopes of IE are 0.08% and 0.04% with t-statistics of 4.16 and 1.46 within the small and big subsamples, respectively. Such a difference in slopes of two subsamples is economically substantial but statistically insignificant. The average slopes of IE are 0.09% and 0.06% with t-statistics of 2.92 and 2.84 within the low and high analyst coverage subsamples, respectively. Furthermore, the average slopes of IE are 0.13% and 0.07% with t-statistics of 2.85 and 2.21 within the low and high advertising expenses subsamples, respectively. The sharp contrasts are robust to alternative measures of R&D intensity based on market equity, total assets, CapEx, and employees. These results thus support the hypothesis that limited investor attention leads to a positive IE-return relation.

To further evaluate the effect of limited attention on the IE-return relation, we perform Fama-MacBeth regressions within subsamples formed on valuation uncertainty (VU). Past literature has reported stronger behavioral biases among stocks or portfolios with higher

[14] To be consistent with the portfolio sorts, we split the sample at the end of February. Splitting the sample at the end of June generates similar results in unreported tables.

VU.[15] We expect the IE-return relation to be stronger among firms with more valuation uncertainty. Following Kumar (2009), we use three measures of VU: idiosyncratic volatility (IVOL), firm age, and turnover ratio.[16] IVOL is the standard deviation of the residuals from regressing daily stock excess returns on market excess returns over a maximum of 250 days. Firm age is the number of years listed on Compustat with non-missing price data. Turnover ratio is the average monthly turnover over the prior year, and the monthly turnover is the number of shares traded during a month divided by the number of shares outstanding at the end of the month.[17]

We interpret firms with lower age, higher turnover ratio, or higher idiosyncratic volatility as having higher valuation uncertainty. We form two age and two IVOL subsamples based on the median of these measures at the end of year $t-1$, and two turnover subsamples based on the median of the turnover ratio at the end of February of year t. Within each VU subsample, we conduct the same Fama-MacBeth regressions as were performed in the attention subsamples. We standardize all independent variables to zero mean and one standard deviation within each subsample to facilitate the comparison of slopes across subsamples.

Panel B of Table 6 shows a stronger IE-return relation in subsamples with higher valuation uncertainty. For example, when R&D intensity is defined as R&D expenditures

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[15] According to Einhorn (1980), overconfidence is greater in decision tasks involving greater uncertainty and less reliable feedback. Chan, Lakonishok, and Sougiannis (2001) find that the value effect (which is often interpreted as a behavioral anomaly) is stronger among firms with high R&D, for which valuation uncertainty is likely to be higher. Mashruwala, Rajgopal, and Shevlin (2006) find that the accrual anomaly is stronger among firms with high idiosyncratic volatility. This is consistent with greater misperceptions about such firms, or with high volatility being a barrier to arbitrage. Teoh, Yang, and Zhang (2009) also report that four financial anomalies are stronger among firms with lower R-squares. In a test of the model of Daniel, Hirshleifer, and Subrahmanyam (2001), Kumar (2009) reports greater individual investor trading biases among stocks with greater valuation uncertainty.

[16] The turnover ratio has alternatively been used as a proxy of investor attention in Hou, Peng, and Xiong (2009), so its interpretation is necessarily mixed. However, the other two measures of VU, idiosyncratic volatility and firm age, are not subject to the concern of dual-interpretations.

[17] Following the literature, e.g., LaPlante and Muscarella (1997) and Hou (2007), we divide the NASDAQ volume by a factor of two.

scaled by sales, the average slopes of IE are 0.13% and 0.02% with *t*-statistics of 4.93 and 0.74 in the young and old age subsamples, respectively. The difference in slopes across the age subsamples is significant at the 1% level (not reported). The average slopes of IE are 0.09% and 0.03% with *t*-statistics of 3.75 and 1.23 in the high and low turnover subsamples, respectively. Similarly, the average slopes of IE are 0.09 and 0.05 in the high and low IVOL subsamples, respectively. Both are statistically significant. Although the differences in slopes across the turnover and IVOL subsamples are statistically insignificant, their magnitude is substantial. These sharp contrasts across VU subsamples are robust to various specifications of R&D intensity, suggesting that the IE-return relation is more likely to be driven by behavioral biases.

4.2. Double-Sorted Portfolios Based upon IE and Attention Measures

To further examine how size affects the IE-return relation, we first double-sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint and three IE groups (low "L", middle "M", or high "H") based on the 33th and 66th percentiles of IE at the end of February of year *t*. Size is the market capitalization at the end of February of year *t*, and IE is measured in year $t - 1$. The intersection of these portfolios results in six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). We then form a zero-investment portfolio (S/H–L or B/H–L) that goes long on the high innovative efficiency portfolio and short on the low innovative efficiency portfolio within each size group. We hold these portfolios over the subsequent twelve months and rebalance them every year.

Table 7 reports the value-weighted monthly average excess returns, alphas, and factor loadings estimated from the CAPM, the Fama-French model, and the Carhart model for these portfolios. It shows the IE-return relation is significantly positive among both small and big firms, and standard risk factor models do not explain this relation among either category of firms. The excess return, the CAPM alpha, the Fama-French alpha, and the Carhart alpha of the S/H–L portfolio are 61, 66, 59, and 55 basis points per month, respectively, all significant at the 1% level. The corresponding estimates for the B/H–L portfolio are 33, 39, 40, and 42 basis points, all at the 1% or 5% level.

