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Innovative efficiency and stock returns ☆

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ABSTRACT

We find that innovative efficiency (IE), patents or citations scaled by research and development expenditures, is a strong positive predictor of future returns after controlling for firm characteristics and risk. The IE-return relation is associated with the loading on a mispricing factor, and the high Sharpe ratio of the Efficient Minus Inefficient (EMI) portfolio suggests that mispricing plays an important role. Further tests based upon attention and uncertainty proxies suggest that limited 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.

1. Introduction

Recent studies provide 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, therefore, argue that limited attention results in underreaction and return predictability. Theoretical models also predict that limited investor attention affects stock prices and can cause market underreaction (Hirshleifer and Teoh, 2003; Hirshleifer, Lim, and Teoh, 2011; 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 that is 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 major

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shifts in industrial organizational structure.[1] 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 positive (negative) abnormal returns after good (bad) news.

In this study, we examine the relation between innovative efficiency and subsequent operating performance as well as stock returns. By innovative efficiency, we mean a firm's ability to generate patents and patent citations per dollar of research and development (R&D) investment. The denominator, R&D, measures resource input to innovation. Patents and citations are measures of innovative output, because innovations are usually officially introduced to the public in the form of approved patents. US 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) owing to the creation of the Court of Appeals for the Federal Circuit in 1982 and several well-documented patent lawsuits (e.g., the Kodak-Polaroid case). Patents are thus the most important measure of contemporary firms' innovative output (Griliches, 1990), and they are actively traded in intellectual property markets (Lev, 2001).

A firm's past innovative efficiency can be less salient to investors than explicitly forward-looking information about the prospects for the particular R&D projects that the firm is undertaking. For example, investors devote considerable attention to analyst reports and news articles about the potential outcomes of clinical phase trials conducted by a biotech and pharmaceutical firm, while historical performance of past R&D efforts receives less media attention. According to Kahneman and Lovallo (1993, p. 17), 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 over-optimistic 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.[2]

Furthermore, extensive evidence exists 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). 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 information 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 and patent citations. If so, then firms that are more efficient in innovations will be undervalued relative to firms that are less efficient in innovations. Therefore, we expect a positive relation between innovative efficiency and future stock returns and operating performance.

An alternative argument for why innovative efficiency would predict higher future returns derives from the q-theory (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-theory implies 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 price it pays is appropriately discounted for risk. For concreteness, we can think, for example, of a firm that acquires a high-tech target at a competitive market price.[3] In this scenario, a firm on average achieves 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 it receives 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 (IE) should subsequently be productive in patenting (Dierickx and Cool, 1989) and earn higher profits and stock returns.[4] In other words, q-theory also predicts a positive IE-return relation.

To test our key hypothesis that innovative efficiency is positively associated with contemporaneous stock market valuation and positively predicts future operating performance, market valuation, and stock returns, we use two measures of innovative efficiency in year t: patents granted in year t scaled by R&D capital in year $t-2$

[1] For example, a firm might not invest in converting approved patents to final products immediately upon approval owing to capital budget constraints, extent of competition, and market demand.

[2] 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 stock investors, who have much less of a personal attachment to the firm's projects. In any case, our focus is on how the degree of optimism or pessimism varies with statistical performance information, not the overall average degree of optimism.

[3] Firms that make acquisitions can, under appropriate circumstances, book part of the expenditure as "in process R&D."

[4] Other possible rational risk arguments are 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 possession of real options and, therefore, high risk and expected return. See, e.g., Greenwood and Jovanovic (1999), Berk, Green, and Naik (2004), Hsu (2009), Pastor and Veronesi (2009), Garleanu, Kogan, and Panageas (2012), and Garleanu, Panageas, and Yu (2012).

(*Patents/RDC*) and adjusted patent citations received in year t by patents granted in years $t-1$ to $t-5$ scaled by the sum of R&D expenses in years $t-3$ to $t-7$ (*Citations/RD*). The lag between the innovative input (*R&D*) and output (*patents*) reflects the average two-year application-grant lag (Section 3.1 provides details). These IE measures are in general not highly correlated with other innovation-related return and operating performance predictors, such as R&D-to-market equity (Chan, Lakonishok, and Sougiannis, 2001), significant R&D growth (Eberhart, Maxwell, and Siddique, 2004), patents-to-market equity, and change in adjusted patent citations scaled by average total assets (Gu, 2005). Therefore, the IE measures potentially contain useful incremental information.

Fama-MacBeth (1973) regressions show that a higher IE measure (using a logarithmic transform of IE) predicts significantly higher return on assets (ROA) and cash flows (CF) over the next year after extensive controls.[5] We also find that both current and lagged IE are significantly positively associated with equity market-to-book (MTB) using Fama-MacBeth regressions that control for abnormal earnings, R&D tax shields, R&D-to-book equity, *RDG*, *PAT/ME*, Δ*APC*, *AD/ME*, *CapEx/ME*, and *industry*.

Furthermore, a significantly positive relation exists between the two IE measures and future stock returns using Fama-MacBeth regressions that control for various possible industry variables and return predictors, including *RD/ME*, *RDG*, *PAT/ME*, Δ*APC*, *size*, book-to-market equity (*BTM*), momentum, *CapEx/ME*, *AD/ME*, *ROA*, asset growth, net stock issues, and institutional ownership. These findings support our hypotheses that innovative efficiency contains distinct information about future operating performance and market valuation that is incremental to that of other innovation measures and firm characteristics.

Portfolio analysis confirms the significantly positive relation between IE and future operating performance as well as stock returns. We sort firms with non-missing IE measures into three IE portfolios (Low, Middle, and High) based on the 33rd and 66th percentiles of the IE measures, and we find that the high IE groups in general have the highest ROA, cash flows, earnings, and profit margin averaged over the subsequent 5 years. The monthly value-weighted size-adjusted returns in excess of the one-month Treasury bill rate for the IE portfolios increase monotonically with IE: 49, 86, and 90 basis points for the low, middle, and high *Patents/RDC* portfolios, respectively, and 59, 81, and 85 basis points for the low, middle, and high *Citations/RD* portfolios, respectively.

The risk-adjusted returns of the IE portfolios also increase monotonically with IE. Specifically, the monthly value-weighted alphas estimated from the Carhart (1997) four-factor model for the low, middle, and high *Patents/RDC* portfolios are -19, 22, and 27 basis points, respectively, and the monthly Carhart alphas for the low, middle, and high *Citations/RD* portfolios are -9, 14, and 26 basis points, respectively. Furthermore, the positive alphas of the high *IE* portfolios are statistically significant at the 1% level, which indicates that high *IE* firms are undervalued relative to the Carhart model benchmark. In unreported results, we find the difference in the Carhart alphas between the high and low *IE* portfolios is also statistically significant at the 1% level for both *IE* measures.

These patterns are similar for alphas estimated from the Fama and French (1993) three-factor model and the investment-based three-factor model (Chen, Novy-Marx, and Zhang, 2011). In addition, the high *IE* portfolio generally has lower loadings than the low *IE* portfolio on the market factor, suggesting that high *IE* firms are less risky than low *IE* firms.

To examine whether the financing-based mispricing factor Undervalued Minus Overvalued (UMO; Hirshleifer and Jiang, 2010) helps explain the IE effect, we add UMO to the Carhart model and the investment-based model. We find the alphas estimated from these augmented models for the high IE portfolios remain significantly positive at the 1% level. This evidence indicates that the IE effect is incremental to the mispricing effect as captured by UMO. In addition, the alphas estimated from these augmented models increase monotonically with IE. In unreported results, we find the difference in the alphas estimated from these two augmented models between the high and low IE portfolios is also statistically significant at the 1% level for both IE measures.

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 stocks with low investor attention and among hard-to-value stocks. To test this hypothesis, we use size and analyst coverage as proxies for attention to a stock (Hong, Lim, and Stein, 2000) and firm age, turnover, and idiosyncratic volatility as proxies for valuation uncertainty (Kumar, 2009).[6] We expect a stronger IE effect among firms with small market capitalization, low analyst coverage (AC), young age, high turnover, and high idiosyncratic volatility (IVOL).

The Fama-MacBeth subsample regressions provide supporting evidence. The average IE slopes among low attention and hard-to-value stocks are in general statistically significant and are substantially larger than those among high attention and easy-to-value stocks, which often are insignificant. For example, the slope on *Citations/RD* is 0.08% (t=2.21) in low AC firms, but only 0.05% (t=1.65) in high AC firms. Similarly, the slope on *Citations/RD* is 0.11% (t=3.26) in young firms, but only 0.02% (t=0.91) in old firms. In addition, the slope on *Citations/RD* is 0.08% (t=2.08) in high IVOL firms, but only 0.03% (t=1.34) in low IVOL firms. Although the cross-

[5] These tests control for *ROA* or *CF*, change in *ROA* or *CF*, R&D-to-market equity (*RD/ME*), significant R&D growth (*RDG*), patents-to-market equity (*PAT/ME*), change in adjusted patent citations scaled by total assets (Δ*APC*), advertising expenditures scaled by market equity (*AD/ME*), capital expenditures scaled by market equity (*CapEx/ME*), and industry.

[6] 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.

subsample differences in the IE slopes are not always statistically significant, their magnitudes are economically substantial.

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, Efficient Minus Inefficient (EMI), based on *Patents/RDC* (*EMI1*) and on *Citations/RD* (*EMI2*) following the procedure in Fama and French (1993). Specifically, at the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint at the end of June of year t, and three IE groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of IE in year $t-1$. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Value-weighted monthly returns on these six portfolios are computed from July of year t to June of year $t+1$. The EMI factor is computed as $(S/H+B/H)/2-(S/L+B/L)/2$.

We find that these two EMI factors are not highly correlated with well-known factors such as the market, size, value and momentum factors (Carhart 1997), the investment and return on equity (ROE) factors (Chen, Novy-Marx, and Zhang, 2011), and the UMO factor (Hirshleifer and Jiang, 2010). The correlations between the EMI factors and these well-known factors range from −0.15 to 0.13.

In addition, we construct four innovation-related factors based on *RD/ME*, *RDG*, *PAT/ME*, and ΔAPC, following the same method in constructing the EMI factors. We find that the *EMI* factors are not highly correlated with these four factors, except for the *PAT/ME* factor. The correlations between the *EMI* factors and the *RD/ME*, *RDG*, and ΔAPC factors range from 0.07 to 0.36. The correlation with the *PAT/ME* factor is 0.66 for *EMI1* and 0.52 for *EMI2*.

The average monthly return of the *EMI1* factor is 0.41%, which is higher than that of the size factor (0.07%), the value factor (0.37%), the investment factor (0.36%), the *RDG* factor (0.21%), the *PAT/ME* factor (0.31%), and the ΔAPC factor (0.00%). Furthermore, *EMI1* offers an ex post Sharpe ratio, 0.23, which is higher than that of all the above factors except the mispricing factor (0.27). The *EMI2* factor has similar but slightly lower average monthly return (0.26%) and ex post Sharpe ratio (0.15). The high level of the equity premium is a well-known puzzle for rational asset pricing theory (Mehra and Prescott, 1985). Therefore, on the face of it, the high ex post Sharpe ratios associated with the *EMI* factors also suggest that the IE-return relation can be too strong to be entirely explained by rational risk premia.

Adding *EMI1* to the Fama and French three factors increases the ex post Sharpe ratio of the tangency portfolio from 0.29 to 0.39 with a weight of 42% on *EMI1*. Even when all of the above factors are included, the weight on *EMI1* in the tangency portfolio is 22%, which is substantially higher than that of any of the other factors. Adding *EMI2* to the Fama and French three factors increases the ex post Sharpe ratio of the tangency portfolio from 0.29 to 0.34 with a weight of 33% on *EMI2*. Even when all of the above factors are included, the weight on *EMI2* in the tangency portfolio is 15.65%, which is higher than that of any of the other factors except the mispricing factor (17.22%) and the market factor (16.00%). These findings imply the IE-return relation captures return predictability effects above and beyond those captured by the other well-known factors and the four innovation-related factors we construct.

Our study offers a new innovation-related measure, IE, which is contemporaneously associated with market valuation and predicts future operating performance and stock returns. Existing studies relating to innovation and the stock market focus on the effects of either the input (R&D) or the output (patents) of innovation separately. (The relevant papers in this literature are discussed in Section 2.) Our paper differs in focusing on innovative efficiency as a ratio of innovative output to input, based on the idea that efficiency should be highly value-relevant. We find that the predictive power of innovative efficiency is incremental to that of other innovation-related variables such as R&D intensity, significant R&D growth, patent counts, and citations. We also examine whether the IE effect is driven by risk or mispricing, and we explore how the IE effect interacts with proxies for limited attention and valuation uncertainty.

The paper continues as follows. Section 2 reviews the literature on innovative input, output, and efficiency. Section 3 discusses the data, IE measures, and summary statistics. Section 4 examines the relation between IE and operating performance as well as market valuation. Section 5 shows the stock return predictability based upon IE using both regression and portfolio analyses. Section 6 examines the IE-return relation within subsamples based on limited attention and valuation uncertainty. Section 7 constructs Efficient Minus Inefficient (EMI) factors and shows their effects on the ex post Sharpe ratio of the tangency portfolio. Section 8 concludes.