In fact, the factor loadings suggest high IE firms are not riskier than low IE firms in general. For example, both S/H–L and B/H–L portfolios load significantly negatively on the market factor in the CAPM: –0.07 (t = –2.55) and –0.09 (t = –2.13). In addition, the B/H–L portfolio also loads significantly negatively on the SMB factor in both Fama-French model and Carhart model: –0.18 (t = –2.71) and –0.18 (t = –2.69).

We also examine whether the IE-return relation across size groups can be explained by the investment-based three-factor model or the investment-based model augmented with the mispricing factor, UMO. As in the one-way sort results, Table 8 shows that the investment-based three-factor model helps explain a portion of the IE-return relation. Among small firms, the investment-based model reduces the return of the S/H–L portfolio from 61 basis points (t = 5.36) to 50 basis points (t = 3.85), mainly due to the significantly positive loading of the S/H–L portfolio on the ROA factor (0.11 with t = 2.37). Nevertheless, there is still a large portion of the return spread left unexplained. Among big firms, the investment-based model reduces the return of the B/H–L portfolio from 33 basis points (t = 2.19) to 24 basis points (t = 1.55), also mainly due to the significantly positive loading of the B/H–L portfolio on the ROA factor (0.14 with t = 2.73).

Adding the UMO factor to the investment-based three-factor model improves the explanatory power. Among small firms, the augmented model reduces the return on the S/H–L portfolio from 61 basis points to 39 basis points, although it is still significant at the 1% level. Furthermore, the mispricing factor dominates the INV and ROA factors in the small size group, suggesting an important role of mispricing in explaining the IE-return relation among small firms. Both INV and ROA loadings of the S/H–L portfolio are no longer significant (–0.00 with t = –0.04 and 0.07 with t = 1.17, respectively).[18] In contrast, the UMO loading of the S/H–L portfolio is positive with marginal significance (0.16 with t = 1.86).

The augmented model also does a better job in explaining the IE-return relation among large firms. It reduces the return on the B/H–L portfolio to 18 basis points (t = 1.10). The ROA loading of the B/H–L portfolio remains positive and significant and only drops slightly (0.11 with t = 2.17). The UMO loading is positive but insignificant (0.08 with t = 0.88). These findings suggest that mispricing contributes to the ability of IE to predict returns among small firms, while profitability contributes to the ability of IE to predict returns among large firms.

Tables 7 and 8 collectively offer three messages. First, the S/H–L portfolio loads heavily on the mispricing factor, while the B/H–L portfolio loads heavily on the ROA factor. Second, the S/H–L alphas are greater than the B/H–L alphas in all model specifications. Third, the S/H-L alphas are always significantly positive for all the factor models considered, but the B/H–L alphas are not. These findings empirically support the hypothesis that the market reacts sluggishly to news of firms with lower attention, leading to return predictability that is not fully explained by existing factor models.

We conduct the same portfolio analyses for the other two proxies of investor attention, analyst coverage and advertising expenses. The results are largely similar. The H–L portfolios

[18] Nevertheless, the ROA factor loadings are significant for all three individual portfolios (S/L, S/M, and S/H).

formed among firms with low attention have higher returns and alphas. These results further support the hypothesis that limited attention contributes to the return predictability associated with innovative efficiency.

5. The EMI (Efficient Minus Inefficient) Factor

To examine if the IE-return relation is driven by risk or mispricing (or both) and whether IE reflects commonality in returns not fully captured by existing factors, we construct an EMI (Efficient Minus Inefficient) factor following Fama and French (1993). Specifically, we form six size-IE portfolios using the same methodology detailed in Section 4.2. The EMI factor is the difference between the average of the value-weighted returns on the two high IE portfolios (S/H and B/H) and the average of the value-weighted returns on the two low IE portfolios (S/L and B/L). In other words, the EMI factor is (S/H + B/H)/2 – (S/L + B/L)/2. This return series tracks any factor return comovement associated with innovative efficiency, regardless of the underlying causes coming from systematic mispricing or rational risk.

Figure 1 plots the EMI factor returns and the MKT factor returns on a per annum basis from 1982 to 2008. Surprisingly, the EMI factor returns are negative for only four years out of 27 years, while the MKT factor returns are negative for eight years. Moreover, the EMI factor also appears to be a good hedge against market downturns; the EMI factor returns are almost always positive in those years in which the MKT factor returns are negative. For example, the MKT factor returns in 1984, 1987, 1990, 1994, 2000, 2001, 2002, and 2008 are –6.1%, –3.5%, –13.0%, –4.5%, –16.1%, –14.6%, –22.1%, and –41.8%, respectively. In contrast, the corresponding EMI factor returns are 4.7%, 18.6%, 7.2%, 9.2%, 30.8%, 1.6%, 11.1%, and 3.5%, respectively. More interestingly, even though the internet bubble burst in 2000, the

EMI factor performed extremely well, with a substantial return of 30.8%.

Table 9 reports the summary statistics for EMI and other well-known factor returns. Panel A describes the means, standard deviations, time series *t*-statistics, and the ex post Sharpe ratios of the monthly returns of EMI, Fama-French three factors (MKT, SMB, and HML), two investment-related factors (INV and ROA), the momentum factor (MOM), and the mispricing factor (UMO). The average return of EMI is 0.47% per month, which is lower than the average returns of MKT (0.66%), ROA (0.82%), MOM (0.80%), and UMO (0.90%); however, it is higher than the average returns of SMB (0.06%), HML (0.39%), and INV (0.22%).

Furthermore, the standard deviation of EMI is 1.88%, which is considerably lower than those of all the other factors except INV (1.79%). This finding indicates that investing based upon innovative efficiency is even more attractive than its substantial returns would suggest. Indeed EMI offers an ex post Sharpe ratio of 0.25, which is higher than that of all the other factors except UMO (0.28).[19]

Panel B reports the correlation between different factor returns, and shows that EMI is distinct from other familiar factors. EMI has a correlation of –0.18 with MKT, –0.25 with SMB, and 0.20 with HML, all of which are small in magnitude. Moreover, EMI has a correlation of 0.11 with INV, 0.33 with ROA, 0.00 with MOM, and 0.31 with UMO. The fairly high correlation between EMI and ROA suggests a link between IE and profitability. The high correlation between EMI and UMO, on the other hand, suggests a link between IE and systematic mispricing.

These findings suggest that investors may be able to do substantially better than the

[19] Ex post Sharpe ratio estimates are upward biased (MacKinlay 1995). However, adjusting for the bias would not change the qualitative nature of our conclusions. Moreover, we find that EMI offers an ex post Sharpe ratio of 0.23 after dropping the year 2000, in which EMI reaches its highest annualized return.

market portfolio, or the three Fama-French factors in optimal combination, by further including the EMI factor in their portfolios. Panel C describes the maximum ex post Sharpe ratios achievable by combining the various factors to form the tangency portfolio, which is, according to the mean-variance portfolio theory, the optimal portfolio of risky assets to select when a risk-free asset is available.

The first row shows that the monthly Sharpe ratio of the market is 0.15. The second row shows that when SMB is available as well, it receives negative weighting in the optimal portfolio (–12%), but that the maximum achievable Sharpe ratio remains the same. The third row shows that when HML is also available, it is weighted extremely heavily (52%), and almost doubles the Sharpe ratio, bringing it to 0.29. The fourth row shows that EMI substantially increases the ex post Sharpe ratio of the tangency portfolio, to 0.40. Moreover, the weight on EMI (42%) is much higher than that of any of the other three factors. The reason that EMI dominates in the tangency portfolio is that it combines three good features: a substantial average return, a very low standard deviation, and a very low (in some cases negative) correlation with the other three Fama-French factors.

The improvement in the maximum Sharpe ratio due to the existence of EMI is a challenge to rational risk premia as an explanation for IE-based return predictability. Previous research on the equity premium puzzle (Mehra and Prescott 1985) already indicates that the high Sharpe ratio of the stock market presents a difficult challenge for rational asset pricing theory. Furthermore, EMI retains its substantial role in the tangency portfolio, with weights ranging from 24% to 36% when combined with INV, ROA, MOM, or UMO. In unreported results, we find even when all the factors are included, the weight on EMI is 23%, which is substantially higher than that of any of the other factors except MKT and UMO. These findings suggest

EMI captures risk or mispricing effects above and beyond those captured by the above factors.

6. Conclusion

We find that firms that are more efficient in innovation earn higher subsequent returns. This relation is robust to controlling for other firm characteristics, such as size, book-to-market, momentum, R&D intensity, investment intensity, ROA, asset growth, net stock issue, and institutional ownership. Traditional empirical factor pricing models do not explain this relation. Our innovative efficiency proxy, patents granted per dollar of R&D capital, is a strong positive predictor of future returns even after adjusting for the Fama-French three-factor model or the Carhart four-factor model.

A model that combines the investment-based three-factor model with the financing-based mispricing factor UMO (Undervalued Minus Overvalued) captures most of the innovative efficiency effect in the full sample and in the large firm subsample, but not in the small firm subsample. Within the large firm subsample, explanatory power comes primarily from the ROA factor, whereas in the small firm subsample, explanatory power comes primarily from the misvaluation factor. These findings suggest that both risk and mispricing play a role in the IE-return relation.

Further analyses show that proxies for investor inattention and valuation uncertainty are associated with stronger ability of IE to predict returns. This provides further support for psychological bias or constraints contributing to the IE-return relation. The high ex post Sharpe ratio of the EMI (Efficient Minus Inefficient) factor also suggests this relation is not entirely explained by rational pricing. Finally, regardless of the source of the effect, the heavy weight of the EMI factor in the tangency portfolio suggests that innovative efficiency captures pricing effects above and beyond those captured by the other well-known factors.

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Table 1
Summary statistics

At the end of February of year t we sort firms into three groups based on the 33[th] and 66[th] percentiles of the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year t - 1. R&D capital is the five-year cumulative R&D expenditure computed in year t – 3 assuming an annual depreciation rate of 20%. The ratio is missing if either patent counts are missing or R&D capital is missing or zero. This table reports the time-series average of cross-sectional mean characteristics from March 1982 to February 2008. Market equity is measured at the end of February of year t. Patent citations are the number of citations received from the granted year till 2006. R&D/Market capitalization is R&D expenditure of fiscal year ending in year t – 1 divided by market equity at the end of year t – 1. R&D/Sales is R&D expenditure divided by sales. Book-to-market is the ratio of book equity of fiscal year ending in year t – 1 to market capitalization at the end of year t – 1. Book equity is the Compustat book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. Depending on availability, we use redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Market capitalization is CRSP price per share times the number of shares outstanding. Net stock issues are the change in the natural log of the split-adjusted shares outstanding. The split-adjusted shares outstanding are Compustat shares outstanding times the Compustat adjustment factor. ROA (in percentage) is income before extraordinary items divided by lagged assets. Asset growth is the change in total assets divided by lagged total assets. CapEx/Assets are capital expenditure divided by lagged total assets. Momentum is the prior six-month returns (with one-month gap between the holding period and the current month). Institutional ownership denotes the fraction of firm shares outstanding owned by institutional investors.