2. Innovative input, output, and efficiency

Existing studies examine the effect of innovative input or output separately on operating performance, market valuation, and stock returns. On the input side, several studies show that expensing or capitalization of R&D contains valuation-relevant information. Lev and Sougiannis (1996) estimate the R&D capital of a large sample of public companies and adjust the reported earnings and book values of sample firms for the R&D capitalization. They find that such adjustments are value-relevant to investors and show a significant association between firms' R&D capital to market equity and subsequent stock returns. Lev, Sarath, and Sougiannis (2005) examine consequences of R&D reporting biases. They detect undervaluation of conservatively reporting firms and overvaluation of aggressively reporting firms. These misvaluations appear to be corrected when the reporting biases reverse from conservative to aggressive and vice versa. They interpret this evidence as consistent with investor cognitive biases.

R&D intensity has also been shown to predict higher level and volatility of future operating performance and stock returns. For example, Chan, Lakonishok, and Sougiannis (2001) find that firms with higher R&D-to-

sales (*R&D/Sales*) or R&D-to-market equity (*R&D/ME*) experience higher future earnings growth. Furthermore, *R&D/ME* predicts higher stock returns, while *R&D/Sales* does not. They interpret this evidence as indicating that investors are overpessimistic about the prospects of beaten-down R&D-intensive firms.

Several studies also show that growth in R&D predicts future stock returns. Lev, Sarath, and Sougiannis (2005) and Penman and Zhang (2002) show a positive association between current or recent changes in R&D investment and subsequent abnormal returns. Eberhart, Maxwell, and Siddique (2004, 2008) report significantly positive abnormal operating performance and abnormal stock returns following substantial R&D increases. They interpret this evidence as indicating that investors underreact to the benefits that derive from R&D increases.

Several studies seek to distinguish between risk versus mispricing as explanations for R&D-related abnormal returns. Chambers, Jennings, and Thompson (2002) provide evidence suggesting that the positive association between R&D investment levels and abnormal returns comes from missing risk factors rather than mispricing. However, they do not rule out mispricing as an alternative explanation, especially for the abnormal returns associated with R&D growth. Li (2011) shows that the return predictability of R&D intensity exists only in financially constrained firms and that this return predictability is robust to measures of R&D intensity. This evidence suggests that risk associated with financial constraints plays a role in the R&D-return relation.

On the innovative output side, several studies have shown that patents and citations also contain valuation-relevant information. For example, Gu (2005) finds that changes in adjusted patent citations scaled by total assets are positively associated with firms' future earnings and stock returns. Matolcsy and Wyatt (2008) find that industry-level technological progress, measured with patent count or journal citations, is positively associated with contemporaneous market valuation and future firm-level earnings. Pandit, Wasley, and Zach (2011) find that firms' patent citations positively correlate with future operating performance.[7]

Overall, these studies indicate an important role of innovations in explaining operating performance, market valuation, and stock returns. However, their focus is on the effects of either innovative input or output separately. Our purpose here is to explore the relevance for firm value of innovative efficiency. Intuitively, we expect it to matter not just whether the firm attempts to innovate, and not just whether it produces innovative output, but whether it is able to attain this output at a reasonable cost. Measuring innovative efficiency inherently requires exploiting the information in innovative input and output taken together. We discuss the detailed difference between our IE measures and the measures used in the literature in Section 3.

Furthermore, we examine the incremental effect of the IE measures after controlling for numerous measures of innovative input and output such as R&D intensity, significant R&D growth, patents intensity, and change in citations intensities. We also explore whether risk or mispricing drives the predictability of IE.

3. The data, the innovative efficiency measures, and summary statistics

We discuss data sources and the construction of IE measures in Section 3.1, and then present the summary statistics of the variables and their correlations in Section 3.2.

3.1. The data and the innovative efficiency measures

Our sample consists of firms in the intersection of Compustat, Center for Research in Security Prices (CRSP), and the National Bureau of Economic Research (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 2 years before including them in our sample. For some of our tests, we also obtain analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) and institutional ownership data from the Thomson Reuters Institutional (13f) Holdings data set.

Patent-related data are from the updated NBER patent database originally developed by Hall, Jaffe, and Trajtenberg (2001).[8] The database contains detailed information on all US patents granted by the US Patent and Trademark Office (USPTO) between January 1976 and December 2006: 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 granted by the USPTO by the end of 2006. 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

[7] Other studies provide further related findings. Griliches (1990) finds that both R&D expenses and patents are positively associated with market capitalization. Lerner (1994) shows that patent count is positively related to market values in a sample of US biotechnology start-up firms. Deng, Lev, and Narin (1999) find that, in a small sample of innovative companies, patent count and patent citations are positively associated with subsequent market-to-book ratios and stock returns. Lanjouw and Schankerman (2004) find that patent capital is positively associated with contemporaneous stock market valuations of firms.

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

and measure firm i's innovation output in year t as the number of patents granted to firm i in year t (patents).

We use two proxies for IE: patents granted scaled by R&D capital (*Patents/RDC*) and adjusted patent citations scaled by R&D expenses (*Citations/RD*). Specifically, Patents/RDC is defined as the ratio of firm i's patents granted in year t ($Patents_{i,t}$) scaled by its R&D capital [the 5-year cumulative R&D expenses assuming an annual depreciation rate of 20% as in Chan, Lakonishok, and Sougiannis (2001) and Lev, Sarath, and Sougiannis (2005)] in fiscal year ending in year $t-2$:

$$Patents_{i,t}/\big(R\&D_{i,t-2}+0.8*R\&D_{i,t-3}+0.6*R\&D_{i,t-4}+0.4*R\&D_{i,t-5}+0.2*R\&D_{i,t-6}\big), \tag{1}$$

where $R\&D_{i,t-2}$ denotes firm i's R&D expenses in fiscal year ending in year $t-2$, and so on. We set missing R&D to zero in computing the denominator. We allow a 2-year gap between R&D capital and patents granted as it takes, on average, 2 years for the USPTO to grant a patent application (Hall, Jaffe, and Trajtenberg, 2001).

The use of cumulative R&D expenses as the denominator in this IE measure is premised on R&D expenses over the preceding 5 years all contributing to successful patent applications filed in year $t-2$ (which are approved in year t with the 2-year application-grant lag). In unreported results, we find assuming only contemporaneous R&D expenses contributing to successful patent applications generates similar results. Although this patents-based IE measure shares the numerator with the patents-to-book equity ratio used in Deng, Lev, and Narin (1999), these two measures differ conceptually. The patents-to-book equity ratio used in Deng, Lev, and Narin (1999) is a patent intensity measure, while our patents-based IE measure reflects efficiency of R&D in the form of patents granted per unit of R&D investment, which we think is more relevant for valuation purpose than patent intensity.

Because the number of citations made to a firm's patents can better reflect those patents' technological or economic significance, the other proxy of IE, *Citations/RD*, is based on citations. A patent's technological or economic significance would ideally be measured using all citations it receives from the grant date through the end of the sample, because it takes time for a patent to be cited.[9] However, to make sure the IE measure is fully observable to investors at the time of their investments, we follow the literature by using the citations received in the year before the forecast period by a firm's patents that were granted over the previous 5 years. Specifically, we define *Citations/RD* in year t as the adjusted number of citations occurring in year t to firm i's patents granted over the previous 5 years scaled by the sum of corresponding R&D expenses:

$$\frac{Citations}{RD}=\frac{\sum_{j=1}^{5}\sum_{k=1}^{N_{t-j}} C_{ik}^{t-j}}{(R\&D_{i,t-3}+R\&D_{i,t-4}+R\&D_{i,t-5}+R\&D_{i,t-6}+R\&D_{i,t-7})}, \tag{2}$$

where C_{ik}^{t-j} is the number of citations received in year t by patent k, granted in year $t-j$ (j=1–5) scaled by the average number of citations received in year t by all patents of the same subcategory granted in year $t-j$, and N_{t-j} is the total number of patents granted in year $t-j$ to firm i.[10] This method for adjusting citations follows Gu (2005) and Pandit, Wasley, and Zach (2011) and helps control for citation propensity attributed to differences in technology fields, grant year, and citing year (the year in which the citations occur). In addition, the 5-year period used in computing the firm-level adjusted citations is roughly consistent with prior findings that technology cycles measured by the duration of the benefits of R&D spending are approximately 5 years in most industries (Lev and Sougiannis, 1996).

The denominator, the sum of R&D expenses in years $t-3$ to $t-7$, is premised on only contemporaneous R&D expenses contributing to successful patent applications and a 2-year application-grant lag. For example, for patents granted in year $t-1$, we assume the associated innovative input is R&D expenses incurred in year $t-3$. We also set missing R&D to zero in computing the denominator.

This citations-based IE measure differs from the measure in Gu (2005) in two main respects. First, Gu (2005) uses the change in scaled adjusted citations as the return predictor. Second, Gu (2005) scales this change by average total assets. In contrast, our IE measure is the level of adjusted citations scaled by innovative input (R&D investment). Thus, the measure in Gu (2005) captures changes in citation activity, whereas our citations-based IE measure captures the efficiency of R&D expenditure in generating citations.

Similarly, this IE measure also differs from the citation intensity measure in Deng, Lev, and Narin (1999), which is defined as the total number of citations received in a given year (t) by a firm's patents that were granted in the previous 5 years ($t-1$ to $t-5$), divided by the average number of citations occurring in year t to all US patents granted in the previous 5 years. This is similar to the numerator of our IE measure, *Citations/RD*, but with a different method for adjusting citations to address spurious effects. A key difference is that their measure focuses on innovative output, whereas our measure focuses on the efficiency with which innovative expenditures are used to generate that output.

We construct these two IE measures for each year from 1981 to 2006. The sample period starts in 1981 to ensure the quality of R&D expenditure data. Because 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 5-year period with reliable R&D expenditure data. Furthermore, the 2-year application-grant lag makes

[9] See, e.g., Trajtenberg (1990), Harhoff, Narin, Scherer, and Vopel (1999), and Hall, Jaffe, and Trajtenberg (2005).

[10] Patent subcategory is based on the technology classification system of the USPTO. A brief description of selected subcategories is as follows: 14 (organic compounds), 21 (communications), 22 (computer hardware and software), 23 (computer peripherals), and 24 (information storage). More details are provided in the updated NBER patent database.

Table 1
Innovative efficiency measures of selected industries.

This table reports the pooled mean, standard deviation, 25th percentile, median, and 75th percentile of the innovative efficiency (IE) measures for selected two-digit Standard Industrial Classification (SIC) industries from 1981 to 2006. *Patents/RDC* in year t is patents granted to a firm in year t scaled by research and development (R&D) capital in year $t-2$. R&D capital is computed as the 5-year cumulative R&D expenses with a 20% annual depreciation. *Citations/RD* in year t is adjusted patent citations received in year t by patents granted to a firm in years $t-1$ to $t-5$ scaled by the sum of R&D expenses in years $t-3$ to $t-7$. The adjusted citations in year t to patent k is citations to patent k in year t divided by the mean citations to patents of the same subcategory and grant year group in year t.

Industries	Mean	Standard deviation	25th percentile	Median	75th percentile
Panel A: *Patents/RDC*					
Biotech and pharmaceuticals (28)	0.49	5.80	0.00	0.07	0.23
Computers and machinery (35)	0.55	6.48	0.00	0.07	0.29
Electrical and electronics (36)	0.56	4.34	0.00	0.09	0.33
Transportation equipment (37)	2.11	40.78	0.02	0.11	0.37
Medical and scientific instruments (38)	0.61	3.87	0.00	0.11	0.37
Other	1.31	38.69	0.00	0.00	0.18
Panel B: *Citations/RD*					
Biotech and pharmaceuticals (28)	2.57	33.67	0.00	0.26	1.07
Computers and machinery (35)	2.49	13.62	0.00	0.29	1.16
Electrical and electronics (36)	2.62	14.86	0.00	0.32	1.33
Transportation equipment (37)	10.66	123.17	0.05	0.35	1.41
Medical and scientific instruments (38)	4.76	57.14	0.00	0.36	1.65
Other	3.42	49.07	0.00	0.02	0.75

1981 the first year for the patents-based IE measure, *Patents/RDC*. To make the results comparable, we use the same sample period for the other citations-based IE measure, *Citations/RD*.

3.2. Summary statistics

Table 1 reports the pooled mean, standard deviation, 25th percentile, median, and 75th percentile of the two IE measures for selected innovation-intensive two-digit SIC industries. We observe significant variation in industrial innovative efficiency. Transportation equipment industry outperforms all the other industries. The average *Patents/RDC* and *Citations/RD* for this industry are 2.11 and 10.66, respectively. In contrast, on average it costs more for the biotech and pharmaceutical industry to create patents and citations. The average *Patents/RDC* and *Citations/RD* for this industry are 0.49 and 2.57, respectively. These statistics suggest that it is important to control for industry effects in examining the relation between IE and subsequent operating performance and stock returns.