	Rank of patent counts/R&D capital			
	Low	Middle	High	Missing
Number of firms	677	248	462	3323
Market capitalization ($million)	1294.03	4809.53	2764.99	798.25
% of total market capitalization	14.6%	19.9%	21.3%	44.2%
Patent counts/R&D capital	0.00	0.07	2.54	
Patent citations/R&D capital	0.01	1.21	48.34	
Citations excluding self-cites/R&D capital	0.01	1.10	45.11	
R&D expenditure ($million)	40.51	187.53	72.81	7.64
R&D expenditure/Market capitalization	0.09	0.11	0.07	0.04
R&D expenditure/Sales	2.78	2.54	0.60	1.75
Book-to-market ratio	0.75	0.70	0.67	0.85
Net stock issues	0.07	0.04	0.04	0.06
ROA (%)	–5.46	–0.04	–0.04	0.59
Asset growth	0.23	0.15	0.18	0.21
CapEx/Assets	0.08	0.07	0.07	0.10
Momentum	0.02	0.06	0.05	0.00
Institutional ownership (IO)	0.29	0.49	0.43	0.31

Table 2
Innovative efficiency portfolio returns and standard risk factor models

At the end of February of year *t* from 1982 to 2007, we sort firms into three innovative efficiency portfolios based on the 33th and 66th percentiles of the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year *t* – 1. R&D capital is the five-year cumulative R&D expenditure computed in year *t* – 3 assuming an annual depreciation rate of 20%. We also form a zero-investment portfolio (H–L) that goes long on the high innovative efficiency portfolio and short on the low innovative efficiency portfolio. We hold the portfolios over the next 12 months and rebalance them each year. This table reports the monthly average value-weighted excess returns (in percentage) to these portfolios and the intercepts (α, in percentage) and slopes on standard risk factors from regressing portfolio excess returns on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess returns are the difference between portfolio returns and one-month Treasury bill rate. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997).

innovative efficiency	Excess return (%)	CAPM		Fama-French three-factor model				Carhart four-factor model				
		α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	MOM
Low	0.41	–0.40	1.21	–0.24	1.08	0.29	–0.24	–0.19	1.07	0.30	–0.25	–0.05
t	(1.30)	(–3.10)	(31.39)	(–2.10)	(29.61)	(7.73)	(–4.53)	(–1.65)	(30.21)	(7.93)	(–4.71)	(–1.40)
Middle	0.62	–0.07	1.02	0.08	0.96	–0.18	–0.25	0.09	0.96	–0.18	–0.25	0.00
t	(2.35)	(–0.75)	(48.84)	(1.03)	(41.18)	(–6.10)	(–6.11)	(1.02)	(39.79)	(–6.11)	(–6.14)	(–0.19)
High	0.79	0.05	1.10	0.21	1.01	–0.05	–0.26	0.27	1.00	–0.04	–0.27	–0.06
t	(2.79)	(0.53)	(38.15)	(2.31)	(39.11)	(–1.24)	(–5.71)	(3.01)	(40.19)	(–1.05)	(–6.26)	(–2.44)
H–L	0.38	0.45	–0.11	0.45	–0.07	–0.34	–0.02	0.46	–0.07	–0.34	–0.02	–0.01
t	(2.54)	(2.98)	(–2.75)	(3.12)	(–1.72)	(–5.97)	(–0.31)	(3.05)	(–1.74)	(–5.98)	(–0.34)	(–0.26)

Table 3
Innovative efficiency portfolio returns and standard risk factor models augmented with the mispricing factor (UMO)

At the end of February of year t from 1982 to 2007, we sort firms into three innovative efficiency portfolios based on the 33[th] and 66[th] percentiles of the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year $t-1$. R&D capital is the five-year cumulative R&D expenditure computed in year $t-3$ assuming an annual depreciation rate of 20%. We also form a zero-investment portfolio (H–L) that goes long on the high innovative efficiency portfolio and short on the low innovative efficiency portfolio. We hold the portfolios over the next 12 months and rebalance them each year. This table reports the monthly average value-weighted excess returns (in percentage) to these portfolios and the intercepts (α, in percentage) and slopes on factors from regressing portfolio excess returns on factor returns. Heteroscedasticity-robust t-statistics are reported in parentheses. Excess returns are the difference between portfolio returns and one-month Treasury bill rate. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). UMO (Undervalued Minus Overvalued) is the mispricing factor of Hirshleifer and Jiang (2010).

		Fama-French three-factor model plus UMO					Carhart four-factor model plus UMO					
innovative efficiency	Excess return (%)	α	MKT	SMB	HML	UMO	α	MKT	SMB	HML	MOM	UMO
Low	0.41	–0.06	1.02	0.29	–0.14	–0.20	–0.06	1.02	0.29	–0.13	0.01	–0.21
t	(1.30)	(–0.48)	(26.77)	(7.85)	(–2.43)	(–4.00)	(–0.48)	(26.63)	(7.70)	(–2.45)	(0.19)	(–3.99)
Middle	0.62	0.02	0.98	–0.18	–0.29	0.07	0.02	0.98	–0.18	–0.31	–0.03	0.10
t	(2.35)	(0.23)	(37.10)	(–5.85)	(–6.88)	(1.59)	(0.25)	(36.03)	(–5.62)	(–7.65)	(–1.07)	(2.05)
High	0.79	0.25	1.00	–0.05	–0.24	–0.04	0.25	1.01	–0.04	–0.29	–0.07	0.03
t	(2.79)	(2.61)	(36.54)	(–1.22)	(–4.52)	(–0.83)	(2.74)	(37.57)	(–1.00)	(–5.71)	(–2.52)	(0.67)
H–L	0.38	0.31	–0.02	–0.34	–0.10	0.16	0.31	–0.01	–0.33	–0.15	–0.08	0.24
t	(2.54)	(1.97)	(–0.45)	(–6.19)	(–1.30)	(2.40)	(2.05)	(–0.23)	(–6.10)	(–1.94)	(–1.64)	(3.54)

Table 4
Innovative efficiency portfolio returns and investment-based factors plus the mispricing factor (UMO)

At the end of February of year *t* from 1982 to 2007, we sort firms into three innovative efficiency portfolios based on the 33th and 66th percentiles of the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year *t* – 1. R&D capital is the five-year cumulative R&D expenditure computed in year *t* – 3 assuming an annual depreciation rate of 20%. We also form a zero-investment portfolio (H–L) that goes long on the high innovative efficiency portfolio and short on the low innovative efficiency portfolio. We hold the portfolios over the next 12 months and rebalance them each year. This table reports the monthly average value-weighted excess returns (in percentage) to these portfolios and the intercepts (αhttp://mailer.fsu.edu/~djiang/, in percentage) and slopes on factors from regressing portfolio excess returns on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess returns are the difference between portfolio returns and one-month Treasury bill rate. MKT is the market factor of Fama and French (1993). INV and ROA are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2010). UMO (Undervalued Minus Overvalued) is the mispricing factor of Hirshleifer and Jiang (2010).

innovative efficiency	Excess return (%)	Investment-based three-factor model				Investment-based three factor model plus UMO				
		α	MKT	INV	ROA	α	MKT	INV	ROA	UMO
Low	0.41	–0.01	1.06	–0.24	–0.28	0.06	1.04	–0.18	–0.26	–0.10
t	(1.30)	(–0.14)	(32.21)	(–3.70)	(–9.37)	(0.48)	(25.80)	(–2.32)	(–7.10)	(–1.63)
Middle	0.62	–0.07	1.02	–0.04	0.02	–0.02	1.00	0.00	0.04	–0.07
t	(2.35)	(–0.77)	(45.89)	(–0.77)	(0.73)	(–0.24)	(37.57)	(–0.02)	(1.33)	(–1.42)
High	0.79	0.23	1.03	–0.16	–0.12	0.25	1.02	–0.14	–0.11	–0.03
t	(2.79)	(2.43)	(39.90)	(–2.72)	(–4.30)	(2.58)	(35.58)	(–1.94)	(–3.45)	(–0.68)
H–L	0.38	0.24	–0.03	0.08	0.17	0.20	–0.02	0.04	0.15	0.07
t	(2.54)	(1.69)	(–0.82)	(0.88)	(3.62)	(1.22)	(–0.31)	(0.40)	(3.14)	(0.87)

Table 5
Fama-MacBeth regressions of stock returns on innovative efficiency and other variables

This table reports the average slopes (in %) and their time series *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions of individual stocks' returns from July of year *t* to June of year *t* + 1 on ln(1+IE) and other control variables in fiscal year ending in year *t* – 1 except size and momentum. IE is the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year *t* – 1. R&D capital is the five-year cumulative R&D expenditure computed in year *t* – 3 assuming an annual depreciation rate of 20%. ln(Size) is the natural log of market capitalization at the end of June of year *t*. ln(B/M) is the natural log of book-to-market ratio. Book equity is the Compustat book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. Depending on availability, we use redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. Market equity (ME) is CRSP price per share times the number of shares outstanding at the end of year *t* – 1. Momentum is the prior six-month returns (with one-month gap between the holding period and the current month). ln(1+R&D) denotes the logarithmic value of one plus R&D intensity, defined as R&D expenditure in fiscal year ending in year *t* – 1 divided by sales or market equity at the end of December of year *t* – 1. CapEx/Assets are capital expenditure divided by lagged total assets. ROA is income before extraordinary items divided by lagged assets. Asset growth is the change in total assets divided by lagged total assets. Net stock issues are the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in *t* – 1 divided by the split-adjusted shares outstanding at the fiscal year ending in *t* – 2. The split-adjusted shares outstanding are Compustat shares outstanding times the Compustat adjustment factor. Institutional ownership denotes the fraction of firm shares outstanding owned by institutional investors. To control for any industry effect, we also include industry dummies based on the 48 industry classification defined in Fama and French (1997) in all multivariate regressions. All independent variables are normalized to have zero mean and one standard deviation after winsorization at the 1% and 99%. The return data are from July of 1982 to June of 2008.