Table 2 reports summary statistics of IE portfolios and correlations between firms' IE measures and other characteristics. At the end of June of year t, we form three portfolios based on the 33rd and 66th percentiles of IE measured in year $t-1$ for the two IE measures separately. Panel A reports the average annual number of firms and median values of characteristics of these portfolios as characteristics are highly skewed within each portfolio.[11]

The average number of firms in the low, middle, and high *Patents/RDC* portfolios is 574, 274, and 424, respectively, while the average number of firms in the low, middle, and high *Citations/RD* portfolios is 531, 313, and 422, respectively. Moreover, the median market equity of the low, middle, and high *Patents/RDC* portfolios is \$42.55 million, \$626.79 million, and \$215.45 million, respectively. The median market equity of the low, middle, and high *Citations/RD* portfolios is \$47.08 million, \$466.93 million, and \$248.28 million, respectively. Overall, firms with non-missing *Patents/RDC* or *Citations/RD* cover 55% of total US market equity, so this is an economically meaningful set of firms to study.

There are significant variations in the two IE measures across the IE groups. The median *Patents/RDC* and *Citations/RD* for the high *Patents/RDC* group are 0.41 and 1.14, respectively. In contrast, the counterparts of these statistics are zero for the low *Patents/RDC* group. Similarly, the median *Patents/RDC* and *Citations/RD* for the high *Citations/RD* group are 0.28 and 1.72, respectively, while the counterparts of these statistics are zero for the low *Citations/RD* group.

To check the relevance of our IE measures in capturing the long-run effect of a firm's patents, we also compute citations and self-citations to a firm's patents occurring from the grant year through the sample end 2006, which we term "resulting citations" and "resulting self-citations," respectively. We find the median resulting citations, resulting citations excluding self-citations, and resulting self-citations (all scaled by R&D capital 2 years prior to the grant year) increase across the low, middle, and high IE groups based on *Patents/RDC* or *Citations/RD*. In other words, our IE measures are positively related to the long-run effect of a firm's R&D investment.

Panel A also reports other characteristics including R&D expenditure, R&D-to-market equity (*RD/ME*), patents-to-market equity (*PAT/ME*), change in adjusted patent citations scaled by total assets (ΔAPC), book-to-market equity (*BTM*), net stock issues, asset growth, capital expenditure scaled by lagged assets (*CapEx/Assets*),

[11] All characteristics are for the year prior to the ranking year except market equity and momentum, which are measured at the end of June of the ranking year.

Table 2
Summary statistics.

At the end of June of year t we sort firms into three groups (low, middle, and high) based on the 33rd and 66th percentiles of the innovative efficiency (IE) measures, *Patents/RDC* or *Citations/RD*, in year $t-1$. The portfolios are formed every year from 1982 to 2007. Patents/RDC and Citations/RD are defined in Table 1. Panel A reports the annual average number of firms and pooled median characteristics of the IE groups. Size is Center for Research in Security Prices (CRSP) price per share times the number of shares outstanding at the end of June of year t. Resulting *citations/RDC* is the number of citations to a firm's patents granted in year t occurring from year t through the sample end 2006 divided by R&D capital in year $t-2$. Resulting citations excluding self-citations/RDC is the number of citations (excluding self-citations) to a firm's patents granted in year t occurring from year t through the sample end 2006 divided by R&D capital in year $t-2$. Resulting self-citations/RDC is the number of self-citations to a firm's patents granted in year t occurred from year t through the sample end 2006 divided by R&D capital in year $t-2$. *RD/ME* is R&D expenses in fiscal year ending in year $t-1$ divided by market equity at the end of year $t-1$. *PAT/ME* denotes the number of patents issued to a firm in year $t-1$ divided by the firm's market value of equity at the end of year $t-1$. ΔAPC is change in adjusted patent citations (i.e., Citations defined in Table 1) in year $t-1$ scaled by total assets averaged over years $t-1$ and $t-2$. Book-to-market equity (BTM) is the ratio of book equity of fiscal year ending in year $t-1$ to market equity 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. Net stock issues (NS) is the change in the natural log of the split-adjusted shares outstanding. Split-adjusted shares outstanding is Compustat shares outstanding times the Compustat adjustment factor. Asset growth (AG) 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 6-month returns (with a one-month gap between the holding period and the current month). Institutional ownership (IO) denotes the fraction of firm shares outstanding owned by institutional investors. Panel B reports each IE portfolio's pooled median return on assets (ROA), cash flows (CF), and profit margin in the formation year (year t) and geometric average growth rates and simple averages of these operating performance measures over the subsequent 5 years (year $t+1$ to year $t+5$) based on these medians. ROA is income before extraordinary items plus interest expenses divided by lagged total assets. Cash flows is income before extraordinary items minus total accruals (i.e., changes in current assets plus changes in short-term debt and minus changes in cash, changes in current liabilities, and depreciation expenses) divided by average total assets. Profit margin is the sum of income before extraordinary items, interest expenses, and total income taxes divided by sales. In Panel B, we also report the time series mean of earnings per dollar invested in each IE portfolios in year t from a value-weighted buy-and-hold strategy. The geometric average growth rates and simple averages of earnings over the subsequent 5 years are computed based on these numbers. Earnings is operating income before depreciation multiplied by its size in December before the formation year. Panel C reports the Pearson correlation coefficients between selected variables. p-values are reported in parentheses.

	Patents/RDC			*Citations/RD*		
Variable	Low	Middle	High	Low	Middle	High
Panel A: Characteristics						
Number of firms	574	274	424	531	313	422
Size (millions of dollars)	42.55	626.79	215.45	47.08	466.93	248.28
Percent of total market equity	9.01	27.80	18.09	6.76	27.85	20.24
Patents/RDC	0.00	0.08	0.41	0.00	0.08	0.28
Citations/RD	0.00	0.30	1.14	0.00	0.27	1.72
Resulting *citations/RDC*	0.00	0.88	5.57	0.00	0.80	3.56
Resulting citations excluding self-citations/RDC	0.00	0.77	4.86	0.00	0.70	3.04
Resulting self-citations/RDC	0.00	0.03	0.25	0.00	0.02	0.14
R&D expenses (millions of dollars)	2.00	28.50	7.37	2.11	20.90	8.98
RD/ME	0.05	0.05	0.04	0.05	0.05	0.04
PAT/ME	0.00	0.02	0.04	0.01	0.01	0.02
ΔAPC (percent)	0.00	0.00	0.33	−0.13	0.39	2.53
BTM	0.55	0.48	0.50	0.57	0.51	0.49
NS	0.01	0.01	0.01	0.01	0.01	0.01
AG	0.06	0.06	0.07	0.06	0.05	0.08
CapEx/Assets	0.04	0.05	0.06	0.04	0.05	0.05
Momentum	0.05	0.09	0.09	0.05	0.09	0.09
IO	0.19	0.54	0.41	0.20	0.51	0.42
Panel B: Operating performance						
ROA						
Formation year	0.04	0.06	0.07	0.05	0.07	0.07
Growth rate over five post-formation years	0.02	0.02	0.00	0.02	0.01	0.01
Average over five post-formation years	0.05	0.07	0.07	0.05	0.07	0.07
Cash flows (CF)						
Formation year	0.04	0.08	0.07	0.05	0.08	0.07
Growth rate over five post-formation years	0.06	0.01	0.02	0.04	0.01	0.02
Average over five post-formation years	0.05	0.08	0.08	0.05	0.08	0.08
Earnings						
Formation year	0.19	0.16	0.20	0.19	0.16	0.20
Growth rate over five post-formation years	0.02	0.05	0.06	0.00	0.08	0.04
Average over five post-formation years	0.20	0.18	0.24	0.16	0.21	0.21
Profit margin						
Formation year	0.04	0.07	0.07	0.05	0.07	0.08
Growth rate over five post-formation years	0.03	0.03	0.01	0.02	0.02	0.01
Average over five post-formation years	0.05	0.08	0.08	0.05	0.08	0.08

Variable	*Patents/RDC*	*Citations/RD*	Resulting *citations/RDC*	*RD/ME*	*PAT/ME*	ΔAPC	*Size*	*BTM*
Panel C: Correlation coefficients								
Patents/RDC	1.00							

Table 2 (*continued*)

Variable	*Patents/RDC*	*Citations/RD*	Resulting *citations/RDC*	*RD/ME*	*PAT/ME*	Δ*APC*	*Size*	*BTM*
Citations/RD	0.09	1.00						
	(0.00)							
Resulting *citations/RDC*	0.83	0.14	1.00					
	(0.00)	(0.00)						
RD/ME	−0.01	−0.02	−0.01	1.00				
	(0.04)	(0.00)	(0.05)					
PAT/ME	0.08	0.20	0.05	0.18	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)				
Δ*APC*	0.01	0.12	0.02	0.01	0.13	1.00		
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)			
Size	0.00	−0.01	0.00	−0.03	−0.02	0.00	1.00	
	(0.41)	(0.09)	(0.41)	(0.00)	(0.00)	(0.49)		
BTM	0.02	0.00	0.01	0.25	0.10	−0.01	−0.04	1.00
	(0.00)	(0.96)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	

momentum, and institutional ownership. *RD/ME* is R&D expenditures divided by year-end market equity. *PAT/ME* is patents granted divided by year-end market equity. BTM is book equity over year-end market equity. Net stock issues (NS) is the change in the natural log of split-adjusted shares outstanding. Asset growth (AG) is the change in total assets divided by lagged total assets. Momentum is the prior 6-month returns (with one-month gap between the holding period and the current month; see, e.g., Hou, Peng, and Xiong, 2009). Institutional ownership (IO) is the fraction of a firm's shares outstanding owned by institutional investors.

High IE firms do not spend most on R&D or have the highest R&D intensity. For example, for *Patents/RDC*, the middle IE portfolio spends most on R&D ($28.5 million) while the high (low) IE portfolio spends $7.37 ($2.00) million. The R&D intensity (*RD/ME*) of the high IE portfolio is 3.98%, which is lower than that of the low IE portfolio (5.37%). These patterns hold for the IE portfolios based on *Citations/RD*, suggesting that greater R&D spending does not necessarily lead to higher innovative efficiency.

In addition, for both IE measures, patent intensity and Δ*APC* increase across the IE portfolios. For the other characteristics, the high IE portfolio has lower BTM, higher AG, higher *CapEx/Assets*, higher momentum, and higher IO than the low IE portfolio. Panel B of Table 2 reports each IE portfolio's return on asset (*ROA*), cash flows, earnings, and profit margin in the formation year (year t) and geometric average growth rates and simple averages of these operating performance measures over the subsequent 5 years (year $t+1$ to year $t+5$).[12]

The results indicate that high IE portfolios generally provide the highest operating performance measures averaged over the 5 post-formation years. Such an IE-related variation in future profitability suggests a positive univariate relation between innovative efficiency and subsequent operating performance, which we examine further in Section 4.1.

Panel C of Table 2 reports the pairwise Pearson correlation coefficients among the IE measures and other characteristics. The two IE measures are positively and significantly correlated (0.09).[13] They are also significantly positively correlated with Resulting *citations/RDC*. Specifically, the correlation between *Patents/RDC* (*Citations/RD*) and Resulting *citations/RDC* is 0.83 (0.14). In unreported results, we find the Spearman rank correlation between Resulting *citations/RDC* and IE is 0.92 for *Patents/RDC* and 0.61 for *Citations/RD*. The high rank correlations suggest that our IE measures are potential predictors of long-run citation performance of a firm's patents and, therefore, can contain value-relevant information. In addition, the two IE measures are negatively correlated with *RD/ME* and are positively correlated with *PAT/ME* and Δ*APC*, consistent with the idea of innovative efficiency. Furthermore, the correlations between the *IE* measures and *RD/ME*, *PAT/ME*, Δ*APC*, *Size* and *BTM* are low in magnitude (though sometimes statistically significant). Therefore the proposed *IE* measures potentially contain independent information.

4. The association of innovative efficiency with operating performance and market valuation

We examine the relation between subsequent operating performance and innovative efficiency in Section 4.1, and

[12] For ROA, cash flows, and profit margin, we report pooled medians in year t. The geometric average growth rates and simple averages of these measures over the subsequent 5 years are computed based on these pooled medians. For earnings, we report the time series mean of earnings per dollar invested in year t in each IE portfolio from a value-weighted buy-and-hold strategy. The geometric average growth rates and simple averages of earnings over the subsequent 5 years are computed based on these numbers. ROA is income before extraordinary items plus interest expenses scaled by lagged total assets. Following Zhang (2006), we measure cash flows as income before extraordinary items minus total accruals (i.e., changes in current assets plus changes in short-term debt and minus changes in cash, changes in current

(*footnote continued*)
liabilities, and depreciation expenses) divided by average total assets. Profit margin is the sum of income before extraordinary items, interest expenses, and total income taxes divided by sales. Earnings is operating income before depreciation.