		R&D/Sales		R&D/ME	
Independent variables	(1)	(2)	(3)	(4)	(5)
ln(1+IE)	0.10	0.09	0.08	0.09	0.08
	(3.38)	(4.24)	(4.09)	(4.34)	(4.10)
ln(Size)		–0.19	–0.31	–0.17	–0.30
		(–1.59)	(–3.22)	(–1.39)	(–3.10)
ln(B/M)		0.44	0.33	0.38	0.26
		(7.01)	(6.11)	(5.16)	(4.25)
Momentum		–0.04	–0.06	–0.05	–0.07
		(–0.35)	(–0.57)	(–0.48)	(–0.70)
ln(1+R&D)		0.01	0.09	0.25	0.26
		(0.22)	(1.58)	(3.85)	(4.43)
CapEx/Asset			–0.06		–0.06
			(–1.88)		(–2.00)
ROA			0.26		0.27
			(4.52)		(4.62)
Asset growth			–0.27		–0.24
			(–6.78)		(–6.25)
Net stock issues			–0.11		–0.13
			(–2.54)		(–3.02)
Institutional ownership			0.12		0.12
			(2.57)		(2.54)

Table 6
Fama-MacBeth regressions: Subsample analysis

This table reports the average slopes (in %) of ln(1+IE) and their time series t-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions of individual stocks' returns from July of year t to June of year $t+1$ on ln(1+IE) and other control variables in fiscal year ending in year $t-1$ except size and momentum in subsamples split by the medians of firm size, analyst coverage, advertising expenses, firm age, turnover ratio, and idiosyncratic volatility (IVOL). IE is the ratio of patent counts to R&D capital. Patent counts are the number of patents granted in year $t-1$. R&D capital is the five-year cumulative R&D expenditure computed in year $t-3$ assuming an annual depreciation rate of 20%. Firm size is the market capitalization at the end of June of year t. Analyst coverage is the average monthly number of stock analyst reports on earnings estimates in year $t-1$. Advertising expenses are measured in year $t-1$. Firm age denotes the number of years listed on Compustat with non-missing price data. Turnover ratio is the average monthly turnover over the prior year, and the monthly turnover is the number of shares traded during a month divided by the number of shares outstanding at the end of the month. IVOL is standard deviation of residuals from regressing daily stock excess returns on market excess returns over a maximum of 250 days ending on December 31. All regressions include the following control variables: ln(Size), ln(B/M), momentum, ln(1+R&D), CapEx/Assets, ROA, asset growth, net stock issues, and institutional ownership. The details of these control variables are provided in Table 5. We also include industry dummies based on the 48 industry classification defined in Fama and French (1997) in all multivariate regressions. All independent variables are normalized to have zero mean and one standard deviation after winsorization at the 1% and 99%. The return data are from July of 1982 to June of 2008.

Panel A: Subsamples split by investor attention proxies					
	R&D/Sales	R&D/ME	R&D/Assets	R&D/CapEx	R&D/Employees
Small size	0.08	0.08	0.08	0.08	0.07
	(4.16)	(4.14)	(4.26)	(4.16)	(3.71)
Big size	0.04	0.05	0.04	0.04	0.04
	(1.46)	(1.99)	(1.55)	(1.72)	(1.53)
Low analyst coverage	0.09	0.09	0.09	0.09	0.08
	(2.92)	(2.92)	(2.93)	(2.90)	(2.77)
High analyst coverage	0.06	0.06	0.06	0.06	0.06
	(2.84)	(2.78)	(2.70)	(2.75)	(2.59)
Low advertising expenses	0.13	0.14	0.13	0.14	0.13
	(2.85)	(2.94)	(2.83)	(2.87)	(2.70)
High advertising expenses	0.07	0.08	0.07	0.07	0.07
	(2.21)	(2.27)	(2.24)	(2.18)	(2.07)

Panel B: Subsamples split by valuation uncertainty proxies					
	R&D/Sales	R&D/ME	R&D/Assets	R&D/CapEx	R&D/Employees
Young age	0.13	0.13	0.13	0.13	0.12
	(4.93)	(4.82)	(4.90)	(4.85)	(4.67)
Old age	0.02	0.02	0.02	0.02	0.01
	(0.74)	(0.99)	(0.97)	(0.71)	(0.44)
High turnover ratio	0.09	0.09	0.09	0.09	0.09
	(3.75)	(3.93)	(3.86)	(3.81)	(3.52)
Low turnover ratio	0.03	0.03	0.03	0.03	0.02
	(1.23)	(1.18)	(1.15)	(1.16)	(0.87)
High IVOL	0.09	0.10	0.10	0.10	0.08
	(3.18)	(3.25)	(3.31)	(3.22)	(2.88)
Low IVOL	0.05	0.05	0.05	0.05	0.05
	(3.24)	(3.23)	(3.08)	(3.18)	(2.95)

Table 7
Size/innovative efficiency portfolio returns and standard risk factor models

At the end of February of year *t* from 1982 to 2007, we sort firms independently into two size groups (S or B) based on NYSE median size breakpoints and three innovative efficiency (IE) groups (L, M, or H) based on the 33[th] and 66[th] percentiles of IE, the ratio of patent counts to R&D capital. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Size is the market capitalization at the end of February of year *t*. Patent counts are the number of patents granted in year *t* – 1. R&D capital is the five-year cumulative R&D expenditure computed in year *t* – 3 assuming an annual depreciation rate of 20%. We also form a zero-investment portfolio (H–L) that goes long on the high innovative efficiency portfolio and short on the low innovative efficiency portfolio within each size group. We hold the portfolios over the next 12 months and rebalance them each year. This table reports the time-series mean of cross-sectional average number of firms for these portfolios. It also reports the monthly average value-weighted excess percent returns to these portfolios and the intercepts (α, in percentage) and slopes on standard risk factors from regressing portfolio excess returns on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess returns are the difference between portfolio returns and one-month Treasury bill rate. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997).