[13] The nonparametric (Spearman) correlation between *Patents/RDC* and *Citations/RD* is 0.63 with statistical significance.

investigate the contemporaneous relation between market valuation and innovative efficiency in Section 4.2.

4.1. Operating performance and innovative efficiency

To examine more carefully the relation of innovative efficiency with subsequent operating performance, we conduct the following annual Fama-MacBeth (1973) cross-sectional regressions:

$$OP_{i,t+1} = \alpha_0 + \alpha_1 \ln(1+IE_{i,t}) + \alpha_2 \ln\left(1+\frac{AD_{i,t}}{ME_{i,t}}\right) + \alpha_3 \ln\left(1+\frac{CapEx_{i,t}}{ME_{i,t}}\right) + \alpha_4 OP_{i,t} + \alpha_5\, \Delta OP_{i,t} + \sum_{j=1}^{48} \gamma_j Industry_j \tag{3}$$

and

$$OP_{i,t+1} = \alpha_0 + \alpha_1 \ln(1+IE_{i,t}) + \alpha_2 \ln\left(1+\frac{AD_{i,t}}{ME_{i,t}}\right) + \alpha_3 \ln\left(1+\frac{CapEx_{i,t}}{ME_{i,t}}\right) + \alpha_4\, OP_{i,t} + \alpha_5\, \Delta OP_{i,t} + \alpha_6 \ln\left(1+\frac{RD_{i,t}}{ME_{i,t}}\right) + \alpha_7\, RDG_{i,t} + \alpha_8 \ln\left(1+\frac{PAT_{i,t}}{ME_{i,t}}\right) + \alpha_9\, \Delta APC_{i,t} + \sum_{j=1}^{48} \gamma_j Industry_{j}, \tag{4}$$

where $OP_{i,t+1}$ is firm i's operating performance in year $t+1$ (ROA or cash flows), $\ln(1+IE)$ is the natural log of one plus IE ($Patents/RDC$ or $Citations/RD$), $\ln(1+AD/ME)$ is the natural log of one plus advertising expenditure to year-end market equity (ME), $\ln(1+CapEx/ME)$ is the natural log of one plus capital expenditure to ME, $\Delta OP_{i,t}$ is the change in operating performance between year t and year $t-1$, $\ln(1+RD/ME)$ is the natural log of one plus RD/ME, RDG is a dummy variable that equals one for significant R&D growth as defined in Eberhart, Maxwell, and Siddique (2004) and zero otherwise, $\ln(1+PAT/ME)$ is the natural log of one plus patents to ME, ΔAPC is the change in adjusted patent citations scaled by average total assets between years t and $t-1$ as in Gu (2005), and $Industry_j$ is a dummy variable that equals one for the industry that firm i belongs to and zero otherwise based on the Fama and French (1997) 48 industry classifications.

As the distributions of IE measures are highly skewed and are often zero, we use $\ln(1+IE)$ in the regression.[14] Because R&D intensity and patent intensity are sometimes zero as well, we also use $\ln(1+RD/ME)$ and $\ln(1+PAT/ME)$ in the regression. We control for advertising expenditure and capital expenditure because they are found to explain operating performance (e.g., Lev and Sougiannis, 1996; Pandit, Wasley, and Zach, 2011). Following Gu (2005) and Pandit, Wasley, and Zach (2011), we include operating performance in the model to accommodate persistence in operating performance. We also control for change in operating performance to accommodate the mean reversion in profitability (e.g., Fama and French, 2000). Both here and in Section 4.2, we winsorize all variables at the 1% and 99% levels to reduce the influence of outliers (Beaver and Ryan, 2000) and standardize all independent variables to zero mean and 1 standard deviation to facilitate the comparison of the economic magnitudes of effects.[15]

Table 3 reports the time series average slopes and intercepts and corresponding t-statistics from the annual cross-sectional regressions specified in Eqs. (3) and (4). We measure IE by $Patents/RDC$ in Panel A and by $Citations/RD$ in Panel B. The results indicate a significantly positive relation between both IE measures and future ROA and cash flows for both specifications. Specifically, a 1 standard deviation increase in $\ln(1+Patents/RDC)$ raises subsequent ROA (cash flows) by 0.52% (0.43%) in the first column and 0.45% (0.49%) in the second column. Similarly, a 1 standard deviation increase in $\ln(1+Citations/RD)$ raises subsequent ROA (cash flows) by 0.56% (0.41%) in the first column and 0.43% (0.31%) in the second column. All these effects are significant at the 1%.

Consistent with the literature, the slopes on the other innovation-related variables are mostly positive and statistically significant. In particular, $\ln(1+RD/ME)$ significantly predicts higher ROA and cash flows, and RDG significantly predicts higher cash flows. Although the slopes on $\ln(1+PAT/ME)$ are sometimes negative, they are insignificant. The slopes on ΔAPC are significantly positive for ROA and cash flows. In unreported results, we find all four of these innovation-related variables predict higher ROA and cash flows with 5% significance if they are included in the regressions one at a time.

In addition, both advertising expenditure and capital expenditure positively correlate with subsequent ROA and cash flows with statistical significance. All these findings suggest that both intangible and tangible investment benefit future profitability. The significantly positive slopes on ROA (cash flows) and the significantly negative slopes on change in ROA (cash flows) confirm both persistence and mean reversion in operating performance. Together these results suggest that both IE measures contain incremental information about firms' future operating performance.

4.2. Market valuation and innovative efficiency

We next examine whether the stock market fully reflects the information contained in IE by adapting an accounting-based asset valuation model developed in Ohlson (1995) and used by Sougiannis (1994), among others, to inspect whether R&D expenses explain market

[14] The logarithmic transformation follows Lerner (1994), who uses the natural log of one plus patent count as the main explanatory variable for biotechnology firm value.

[15] ROA, cash flows, and market-to-book equity (MTB) contain extreme values in our sample. For example, MTB can be extreme owing to low book value firms. The maximum MTB in the sample is 783.

Table 3
Innovative efficiency and subsequent operating performance.

This table reports the average slopes (in percent) and their time series t-statistics in parentheses from annual Fama-MacBeth (1973) cross-sectional regressions of individual stocks' operating performance measures in year $t+1$ on innovative efficiency (IE) and other control variables in year t. We measure operating performance by ROA and cash flow (CF) as defined in Table 2. ln(1+*IE*) is the natural log of *Patents*/*RDC* or *Citations*/*RD* (both defined in Table 1). ln(1+*RD*/*ME*) is the natural log of one plus annual R&D expenditure divided by year-end market equity. *RDG* is a dummy for significant R&D growth as defined in Eberhart, Maxwell, and Siddique (2004). ln(1+*PAT*/*ME*) denotes the natural log of one plus patent counts divided by year-end market equity. Δ*APC* is change in adjusted patent citations scaled by average total assets (defined in Table 2). ln(1+*AD*/*ME*) is the natural log of one plus annual advertising expenditure divided by year-end market equity. ln(1+*CapEx*/*ME*) is the natural log of one plus annual capital expenditure divided by year-end market equity. Current *ROA* (*CF*) is *ROA* (*CF*) in year t. Δ*ROA* (Δ*CF*) is change in *ROA* (*CF*) from year $t-1$ to year t. Industry dummies are based on the Fama and French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and 1 standard deviation. The reported adjusted R^2 is the time series average of the adjusted R^2 of each annual cross-sectional regression.

	Panel A: *IE*=*Patents*/*RDC*				Panel B: *IE*=*Citations*/*RD*			
Explanatory variable	*ROA*	*ROA*	*CF*	*CF*	*ROA*	*ROA*	*CF*	*CF*
ln(1+*IE*)	0.52	0.45	0.43	0.49	0.56	0.43	0.41	0.31
	(4.96)	(2.68)	(5.44)	(3.71)	(4.98)	(3.50)	(4.68)	(3.49)
ln(1+*RD*/*ME*)		0.74		0.87		0.66		0.77
		(4.31)		(3.89)		(3.75)		(3.30)
RDG		0.15		1.20		0.21		1.28
		(0.29)		(3.05)		(0.42)		(3.25)
ln(1+*PAT*/*ME*)		0.02		−2.28		0.15		−0.37
		(0.08)		(−1.18)		(1.11)		(−0.25)
Δ*APC*		0.16		0.21		0.13		0.20
		(1.82)		(2.84)		(1.51)		(2.71)
ln(1+*AD*/*ME*)	0.41	0.34	0.59	0.51	0.43	0.35	0.60	0.51
	(4.35)	(3.78)	(5.50)	(5.65)	(4.57)	(3.94)	(5.70)	(5.78)
ln(1+*CapEx*/*ME*)	2.44	2.35	2.43	2.38	2.44	2.34	2.42	2.35
	(6.99)	(7.36)	(5.79)	(6.28)	(6.98)	(7.22)	(5.76)	(6.11)
Current *ROA*	83.53	83.13			83.43	83.06		
	(31.22)	(31.33)			(31.19)	(31.24)		
Δ*ROA*	−11.58	−11.44			−11.56	−11.41		
	(−10.66)	(−10.42)			(−10.57)	(−10.36)		
Current *CF*			83.77	83.16			83.76	83.23
			(51.43)	(49.72)			(50.87)	(49.17)
Δ*CF*			−15.77	−15.60			−15.76	−15.62
			(−21.31)	(−20.83)			(−21.47)	(−21.03)
Intercept	−12.48	−12.48	−10.38	−10.45	−12.50	−12.51	−10.35	−10.41
	(−14.18)	(−14.01)	(−12.29)	(−12.20)	(−14.08)	(−13.93)	(−12.10)	(−11.97)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	73.97	74.10	75.51	75.70	73.98	74.09	75.51	75.68

valuation in addition to reported earnings.[16] Specifically, we run the following annual Fama-MacBeth (1973) cross-sectional regressions:

$$\begin{aligned}\ln(MTB_{i,t}) &= \alpha_0+\alpha_1 \ln(1+IE_{i,t})+\alpha_2 \ln(1+IE_{i,t-1})\\&\quad+\alpha_3\, RDG_{i,t}+\alpha_4 \ln\left(1+\frac{PAT_{i,t}}{ME_{i,t}}\right)+\alpha_5\, \Delta APC_{i,t}\\&\quad+\alpha_6 \frac{RD_{i,t}}{BE_{i,t}}+\alpha_7 \frac{1}{BE_{i,t}}+\alpha_8 \frac{E^B_{i,t}(1-\tau_{i,t})-r_t BE_{i,t-1}}{BE_{i,t}}\\&\quad+\alpha_9 \frac{\tau_{i,t} RD_{i,t}}{BE_{i,t}}+\alpha_{10} \ln\left(1+\frac{AD_{i,t}}{ME_{i,t}}\right)\\&\quad+\alpha_{11} \ln\left(1+\frac{CapEx_{i,t}}{ME_{i,t}}\right)+\sum_{j=1}^{48}\gamma_j Industry_j, \qquad (5)\end{aligned}$$

where $\ln(MTB_{i,t})$ denotes the natural log of firm i's equity market-to-book ratio in year t, $BE_{i,t}$ is firm i's book value of equity in year t, $E^B_{i,t}$ is firm i's earnings after extraordinary items less preferred dividends and before expensing R&D expenses, $\tau_{i,t}$ is tax rate (total tax expenses divided by pretax book income) for firm i in year t, and r_t is the one-year Treasury bill rate in year t. All the other independent variables are defined in Section 4.1.

Table 4 reports the time series average slopes and corresponding t-statistics from the annual cross-sectional regressions specified in Eq. (5). We measure IE by *Patents*/*RDC* in Panel A and by *Citations*/*RD* in Panel B. As a comparison, we also report results from alternative specifications that excludes lagged *IE* or the following three innovation-related variables: *RDG*, ln(1+*PAT*/*ME*), and Δ*APC*. The results indicate that both current and lagged *IE* measures are positively associated with the natural log of market-to-book ratio, regardless of whether we control for the other innovation-related variables. A 1 standard deviation increase in ln(1+*IE*) is associated with an increase in contemporaneous ln(*MTB*) of 1.90–6.35% with t-statistics of at least 4.65. This evidence suggests that the stock market recognizes the value of innovative efficiency and accords higher valuations to more efficient firms.

However, there is also an indication that the market does not seem to fully reflect the effect of innovative efficiency. As shown in Table 4, a significantly positive relation exists between both *IE* measures and the

[16] Other studies using an Ohlson-based model include Amir (1993) and Barth, Beaver, and Landsman (1998).

Table 4
Innovative efficiency and market valuation.

This table reports the average slopes (in percent) and their time series t-statistics in parentheses from annual Fama-MacBeth (1973) cross-sectional regressions of the natural log of firms' market-to-book equity (MTB) ratio (defined in Table 2) in year t on innovative efficiency (IE) in year t and year $t-1$ and other control variables in year t. The subscript i denotes firm i. $\ln(1+IE)$ is the natural log of $Patents/RDC$ or $Citations/RD$ (both defined in Table 1). RDG is a dummy for significant R&D growth. $\ln(1+PAT/ME)$ denotes the natural log of one plus patent counts divided by year-end market equity. ΔAPC is change in adjusted patent citations scaled by average total assets (defined in Table 2). RD/BE denotes R&D expenditure divided by book value of equity. Abnormal earnings is defined as $\left(E^B_{i,t}(1-\tau_{i,t})-r_t BE_{i,t-1}\right)/BE_{i,t}$, where $E^B_{i,t}$ is earnings after extraordinary items before expensing R&D expenses and less preferred dividends for firm i in year t, $\tau_{i,t}$ is tax rate (total tax expenses divided by pretax book income) for firm i in year t, and r_t is the one-year Treasury bill rate in year t. R&D tax shields denotes R&D expenditure multiplied by tax rate, scaled by book value of equity. $\ln(1+AD/ME)$ is the natural log of one plus annual advertising expenditure divided by year-end market equity. $\ln(1+CapEx/ME)$ is the natural log of one plus annual capital expenditure divided by year-end market equity, and Industry dummies are based on the Fama and French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and 1 standard deviation. The reported adjusted R^2 is the time series average of the adjusted R^2 of each annual cross-sectional regression.

Explanatory variable	Panel A: $IE=Patents/RDC$				Panel B: $IE=Citations/RD$			
$\ln(1+IE_{i,t})$	1.95	1.90	6.35	1.99	2.69	2.90	4.82	3.91
	(5.57)	(4.65)	(11.25)	(4.97)	(5.77)	(6.70)	(7.40)	(8.52)
$\ln(1+IE_{i,t-1})$		0.92		4.52		0.41		1.48
		(2.74)		(10.93)		(1.91)		(2.97)
$RDG_{i,t}$			−17.05	−11.86			−16.62	−11.72
			(−8.99)	(−6.32)			(−8.89)	(−6.31)
$\ln(1+PAT_{i,t}/ME_{i,t})$			−8.98	−7.04			−6.94	−5.66
			(−11.48)	(−18.68)			(−9.20)	(−14.32)
$\Delta APC_{i,t}$			1.30	1.07			0.89	0.83
			(3.79)	(4.31)			(2.71)	(3.43)
$RD_{i,t}/BE_{i,t}$	18.43	18.82	21.76	20.67	18.28	18.68	21.00	20.24
	(29.18)	(28.78)	(30.66)	(30.99)	(29.64)	(29.19)	(10.99)	(31.06)
$1/BE_{i,t}$	25.27	24.69	25.04	24.43	25.42	24.82	25.53	24.66
	(13.57)	(13.54)	(13.63)	(13.45)	(13.76)	(13.67)	(14.43)	(13.75)
Abnormal earnings$_{i,t}$	79.16	75.77	79.78	76.26	79.09	75.73	80.10	76.33
	(28.91)	(29.33)	(28.76)	(29.67)	(28.99)	(29.43)	(28.95)	(29.82)
RD tax shields$_{i,t}$	14.64	14.03	14.77	13.92	14.27	13.68	14.39	13.57
	(7.78)	(7.84)	(8.22)	(8.26)	(7.80)	(7.87)	(8.20)	(8.22)
$\ln(1+AD_{i,t}/ME_{i,t})$	−5.80	−4.58	−5.38	−4.22	−5.74	−4.52	−5.34	−4.18
	(−8.44)	(−7.04)	(−7.49)	(−6.36)	(−8.33)	(−6.89)	(−7.18)	(−6.12)
$\ln(1+CapEx_{i,t}/ME_{i,t})$	−20.94	−17.14	−19.43	−15.89	−20.87	−17.08	−19.76	−15.99
	(−23.19)	(−28.75)	(−22.37)	(−25.74)	(−23.56)	(−29.62)	(−22.91)	(−26.67)
Intercept	−34.43	−36.71	−33.10	−36.04	−34.49	−36.76	−33.04	−36.09
	(−5.90)	(−5.94)	(−5.31)	(−5.81)	(−5.49)	(−5.94)	(−5.31)	(−5.82)
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	75.51	74.15	76.15	74.10	75.55	73.81	76.09	74.14

subsequent ln(MTB) in all specifications. For example, in the full specification as described in Eq. (5), a 1 standard deviation increase in $\ln(1+IE_{i,t-1})$ is associated with a subsequent increase in $\ln(1+MTB_{i,t})$ by 4.52% (t=10.93) for $Patents/RDC$ and by 1.48% (t=2.97) for $Citations/RD$. This evidence suggests that market underreaction to IE is substantial.

5. Predictability of returns based upon innovative efficiency

We next examine whether innovative efficiency predicts stock returns using regression and portfolio approaches in Sections 5.1 and 5.2, respectively.

5.1. Fama-MacBeth regression results

In this subsection, we examine the ability of IE to predict returns using monthly Fama-MacBeth (1973) cross-sectional regressions to control for other characteristics that can predict returns and make sure that any relation between stock returns and IE measures is not driven by familiar effects or industry characteristics. For each month from July of year t to June of year $t+1$, we regress monthly returns net of the one-month Treasury bill rate of individual stocks on $\ln(1+IE)$ of year $t-1$ and other control variables including $\ln(1+RD/ME)$, a dummy for significant R&D growth (RDG), $\ln(1+PAT/ME)$, ΔAPC, size, book-to-market ratio, momentum, $\ln(1+AD/ME)$, $\ln(1+CapEx/ME)$, ROA, asset growth, net stock issues, institutional ownership, and industry dummies based on the Fama and French (1997) 48 industries.[17]

All control variables are measured in the fiscal year ending in year $t-1$ except size and momentum, which are measured at the end of June of year t. The definitions of all control variables are detailed in Section 3. Following Gu (2005), we use the quartile rank instead of the raw value of ΔAPC in the regressions. Following Fama and French

[17] 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). Similar results are obtained in Fama-MacBeth regressions without industry dummies.

Table 5

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

This table reports the average slopes (in percent) and their time series *t*-statistics in parentheses from monthly Fama-MacBeth (1973) cross-sectional regressions of individual stocks' excess returns from July of year *t* to June of year $t+1$ on $\ln(1+IE)$ and different sets of control variables in fiscal year ending in year $t-1$ except size and momentum. $\ln(1+IE)$ is the natural log of *Patents/RDC* or *Citations/RD* (both defined in Table 1). $\ln(1+RD/ME)$ is the natural log of one plus annual R&D expenditure divided by year-end market equity. *RDG* is a dummy for significant R&D growth. $\ln(1+PAT/ME)$ denotes the natural log of one plus patent counts divided by year-end market equity. Quartile (ΔAPC) denotes the quartile rank of ΔAPC. ln(*Size*) is the natural log of market equity at the end of June of year *t*. ln(*BTM*) is the natural log of book-to-market equity 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 6-month returns (with a one-month gap between the holding period and the current month). *AD/ME* is annual advertising expenditure dividend by year-end market equity. *CapEx/ME* is capital expenditure divided by year-end market equity. *ROA* is income before extraordinary items plus interest expense divided by lagged total assets. Asset growth (AG) is the change in total assets divided by lagged total assets. Net stock issues (NS) is the change in the natural log of the split-adjusted shares outstanding. Split-adjusted shares outstanding is Compustat shares outstanding times the Compustat adjustment factor. Institutional ownership (IO) denotes the fraction of firm shares outstanding owned by institutional investors. Industry dummies are based on the 48 industry classification defined in Fama and French (1997). All independent variables are normalized to zero mean and 1 standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1982 to June of 2008. The reported adjusted R^2 is the time series average of the adjusted R^2 of each monthly cross-sectional regression.

Explanatory variable	Panel A: *IE*=*Patents/RDC*		Panel B: *IE*=*Citations/RD*	
$\ln(1+IE)$	0.08	0.04	0.11	0.07
	(4.44)	(1.81)	(5.13)	(2.92)
$\ln(1+RD/ME)$		0.13		0.13
		(3.28)		(3.22)
RDG		0.12		0.12
		(1.08)		(1.11)
$\ln(1+PAT/ME)$		0.05		0.05
		(1.78)		(2.29)
Quartile (ΔAPC)		0.07		0.05
		(2.65)		(1.94)
ln(*Size*)	−0.30	−0.30	−0.30	−0.30
	(−3.06)	(−3.13)	(−3.13)	(−3.14)
ln(*BTM*)	0.39	0.37	0.39	0.37
	(6.76)	(6.32)	(6.73)	(6.34)
Momentum	−0.05	−0.06	−0.05	−0.06
	(−0.48)	(−0.60)	(−0.47)	(−0.60)
$\ln(1+AD/ME)$	0.06	0.05	0.06	0.06
	(1.81)	(1.74)	(1.81)	(1.76)
$\ln(1+CapEx/ME)$	−0.11	−0.12	−0.11	−0.12
	(−3.09)	(−3.25)	(−3.09)	(−3.25)
ROA	0.15	0.16	0.15	0.15
	(2.96)	(3.20)	(2.93)	(3.16)
AG	−0.26	−0.24	−0.26	−0.24
	(−6.36)	(−5.89)	(−6.32)	(−5.89)
NS	−0.12	−0.14	−0.12	−0.14
	(−2.54)	(−3.26)	(−2.56)	(−3.30)
IO	0.14	0.14	0.14	0.14
	(3.00)	(2.90)	(2.94)	(2.89)
Intercept	1.03	0.99	1.04	1.02
	(2.27)	(2.16)	(2.29)	(2.22)
Industry dummy	Yes	Yes	Yes	Yes
Adjusted R^2	6.55	6.83	6.56	6.83

(1992), we allow for a minimum 6-month lag between stock returns and the control variables to ensure the accounting variables are fully observable. Because the USPTO full discloses patents granted in weekly *Official Gazette of the United States Patent and Trademark Office*, our IE measures are also fully observable to the public. We winsorize all independent variables at the 1% and 99% levels, and we standardize all independent variables to zero mean and 1 standard deviation.

Table 5 reports the time series average slopes and corresponding *t*-statistics from series of monthly cross-sectional regressions with and without the four additional innovation-related control variables (*RD/ME*, *RDG*, *PAT/ME*, and ΔAPC) for both *IE* measures. In all specifications, the slopes on the *IE* measures are significantly positive, ranging from 0.04% to 0.11% with *t*-statistics ranging from 1.81 to 5.13. The magnitudes of the *IE* slopes are similar to those of the slopes on *PAT/ME* and ΔAPC, ranging from 0.05% to 0.07%. Although the slopes on *RD/ME* and *RDG* (0.13% and 0.12%, respectively) are larger than that on *IE* measures, the slopes on *RDG* are not significant.[18] Furthermore, we find in Section 7 that after size adjustment, the factor that is based upon *Patents/RDC* offers a higher average return and a higher ex post Sharpe ratio than the *RD/ME* and *RDG* factors. The innovative efficiency factor based on *Citations/RD* also offers a higher ex post Sharpe ratio than the *RD/ME* and *RDG* factors.

[18] The slope on *RDG* is significantly positive, consistent with Eberhart, Maxwell, and Siddique (2004), when the regression does not include the correlated innovation-related independent variables (unreported test).

Table 6
Innovative efficiency (IE) portfolio returns and risk factor models.

At the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint at the end of June of year t and three IE groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of *IE* in year $t-1$. We measure IE by *Patents/RDC* and *Citations/RD* defined in Table 1 in Panels A and B, respectively. We hold these portfolios over the next 12 months and compute value-weighted monthly returns of these size-IE portfolios (S/H, B/H, S/M, B/M, S/L, and B/L). We then calculate monthly size-adjusted returns of the low, middle, and high IE portfolios as (S/L+B/L)/2, (S/M+B/M)/2, and (S/H+B/H)/2, respectively. This table reports the monthly average size-adjusted excess returns to these portfolios and the intercepts (α, in percentage) and risk factor loadings from regressing portfolio excess returns on factor returns. Heteroskedasticity-robust t-statistics are reported in parentheses. Excess return is the difference between size-adjusted portfolio returns and the one-month Treasury bill rate. *MKT*, *SMB*, and *HML* are the market, size, and book-to-market ratio factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). INV and ROE are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2011).