	No. of	Excess	CAPM		Fama-French three-factor model				Carhart four-factor model				
Size/IE	firms	return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	MOM
S/L	616	0.35	–0.55	1.35	–0.42	1.14	1.04	–0.14	–0.35	1.13	1.05	–0.16	–0.08
t		(0.89)	(–2.58)	(26.24)	(–4.46)	(37.68)	(16.67)	(–2.88)	(–3.70)	(41.14)	(17.64)	(–3.06)	(–2.18)
S/M	138	0.89	–0.04	1.38	0.13	1.15	1.08	–0.19	0.22	1.13	1.09	–0.21	–0.10
t		(2.13)	(–0.15)	(26.37)	(0.90)	(26.73)	(12.08)	(–2.67)	(1.59)	(28.95)	(12.12)	(–2.87)	(–1.90)
S/H	310	0.96	0.10	1.28	0.16	1.11	1.00	–0.03	0.20	1.11	1.00	–0.04	–0.04
t		(2.56)	(0.50)	(27.16)	(1.42)	(29.12)	(11.72)	(–0.61)	(1.78)	(30.80)	(11.97)	(–0.74)	(–0.91)
S/H–L		0.61	0.66	–0.07	0.59	–0.03	–0.04	0.11	0.55	–0.02	–0.05	0.11	0.04
t		(5.36)	(5.77)	(–2.55)	(5.02)	(–0.87)	(–0.67)	(2.22)	(4.71)	(–0.69)	(–0.81)	(2.51)	(0.99)
B/L	61	0.46	–0.33	1.18	–0.17	1.08	0.09	–0.25	–0.14	1.07	0.09	–0.26	–0.04
t		(1.46)	(–2.45)	(27.08)	(–1.26)	(23.45)	(1.74)	(–3.99)	(–1.00)	(24.12)	(1.83)	(–4.18)	(–0.95)
B/M	110	0.62	–0.06	1.01	0.09	0.95	–0.21	–0.26	0.09	0.95	–0.21	–0.26	0.00
t		(2.35)	(–0.68)	(47.39)	(1.08)	(39.96)	(–6.88)	(–6.18)	(1.05)	(38.71)	(–6.94)	(–6.21)	(–0.12)
B/H	152	0.79	0.06	1.09	0.23	1.01	–0.10	–0.27	0.28	1.00	–0.09	–0.28	–0.06
t		(2.80)	(0.57)	(36.09)	(2.36)	(37.68)	(–2.36)	(–5.75)	(3.00)	(38.73)	(–2.16)	(–6.26)	(–2.26)
B/H–L		0.33	0.39	–0.09	0.40	–0.07	–0.18	–0.02	0.42	–0.07	–0.18	–0.03	–0.02
t		(2.19)	(2.49)	(–2.13)	(2.45)	(–1.49)	(–2.71)	(–0.27)	(2.50)	(–1.56)	(–2.69)	(–0.33)	(–0.47)

Table 8
Size/innovative efficiency portfolio returns and investment-based factors plus the mispricing factor (UMO)

At the end of February of year *t* from 1982 to 2007, we sort firms independently into two size groups (S or B) based on NYSE median size breakpoints and three innovative efficiency (IE) groups (L, M, or H) based on the 33th and 66th percentiles of IE, the ratio of patent counts to R&D capital. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Size is the market capitalization at the end of February of year *t*. Patent counts are the number of patents granted in year *t* – 1. R&D capital is the five-year cumulative R&D expenditure computed in year *t* – 3 assuming an annual depreciation rate of 20%. We also form a zero-investment portfolio (H–L) that is long the high innovative efficiency portfolio and short the low innovative efficiency portfolio within each size group. We hold the portfolios over the next 12 months and rebalance them each year. This table reports the monthly average value-weighted excess percent returns to these portfolios and the intercepts (α, in percentage) and slopes on standard risk factors from regressing portfolio excess returns on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess returns are the difference between portfolio returns and one-month Treasury bill rate. MKT is the market factor of Fama and French (1993). INV and ROA are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2010). UMO (Undervalued Minus Overvalued) is the mispricing factor of Hirshleifer and Jiang (2010).