	Excess return (percent)	Carhart four-factor model					Investment-based three-factor model			
IE		α (percent)	*MKT*	*SMB*	*HML*	*MOM*	α (percent)	*MKT*	*INV*	*ROE*
Panel A: *Patents/RDC*										
Low	0.49	−0.19	1.08	0.57	−0.14	−0.05	0.10	1.10	−0.13	−0.37
t	(1.48)	(−2.20)	(45.31)	(16.47)	(−3.22)	(−1.70)	(0.74)	(31.74)	(−1.89)	(−6.74)
Middle	0.86	0.22	1.01	0.49	−0.18	−0.02	0.39	1.07	−0.00	−0.29
t	(2.78)	(2.48)	(43.89)	(10.42)	(−3.67)	(−0.61)	(2.40)	(30.98)	(−0.05)	(−3.80)
High	0.90	0.27	1.04	0.53	−0.21	−0.04	0.50	1.08	−0.04	−0.37
t	(2.79)	(3.08)	(41.96)	(10.79)	(−5.80)	(−1.35)	(3.08)	(31.25)	(−0.63)	(−5.22)
Panel B: *Citations/RD*										
Low	0.59	−0.09	1.05	0.55	−0.13	−0.03	0.17	1.08	−0.07	−0.33
t	(1.86)	(−0.94)	(40.67)	(13.72)	(−2.94)	(−0.95)	(1.15)	(30.00)	(−1.04)	(−5.33)
Middle	0.81	0.14	1.01	0.44	−0.06	−0.03	0.25	1.05	0.08	−0.21
t	(2.78)	(1.65)	(49.27)	(13.02)	(−1.44)	(−1.00)	(1.85)	(31.16)	(1.20)	(−3.60)
High	0.85	0.26	1.04	0.49	−0.26	−0.05	0.49	1.08	−0.11	−0.38
t	(2.65)	(3.07)	(41.67)	(10.34)	(−7.23)	(−1.68)	(3.15)	(33.73)	(−1.69)	(−5.62)

The slopes on the control variables are in general consistent with the literature. Firms with higher *RD/ME*, higher *PAT/ME*, higher ΔAPC, smaller size, higher book-to-market ratio, higher *AD/ME*, lower *CapEx/ME*, higher *ROA*, lower asset growth, lower net stock issuance, and higher institutional ownership provide significantly higher future stock returns. The slope on momentum is insignificant.

These results indicate that innovative efficiency provides incremental value-related information. Furthermore, the IE effect is commensurate with the effects of significant R&D growth, patent-to-market ratio, and change in adjusted patent citations. Overall, these findings indicate that the explanatory power of IE is distinct from, and robust to the inclusion of, other commonly known return predictors and innovation-related variables.

5.2. Portfolio tests

In this subsection, we examine the ability of IE to predict portfolio returns and whether the IE effect is explained by risk or mispricing. At the end of June of year t, we 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 33rd and 66th percentiles of IE for each of the two IE measures. Size is the market value of equity at the end of June of year t, and IE is measured in year $t-1$.[19] The intersection forms six size-IE portfolios (S/H, B/H, S/M, B/M, S/L, and B/L).

We hold these portfolios over the next 12 months (July of year t to June of year $t+1$) and compute value-weighted monthly returns of the six portfolios. We then calculate monthly size-adjusted returns of the low, middle, and high IE portfolios using the formulas (S/L+B/L)/2, (S/M+B/M)/2, and (S/H+B/H)/2, respectively.

Table 6 shows that average monthly size-adjusted portfolio return net of the one-month Treasury bill rate (excess returns) increases monotonically with IE for both IE measures. Specifically, for Patents/RDC, the monthly size-adjusted excess returns on the low, middle, and high IE portfolios are 49 basis points ($t=1.48$), 86 basis points ($t=2.78$), and 90 basis points ($t=2.79$), respectively. For Citations/RD, the monthly size-adjusted excess returns on the low, middle, and high IE portfolios are 59 basis points ($t=1.86$), 81 basis points ($t=2.78$), and 85 basis points ($t=2.65$), respectively. Furthermore, the return spread between the high and low IE portfolios is significant at the 1% level for both IE measures (unreported test).

We also examine whether the size-adjusted returns of the IE portfolios is captured by risk factor models, such as the Carhart (1997) four-factor model or the investment-based three-factor model (Chen, Novy-Marx, and Zhang, 2011), by regressing the time series of size-adjusted portfolio excess returns on corresponding factor returns.[20] The Carhart model includes the market factor (MKT), the size factor (small minus big, SMB), the value factor (high minus low, HML), and the momentum factor (MOM).

[19] Although the IE measures in year $t-1$ are fully observable at the end of year $t-1$, we form IE portfolios at the end of June of year t to make the portfolio results comparable to prior studies. In unreported tables, we form IE portfolios at the end of February of year t and obtain similar results.

[20] We obtain similar results in unreported tests using the Fama and French (1993) three-factor model.

The investment-based factor model consists of MKT, the investment factor (INV), and the return on equity factor (ROE). MKT is the return on the value-weighted NYSE, Amex, and Nasdaq portfolio minus the one-month Treasury bill rate. SMB, HML, and MOM are returns on the factor-mimicking portfolios associated with the size effect, the value effect, and the momentum effect, respectively. INV and ROE are returns on the factor-mimicking portfolios associated with the negative relation between capital investment and stock returns and the positive relation between profitability and stock returns.[21]

Debate is ongoing about the extent to which these factors capture risk versus mispricing, but controlling for them provides a more conservative test of whether the innovative efficiency effect comes from mispricing. For example, 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 (2011) provide a model in which profitability predicts returns because of imperfect rationality.

Table 6 shows that the risk-adjusted returns of the IE portfolios also increase monotonically with IE for both IE measures. Specifically, the monthly value-weighted alphas estimated from the Carhart model for the low, middle, and high *Patents/RDC* portfolios are –19, 22, and 27 basis points, respectively. The monthly value-weighted alphas estimated from the investment-based model for the low, middle, and high *Patents/RDC* portfolios are 10, 39, and 50 basis points, respectively. Similarly, the monthly Carhart alphas for the low, middle, and high *Citations/RD* portfolios are –9, 14, and 26 basis points, respectively. The monthly investment-based alphas for the low, middle, and high *Citations/RD* portfolios are 17, 25, and 49 basis points, respectively.

Furthermore, the positive alphas of the high IE portfolios are statistically significant at the 1% level, suggesting that high IE firms are undervalued. In unreported results, we find the difference in the alphas between the high and low IE portfolios is also statistically significant at the 1% level for both IE measures. In addition, the high and low IE portfolios have similar loadings on various risk factors, indicating that the high returns provided by high IE firms cannot be simply attributed to systematic risk.

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; Barberis and Shleifer, 2003). For example, if investors do not fully impound information about correlated shifts in innovative efficiency (arising, for example, from technological change), we would expect a degree of commonality in the mispricing of innovative efficiency.

To examine whether a proposed measure of commonality in mispricing helps capture the IE effect, we augment the Carhart model and the investment-based model by adding the mispricing factor (UMO, Undervalued Minus Overvalued) of Hirshleifer and Jiang (2010).[22] 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 initial public offerings (IPOs), seasoned equity offerings (SEOs), and debt issuances over the past 24 months. The authors interpret the new issue and repurchase activities as managers' response to overvaluation and undervaluation of their firms, respectively, and provide evidence suggesting the UMO loadings proxy for the common component of a stock's mispricing.

Table 7 shows that adding UMO to the Carhart model reduces the alphas for the three IE portfolios for both IE measures. Specifically, the monthly alphas estimated from the augmented model are reduced to –13, 14, and 22 basis points for the low, middle, and high *Patents/RDC* portfolios, respectively, and to –5, 4, and 24 basis points for the low, middle, and high *Citations/RD* portfolios, respectively. However, the alphas of the high IE portfolios remain significant at the 1% level.

In unreported tests, we find that the differences in these alphas between the high and low IE portfolios are also significant at the 1% level. In addition, the loadings on UMO are negative for low IE portfolio, but positive for high IE portfolio. This suggests that low (high) IE firms are overvalued (undervalued), although the loadings on UMO are sometimes insignificant.

Adding UMO to the investment-based model does not have a big effect on the alphas of the IE portfolios. The alphas estimated from the augmented investment-based model for the high IE portfolios remain significantly positive. The alphas from the augmented model for the high *Patents/RDC* and high *Citations/RD* portfolios are 50 ($t=3.68$) and 51 ($t=3.84$), respectively. The alphas estimated from these augmented models also increase monotonically with IE. The loadings on UMO are insignificant, possibly because the INV and ROE factors are subject to dual interpretations as risk or mispricing.

Overall, these findings suggest that the IE effect is incremental to existing risk or mispricing factors.

6. Limited attention, valuation uncertainty, and the strength of return predictability based upon innovative efficiency

To test our proposed hypothesis that limited investor attention leads to a positive IE-return relation, we conduct the same Fama-MacBeth regressions as in Section 5.1 within subsamples split by size and analyst coverage as proxies for investor attention to a stock.[23] Firms with smaller size and lower analyst coverage receive less attention from investors and, therefore, should have more sluggish short-term stock price reactions to the information contained in innovative

[21] We obtain the Carhart (1997) four-factor returns and the one-month Treasury bill rate from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

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

[23] Size is market equity, and analyst coverage is the average monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous year. The Pearson and Spearman correlation coefficients between size and analyst coverage are 0.37 and 0.75, respectively.

Table 7
Innovative efficiency (IE) portfolio returns and risk factor models augmented with Undervalued Minus Overvalued (UMO).

At the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint at the end of June of year t and three IE groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of *IE* in year $t-1$. We measure *IE* by *Patents/RDC* and *Citations/RD* defined in Table 1 in Panels A and B, respectively. We hold these portfolios over the next 12 months and compute value-weighted monthly returns of these size-IE portfolios (S/H, B/H, S/M, B/M, S/L, and B/L). We then calculate monthly size-adjusted returns of the low, middle, and high *IE* portfolios as (S/L+B/L)/2, (S/M+B/M)/2, and (S/H+B/H)/2, respectively. This table reports the monthly average size-adjusted excess returns to these portfolios and the intercepts (α) and factor loadings from regressing portfolio excess returns on factor returns. Heteroskedasticity-robust t-statistics are reported in parentheses. Excess return is the difference between size-adjusted portfolio returns and the one-month Treasury bill rate. *MKT* is the market factor of Fama and French (1993). *INV* and *ROE* are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2011). *UMO* is the mispricing factor of Hirshleifer and Jiang (2010).

	Excess return (percent)	Carhart four-factor model plus UMO						Investment-based three-factor model plus UMO				
IE		α (percent)	*MKT*	*SMB*	*HML*	*MOM*	*UMO*	α (percent)	*MKT*	*INV*	*ROE*	*UMO*
Panel A: *Patents/RDC*												
Low	0.49	−0.13	1.06	0.57	−0.09	−0.02	−0.10	0.15	1.08	−0.07	−0.34	−0.08
t	(1.48)	(−1.43)	(42.16)	(15.73)	(−1.86)	(−0.74)	(−2.21)	(1.11)	(26.26)	(−0.75)	(−4.62)	(−0.92)
Middle	0.86	0.14	1.05	0.50	−0.25	−0.06	0.14	0.38	1.07	−0.02	−0.30	0.02
t	(2.78)	(1.42)	(41.36)	(10.91)	(−4.64)	(−1.89)	(2.43)	(2.77)	(27.82)	(−0.19)	(−3.00)	(0.21)
High	0.90	0.22	1.06	0.53	−0.25	−0.06	0.08	0.50	1.08	−0.04	−0.37	0.00
t	(2.79)	(2.52)	(41.12)	(10.88)	(−4.97)	(−2.18)	(1.51)	(3.68)	(27.63)	(−0.43)	(−3.86)	(0.03)
Panel B: *Citations/RD*												
Low	0.59	−0.05	1.04	0.55	−0.10	−0.01	−0.06	0.21	1.06	−0.02	−0.31	−0.07
t	(1.86)	(−0.55)	(38.61)	(13.16)	(−1.89)	(−0.41)	(−1.11)	(1.52)	(24.58)	(−0.22)	(−3.68)	(−0.72)
Middle	0.81	0.04	1.05	0.45	−0.16	−0.08	0.18	0.22	1.06	0.04	−0.22	0.05
t	(2.78)	(0.40)	(48.59)	(14.16)	(−3.65)	(−2.64)	(4.32)	(1.85)	(29.06)	(0.51)	(−3.11)	(0.60)
High	0.85	0.24	1.04	0.49	−0.28	−0.06	0.03	0.51	1.07	−0.09	−0.37	−0.03
t	(2.65)	(2.67)	(40.42)	(10.17)	(−5.25)	(−1.97)	(0.51)	(3.84)	(28.60)	(−0.89)	(−3.98)	(−0.34)

efficiency and greater predictability of stock 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 a 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 from large to small firms, across industries, 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).

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 stronger among small firms (Mashruwala, Rajgopal, and Shevlin, 2006).

Analyst stock coverage is often used as a proxy for analyst or investor attention. Irvine (2003) shows a rise in liquidity following initiation of analyst coverage of a stock. Bushee and Miller (2007) show 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 they show 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.

At the end of June of year t, we construct three size subsamples (micro, small, and big) based on the 20th and 50th percentiles of NYSE firms' size and two analyst coverage subsamples based on the median of analyst coverage calculated at the end of year $t-1$.[24] Within these subsamples, we then conduct monthly Fama-MacBeth cross-sectional regressions as in Section 5.1. For brevity, Table 8 reports the time series average slopes on IE only and corresponding t-statistics from these subsample regressions.

Panel A shows that the IE-return relation is stronger among firms with smaller size and lower analyst coverage for both IE measures. In the "IE only" specification that does not include the other innovation-related variables (*RD/ME*, *RDG*, *PAT/ME*, and ΔAPC), the average IE slopes among low attention stocks are always significant at the 1% level and are larger than those among high attention stocks. For example, the slopes on *Patents/RDC* are 0.09% (t=3.58), 0.09% (t=3.17), and 0.05% (t=2.07) for micro, small, and big firms, respectively. Similarly, the slopes on *Citations/RD* are 0.13% (t=4.42), 0.09% (t=2.81), and 0.04% (t=1.49) for

[24] We define microstocks as the stocks below the 20th percentile of NYSE firms' size following Fama and French (2008).

Table 8

Fama-MacBeth regressions of stock returns on innovative efficiency (IE) and other variables: subsample analysis.

This table reports the average slopes (in percent) of ln(1+*IE*) and their time series *t*-statistics in parentheses from monthly Fama-MacBeth (1973) cross-sectional regressions of individual stocks' excess returns from July of year t to June of year $t+1$ on ln(1+*IE*) and different sets of control variables in fiscal year ending in year $t-1$ except size and momentum (measured at the end of June of year t) in subsamples split by size, analyst coverage, firm age, turnover, and idiosyncratic volatility (*IVOL*). We measure *IE* by *Patents/RDC* and *Citations/RD* as defined in Table 1. Firm size is the market equity at the end of June of year *t*. Micro size stocks denote stocks with market capitalization lower than the 20th percentile of NYSE stocks, small size stocks denote stocks with market capitalization between the 20th percentile and the 50th percentile of NYSE stocks, and big stocks denote stocks with market capitalization higher than the 50th percentile of NYSE stocks. All the other subsamples are split by the median value of the corresponding measure. Analyst coverage (AC) is the average monthly number of stock analyst reports on earnings estimates in year $t-1$. Firm age denotes the number of years listed on Compustat with non-missing price data at the end of year $t-1$. Turnover is the average monthly turnover over the prior 12 months at the end of June of year *t*, 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 the standard deviation of the residuals from regressing daily stock returns on market returns over a maximum of 250 days ending on December 31 of year $t-1$. Following Table 5, we consider two models: the IE only model and the augmented model. The IE only model includes the following control variables defined in Table 5: ln(*Size*), ln(*BTM*), momentum, *CapEx/ME*, ln(1+*AD/ME*), *ROA*, asset growth, net stock issues, and institutional ownership. The augmented model expands the *IE*-only model by including other innovation-related variables: ln(1+*RD/ME*), *RDG*, ln(1+*PAT/ME*), and Quartile (ΔAPC). We also include industry dummies based on the 48 industry classification defined in Fama and French (1997) in all regressions. All independent variables are normalized to zero mean and 1 standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1982 to June of 2008.

	IE=*Patents/RDC*		IE=*Citations/RD*	
	IE only	Augmented	IE only	Augmented
Panel A: Subsamples split by investor attention proxies				
Micro size	0.09	0.09	0.13	0.07
	(3.58)	(2.32)	(4.42)	(2.34)
Small size	0.09	0.08	0.09	0.07
	(3.17)	(1.87)	(2.81)	(1.80)
Big size	0.05	0.01	0.04	0.02
	(2.07)	(0.32)	(1.49)	(0.61)
Low AC	0.09	0.06	0.10	0.08
	(2.64)	(1.62)	(3.07)	(2.21)
High AC	0.06	0.04	0.07	0.05
	(2.61)	(1.53)	(2.72)	(1.65)
Panel B: Subsamples split by valuation uncertainty proxies				
Young age	0.12	0.07	0.14	0.11
	(4.33)	(1.96)	(4.86)	(3.26)
Old age	0.02	−0.00	0.05	0.02
	(0.71)	(−0.63)	(2.10)	(0.91)
High turnover	0.10	0.08	0.10	0.07
	(4.12)	(2.74)	(4.12)	(2.37)
Low turnover	0.03	−0.00	0.09	0.06
	(1.09)	(−0.91)	(3.05)	(1.79)
High IVOL	0.09	0.07	0.14	0.08
	(4.66)	(3.18)	(4.19)	(2.08)
Low IVOL	0.08	0.02	0.05	0.03
	(2.80)	(0.59)	(2.49)	(1.34)

micro, small, and big firms, respectively. This evidence shows that the positive IE effect is not limited in microfirms. In addition, the IE slope is larger in the low analyst coverage (AC) subsample than that in the high AC subsample, although the difference across the AC subsamples is not substantial. For example, the slopes on *Citations/RD* are 0.10% (t=3.07) and 0.07% (t=2.72) for the low and high AC subsamples, respectively.

Similar patterns are found in the "Augmented" specification, which controls for the four innovation-related variables listed above. For example, the average IE slopes on *Citations/RD* are 0.07% (t=2.34), 0.07% (t=1.80), and 0.02% (t=0.61) for micro, small, and big firms, respectively, and are 0.08% (t=2.21) and 0.05% (t=1.65) for low AC and high AC firms, respectively. Although the cross-subsample differences in the IE slopes are not always statistically significant, their magnitudes are economically substantial. These contrasts tend to 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 VU.[25] We expect the IE-return relation to be stronger among firms

[25] 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.

with more valuation uncertainty, which place a greater cognitive burden on investor attention.

Following Kumar (2009), we use three measures of VU: firm age, turnover, and idiosyncratic volatility (IVOL).[26] Firm age is the number of years listed on Compustat with non-missing price data. Turnover 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.[27] IVOL is the standard deviation of the residuals from regressing daily stock return on daily CRSP value-weighted index return (the market return) over a maximum of 250 days.

We interpret firms with younger age, higher turnover, or higher idiosyncratic volatility as having higher valuation uncertainty. We form two age and two IVOL subsamples based on the medians of these measures at the end of year $t-1$ and two turnover subsamples based on the median of turnover at the end of June of year t. Within each VU subsample, we conduct the same Fama-MacBeth regressions as were performed in the attention subsamples (Panel A).

Panel B of Table 8 shows a stronger IE-return relation in subsamples with higher valuation uncertainty. For example, in the "Augmented" specification, the slopes on *Patents/RDC* are 0.07 (t=1.96), 0.08 (t=2.74), and 0.07 (t=3.18) in the young age, high turnover, and high IVOL subsamples, respectively. In contrast, these slopes are only −0.00 (t=−0.63), −0.00 (t=−0.91), and 0.02 (t=0.59) in the old age, low turnover, and low IVOL subsamples, respectively. This sharp contrast holds for *Citations/RD* across the age and IVOL subsamples, but not for across the turnover subsamples. For example, in the "Augmented" specification, the slopes on *Citations/RD* are 0.11 (t=3.26), 0.07 (t=2.37), and 0.08 (t=2.08) in the young age, high turnover, and high IVOL subsamples, respectively. In contrast, these slopes are 0.02 (t=0.91), 0.06 (t=1.79), and 0.03 (t=1.34) in the old age, low turnover, and low IVOL subsamples, respectively.

Furthermore, the differences in IE slopes across the age subsamples are statistically significant with t-statistics of at least 2.03 (unreported results). Although the differences in IE slopes across the IVOL subsamples are not always statistically significant, their magnitudes are substantial. These generally sharp contrasts across valuation uncertainty subsamples are robust to measures of IE and model specifications, suggesting that the IE-return relation is more likely to be driven by behavioral biases.

7. The EMI factor

To further 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 a factor-mimicking portfolio for innovative efficiency, Efficient Minus Inefficient (EMI), based on *Patents/RDC* (EMI1) and on *Citations/RD* (EMI2) following the procedure in Fama and French (1993). At the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint at the end of June of year t and three IE groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of IE in year $t-1$. The intersection of these portfolios forms six size-IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H).

Value-weighted monthly returns on these six portfolios are computed from July of year t to June of year $t+1$. The EMI factor is computed as (S/H+B/H)/2−(S/L+B/L)/2, i.e., 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). These return series track return comovement associated with innovative efficiency, regardless of whether the comovement is associated with any risk premium or mispricing.

Fig. 1 plots the two EMI factors returns and the market factor (MKT) returns on a per annum basis from 1982 to 2008. While the market factor return is negative for eight out of 27 years, the *EMI1* (*EMI2*) factor return is negative for only 4 (6) years. Moreover, the EMI factors appear to be a good hedge against market downturns. The EMI factor returns are almost always positive in those years in which the market factor returns are negative. For example, the market factor returns in 1984, 1987, 1990, 1994, 2000, 2001, 2002, and 2008 are −6.12%, −3.55%, −13.00%, −4.50%, −16.10%, −14.63%, −22.15%, and −20.68%, respectively. In contrast, the corresponding *EMI1* factor returns are 2.92%, 13.37%, 10.13%, 6.05%, 25.76%, 2.40%, 6.14%, and 13.08%. Similarly, the corresponding *EMI2* factor returns are 0.03%, 12.03%, 9.34%, 5.70%, 13.00%, 0.75%, 4.77%, and −9.19%. When the Internet bubble burst in 2000, the EMI factors performed extremely well, with a substantial return of 25.76% for *EMI1* and 13.00% for *EMI2*.

To verify whether there is an incremental effect of innovative efficiency relative to other innovation-related measures, we also construct four innovation-related factors based on *RD/ME*, *RDG*, *PAT/ME*, and ΔAPC, using the formula (S/H+B/H)/2−(S/L+B/L)/2. "S" and "B" refer to the small and big portfolios based on the NYSE median size breakpoint for all factors, "H" and "L" refer to the top and bottom terciles based on *RD/ME* for the *RD/ME* factor and on ΔAPC for the ΔAPC factor. For the *RDG* factor, "H" and "L" refer to portfolios of firms with and without significant R&D growth as defined in Eberhart, Maxwell, and Siddique (2004). For the *PAT/ME* factor, "H" and "L" refer to the high and low *PAT/ME* portfolios based on the median of *PAT/ME*.[28]

Panel A of Table 9 describes the means, standard deviations, time series t-statistics, and ex post Sharpe ratios of the monthly returns of *EMI1*, *EMI2*, the *RD/ME* factor, the *RDG* factor, the *PAT/ME* factor, the ΔAPC factor, the market factor (MKT), the size factor (SMB), the value

[26] The turnover 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, firm age and idiosyncratic volatility, are not subject to the concern of dual interpretations.

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

[28] Due to many tied values for *PAT/ME*, we form two instead of three *PAT/ME* portfolios in constructing the *PAT/ME* factor.

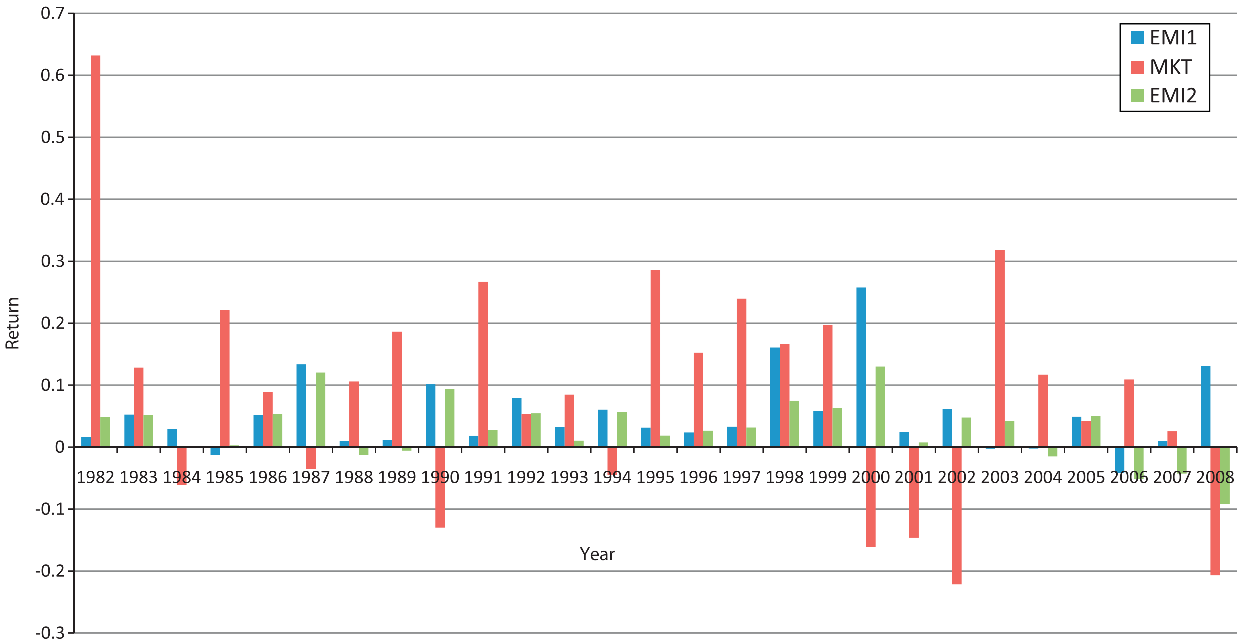

Fig. 1. Efficient Minus Inefficient (EMI) factors and market factor returns over time. This figure plots the return (on a per annum basis) for the *EMI1* and *EMI2* factors and the market factor from 1982 to 2008. MKT is the return on the value-weighted NYSE, Amex, and Nasdaq portfolio minus the one-month Treasury bill rate. At the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint and three innovative efficiency (IE) groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of our IE measures, *Patents/RDC* and *Citations/RD* (defined in Table 1), in year $t-1$. Size is the market equity at the end of June of year t. The intersection of these portfolios forms six size–IE portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Value-weighted monthly returns on these six double-sorted portfolios in excess of the one-month Treasury bill rate are computed from July of year t to June of year $t+1$. *EMI1* (*EMI2*) is computed as (S/H+B/H)/2−(S/L+B/L)/2, where "H" and "L" refer to IE portfolios based on *Patents/RDC* (*Citations/RD*).

factor (HML), the investment factor (INV), the ROE factor, the momentum factor (MOM), and the mispricing factor (UMO). The average return of *EMI1* is 0.41% per month, which is lower than that of the *RD/ME* factor (0.45%), *MKT* (0.68%), *ROE* (0.86%), *MOM* (0.83%), and *UMO* (0.87%); however, it is higher than the average returns of the *RDG* factor (0.21%), the *PAT/ME* factor (0.31%), the ΔAPC factor (0.00%), *SMB* (0.07%), *HML* (0.37%), and *INV* (0.36%). The average return of *EMI2* is 0.26% per month, which is higher than that of many of the previous factors.