		Investment-based three-factor model				Investment-based three-factor model plus UMO				
Size/IE	Excess return	α	MKT	INV	ROA	α	MKT	INV	ROA	UMO
S/L	0.35	0.02	1.13	–0.25	–0.46	0.08	1.11	–0.21	–0.43	–0.08
t	(0.89)	(0.10)	(19.24)	(–2.01)	(–6.32)	(0.38)	(17.25)	(–1.18)	(–4.18)	(–0.52)
S/M	0.89	0.53	1.17	–0.38	–0.41	0.51	1.17	–0.39	–0.41	0.02
t	(2.13)	(1.70)	(16.37)	(–2.37)	(–3.42)	(2.11)	(17.55)	(–1.53)	(–2.44)	(0.08)
S/H	0.96	0.53	1.12	–0.16	–0.34	0.47	1.14	–0.21	–0.36	0.08
t	(2.56)	(1.90)	(17.19)	(–1.16)	(–3.38)	(2.21)	(18.86)	(–0.94)	(–2.50)	(0.40)
S/H–L	0.61	0.50	–0.01	0.09	0.11	0.39	0.03	–0.00	0.07	0.16
t	(5.36)	(3.85)	(–0.43)	(1.23)	(2.37)	(3.46)	(1.03)	(–0.04)	(1.17)	(1.86)
B/L	0.46	–0.01	1.05	–0.18	–0.25	0.07	1.02	–0.11	–0.22	–0.11
t	(1.46)	(–0.09)	(29.11)	(–2.48)	(–7.41)	(0.53)	(23.56)	(–1.27)	(–5.79)	(–1.62)
B/M	0.62	–0.08	1.02	–0.04	0.03	–0.03	1.00	0.00	0.05	–0.07
t	(2.35)	(–0.81)	(44.69)	(–0.66)	(0.99)	(–0.29)	(36.74)	(0.07)	(1.54)	(–1.37)
B/H	0.79	0.23	1.02	–0.15	–0.11	0.25	1.01	–0.13	–0.10	–0.03
t	(2.80)	(2.31)	(37.52)	(–2.61)	(–4.00)	(2.42)	(33.30)	(–1.89)	(–3.33)	(–0.66)
B/H–L	0.33	0.24	–0.03	0.02	0.14	0.18	–0.01	–0.02	0.11	0.08
t	(2.19)	(1.55)	(–0.77)	(0.24)	(2.73)	(1.10)	(–0.22)	(–0.20)	(2.17)	(0.88)

Table 9
Summary statistics of monthly factor returns and Sharpe Ratio (SR)

At the end of February of year *t* from 1982 to 2007, we sort firms independently into two size groups (S or B) based on NYSE size breakpoints and three innovative efficiency (IE) groups (L, M, or H) based on the 33th and 66th percentiles of IE, the ratio of patent counts to R&D capital. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Size is the market capitalization at the end of February of year *t*. Value-weighted monthly excess returns on these six double-sorted portfolios are computed from March of year *t* to February of year *t* + 1. The innovation-efficiency factor—EMI (Efficient Minus Inefficient)—is (S/H+B/H)/2-(S/L+B/L)/2. MKT is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. SMB and HML are the returns on two factor-mimicking portfolios associated with the size effect and book-to-market effect, respectively. MOM denotes the momentum factor, while INV and ROA are two investment-based factors based on investment intensity and ROA, respectively. UMO is the mispricing factor. Panel C reports the monthly Sharpe ratios of ex post tangency portfolios based on investing in subsets of the four factor-mimicking portfolios. Portfolio weights are determined by $\Omega^{-1}r$, normalized to sum to one. Ω is the sample covariance matrix and *r* is the column vector of average excess returns of the factor mimicking portfolios. All returns are in percentage.

Panel A: Summary statistics of factor-mimicking portfolios

	MKT	SMB	HML	EMI	INV	ROA	MOM	UMO
Mean	0.66	0.06	0.39	0.47	0.22	0.82	0.80	0.90
Std	4.29	3.25	3.06	1.88	1.79	4.61	4.22	3.26
t-stat	2.73	0.32	2.27	4.46	2.15	3.16	3.34	4.87
Ex post SR	0.15	0.02	0.13	0.25	0.12	0.18	0.19	0.28

Panel B: Correlation matrix of factor-mimicking portfolios

	MKT	SMB	HML	EMI	INV	ROA	MOM	UMO
MKT	1.00							
SMB	0.20	1.00						
HML	–0.49	–0.42	1.00					
EMI	–0.18	–0.25	0.20	1.00				
INV	–0.31	–0.16	0.43	0.11	1.00			
ROA	–0.37	–0.50	0.47	0.33	0.14	1.00		
MOM	–0.09	0.11	–0.08	0.00	0.14	0.20	1.00	
UMO	–0.62	–0.28	0.66	0.31	0.50	0.57	0.34	1.00

Panel C: Ex post tangency portfolio

Portfolio weights								Tangency portfolio		
MKT	SMB	HML	EMI	INV	ROA	MOM	UMO	Mean	Std	Ex post SR
1								0.66	4.29	0.15
1.12	–0.12							0.73	4.75	0.15
0.34	0.14	0.52						0.44	1.50	0.29
0.20	0.12	0.26	0.42					0.44	1.09	0.40
0.19	0.11	0.19	0.36	0.15				0.41	0.99	0.42
0.20	0.17	0.19	0.32		0.12			0.47	1.07	0.44
0.19	0.09	0.24	0.35			0.13		0.50	1.07	0.46
0.27	0.09	0.03	0.24				0.38	0.64	1.19	0.54

Figure 1
EMI (Efficient Minus Inefficient) and market factor returns over time

This figure plots the value-weighted return (on a per annum basis) for the EMI (Efficient Minus Inefficient) factor and the market factor from 1982 to 2008. Rm–Rf (or MKT) is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. At the end of February of year t from 1982 to 2007, we sort firms independently into two size groups (S or B) based on NYSE size breakpoints and three innovative efficiency (IE) groups (L, M, or H) based on the 33th and 66th percentiles of IE, the ratio of patent counts to R&D capital. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Size is the market capitalization at the end of February of year t. Patent counts are the number of patents granted in year t – 1. R&D capital is the five-year cumulative R&D expenditure computed in year t – 3 assuming an annual depreciation rate of 20%. Value-weighted monthly excess returns on these six double-sorted portfolios are computed from March of year t to February of year t + 1. The innovation-efficiency factor—EMI (Efficient Minus Inefficient)—is (S/H+B/H)/2–(S/L+B/L)/2.