Furthermore, the standard deviations of *EMI1* and *EMI2* are 1.75% and 1.80%, respectively, which are considerably lower than those of the other factors except the *PAT/ME* factor (1.65%), the ΔAPC factor (1.54%), and *INV* (1.78%). This finding indicates that investing based upon innovative efficiency is even more attractive than its substantial returns would suggest. *EMI1* offers an ex post Sharpe ratio of 0.23, which is higher than that of all the other factors except UMO (0.27).[29] In addition, *EMI2* provides an ex post Sharpe ratio of 0.15, which is higher than those of *SMB* (0.02), *HML* (0.12), the *RDG* factor (0.07), the ΔAPC factor (0.00), and the *RD/ME* factor (0.12).

Panel B reports the correlation between different factor returns and shows that the two *EMI* factors are distinct from other familiar factors. *EMI1* has a correlation of –0.07 with MKT, –0.05 with SMB, –0.03 with HML, 0.10 with INV, 0.02 with ROE, 0.04 with MOM, and 0.13 with UMO, all of which are modest in magnitude. Correlations of similar magnitude are found between *EMI2* and other familiar factors. In addition, we find that both *EMI1* and *EMI2* are positively correlated with the other four innovation-related factors. In particular, *EMI1* (*EMI2*) has a correlation of 0.16 (0.16) with the *RD/ME* factor, 0.66 (0.52) with the *PAT/ME* factor, 0.21 (0.36) with the ΔAPC factor, and 0.07 (0.07) with the *RDG* factor.

These findings suggest that investors can do substantially better than the market portfolio, or the three Fama and French factors in optimal combination, by further adding the EMI factor to their portfolios. Panel C (D) describes the maximum ex post Sharpe ratios achievable by combining *EMI1* (*EMI2*) with 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.

In Panel C, the first row shows that the monthly ex post Sharpe ratio of *MKT* is 0.16. The second row shows that when SMB is available as well, it receives negative weighting in the optimal portfolio (–9%) 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 (51%) and almost doubles the Sharpe ratio, bringing it to 0.29. The fourth row shows

[29] 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 *EMI1* (*EMI2*) offers an ex post Sharpe ratio of 0.21 (0.14) after dropping the year 2000, in which EMI1 (EMI2) reaches its highest annualized return. The corresponding Sharpe ratio for *MKT* is 0.18 the annualized return for *MKT* in 2000 is –16.10%.

Table 9

At the end of June of year t from 1982 to 2007, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint and three innovative efficiency (IE) groups (low "L," middle "M," or high "H") based on the 33rd and 66th percentiles of *IE* in year $t-1$. Size is the market equity at the end of June of year t. The intersection of these portfolios forms six *size–IE* portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). Value-weighted monthly returns on these six portfolios are computed from July of year t to June of year $t+1$. The innovative efficiency factor, Efficient Minus Inefficient (EMI), is computed as (S/H+B/H)/2−(S/L+B/L)/2. *EMI1* and *EMI2* are based on *Patents/RDC* and *Citations/RD*, respectively. We also construct four innovation-related factors based on *RD/ME*, *RDG*, *PAT/ME*, and *ΔAPC*, respectively, using the formula (S/H+B/H)/2−(S/L+B/L)/2. "S" and "B" refer to the small and big portfolios based on the NYSE median size breakpoint for all factors. "H" and "L" refer to the top and bottom terciles based on *RD/ME* for the *RD/ME* factor and on *ΔAPC* for the *ΔAPC* factor. For the *RDG* factor, "H" and "L" refer to portfolios of firms with and without significant R&D growth as defined in Eberhart, Maxwell, and Siddique (2004). For the *PAT/ME* factor, "H" and "L" refer to the high and low *PAT/ME* portfolios based on the median of *PAT/ME*. *MKT* is the return on the value-weighted NYSE, Amex, and 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 the book-to-market effect, respectively. *MOM* denotes the momentum factor. *INV* and *ROE* are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2011). Undervalued Minus Overvalued (UMO) is the mispricing factor of Hirshleifer and Jiang (2010). Panel A reports the mean, standard deviation, t-statistics, and ex post Sharpe ratio (SR) for these factors. Panel B reports the Pearson correlation coefficients among these factors. Panels C and D report the monthly Sharpe ratios of ex post tangency portfolios based on investing in subsets of these 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 and standard deviations are in percentage.

Panel A: Summary statistics of factor-mimicking Portfolios

	EMI1	*EMI2*	*MKT*	*SMB*	*HML*	*INV*	*ROE*	*MOM*	*UMO*	*RDG*	*ΔAPC*	*RD/ME*	*PAT/ME*
Mean	0.41	0.26	0.68	0.07	0.37	0.36	0.86	0.83	0.87	0.21	0.00	0.45	0.31
Standard deviation	1.75	1.80	4.31	3.26	3.05	1.78	3.72	4.27	3.26	3.04	1.54	3.73	1.65
t-statistic	4.13	2.60	2.77	0.37	2.15	3.60	4.06	3.43	4.74	1.24	0.04	2.12	3.31
SR	0.23	0.15	0.16	0.02	0.12	0.20	0.230	0.19	0.27	0.07	0.00	0.12	0.19

Panel B: Correlation matrix of factor-mimicking portfolios

	EMI1	*EMI2*	*MKT*	*SMB*	*HML*	*INV*	*ROE*	*MOM*	*UMO*	*RD/ME*	*PAT/ME*	*ΔAPC*	*RDG*
EMI1	1.00												
EMI2	0.70	1.00											
MKT	−0.07	0.06	1.00										
SMB	−0.05	−0.03	0.19	1.00									
HML	−0.03	−0.15	−0.48	−0.42	1.00								
INV	0.10	−0.06	−0.29	−0.11	0.38	1.00							
ROE	0.02	−0.11	−0.32	−0.45	0.40	0.13	1.00						
MOM	0.04	−0.04	−0.10	0.12	−0.09	0.17	0.29	1.00					
UMO	0.13	−0.06	−0.61	−0.28	0.66	0.54	0.52	0.32	1.00				
RD/ME	0.16	0.16	0.35	0.55	−0.42	−0.02	−0.60	0.05	−0.30	1.00			
PAT/ME	0.66	0.52	0.18	0.19	−0.29	0.12	−0.29	0.00	−0.05	0.59	1.00		
ΔAPC	0.21	0.36	0.27	0.45	−0.55	−0.16	−0.47	0.06	−0.39	0.54	0.40	1.00	
RDG	0.07	0.07	0.34	0.38	−0.61	-0.18	−0.44	0.13	−0.39	0.74	0.48	0.46	1.00

	Portfolio weights												Tangency portfolio		
Portfolio	*MKT*	*SMB*	*HML*	*EMI*	*INV*	*ROE*	*MOM*	*UMO*	*RDG*	*ΔνAPC*	*RDME*	*PAT/ME*	Mean	Standard deviation	Ex post SR
Panel C: Ex post tangency portfolio (EMI is created based on *Patents/RDC*)															
1	1.00												0.68	4.31	0.16
2	1.09	−0.09											0.73	4.65	0.16
3	0.34	0.15	0.51										0.43	1.51	0.29
4	0.20	0.09	0.29	0.42									0.42	1.06	0.39
5	0.18	0.07	0.19	0.32	0.24								0.41	0.97	0.43
6	0.17	0.14	0.18	0.32		0.19							0.48	0.99	0.49
7	0.19	0.06	0.27	0.35			0.13						0.48	1.05	0.46
8	0.26	0.07	0.04	0.26				0.37					0.62	1.16	0.53

Table 9 (*continued*)

Portfolio	Portfolio weights												Tangency portfolio		
	MKT	*SMB*	*HML*	*EMI*	*INV*	*ROE*	*MOM*	*UMO*	*RDG*	*ΔνAPC*	*RDME*	*PAT/ME*	Mean	Standard deviation	Ex post SR
9	0.16	0.06	0.31	0.34					0.13				0.39	0.95	0.41
10	0.20	0.10	0.29	0.44						−0.03			0.43	1.09	0.39
11	0.19	0.06	0.30	0.40							0.05		0.43	1.08	0.40
12	0.18	0.08	0.29	0.34								0.10	0.41	1.03	0.40
13	0.17	0.06	0.08	0.22	0.08	0.13	−0.01	0.18	0.10	0.06	0.04	−0.13	0.53	0.89	0.60
Panel D: Ex post tangency portfolio (EMI is created based on *Citations/RD*)															
1	1.00												0.68	4.31	0.16
2	1.09	−0.09											0.73	4.65	0.16
3	0.34	0.15	0.51										0.43	1.51	0.29
4	0.21	0.11	0.35	0.33									0.37	1.08	0.34
5	0.18	0.07	0.21	0.25	0.29								0.37	0.95	0.39
6	0.17	0.16	0.20	0.26		0.21							0.45	0.98	0.46
7	0.19	0.07	0.31	0.28			0.15						0.45	1.06	0.42
8	0.27	0.08	0.04	0.21				0.41					0.61	1.17	0.52
9	0.16	0.06	0.36	0.26					0.16				0.35	0.93	0.37
10	0.22	0.12	0.35	0.35						−0.03			0.38	1.11	0.34
11	0.19	0.06	0.36	0.29							0.10		0.39	1.11	0.35
12	0.17	0.07	0.32	0.15								0.29	0.37	1.00	0.37
13	0.16	0.07	0.09	0.16	0.08	0.14	−0.01	0.17	0.10	0.04	0.04	−0.03	0.51	0.86	0.59

that *EMI1* substantially increases the Sharpe ratio of the tangency portfolio, to 0.39. Moreover, the weight on *EMI1* (42%) is much higher than that of any of the other three factors. The reason that *EMI1* 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 and French factors.

Similar results are found for *EMI2* in Panel D. When combined with the three Fama and French factors, *EMI2* is weighted heavily (33%) and raises the Sharpe ratio of the tangency portfolio to 0.34. The improvement in the maximum Sharpe ratio from inclusion of EMI is a challenge to variation in risk premia as an explanation for IE-based return predictability. Previous research on the equity premium puzzle (Mehra and Prescott, 1985) indicates that the high Sharpe ratio of the stock market already presents a difficult challenge for rational asset pricing theory.

Furthermore, *EMI1* (*EMI2*) retains its substantial role in the tangency portfolio, with weights ranging from 26% to 35% (21% to 28%) when combined with INV, ROE, MOM, or UMO. The importance of EMI is robust to the inclusion of the other innovation-related factors. *EMI1* (*EMI2*) still retains a substantial weight in the tangency portfolio, ranging from 34% to 44% (15% to 35%) when combined with one of the *RD/ME*, *RDG*, *PAT/ME*, and Δ*APC* factors. Even when all the other 11 factors are included, the weight on *EMI1* is 22%, which is higher than that of any of the other factors. Similarly, the weight on *EMI2* is 16%, which is higher than that of any of the other factors except MKT and UMO. These findings suggest that EMI factors capture risk or mispricing effects above and beyond those captured by the well-known factors and the other innovation-related factors.

8. Conclusion

We find that firms that are more efficient in innovation on average have higher contemporaneous market valuations and superior future operating performance, market valuation, and stock returns. The relation between innovative efficiency (IE) and operating performance is robust to controlling for innovation-related variables suggested by other studies, such as R&D-to-market equity, significant R&D growth, patent-to-market equity, and change in adjusted patent citations scaled by average total assets. Similarly, the relation between IE and current (and future) market valuation is also robust to a variety of controls. The positive association of IE with subsequent stock returns is robust to controlling for standard return predictions and innovation-related variables.

Empirical factor pricing models, such as the Carhart four-factor model and the investment-based three-factor model, do not fully explain the IE-return relation. Adding the financing-based mispricing factor UMO to these models improves the models' explanatory power, but substantial and significant abnormal return performance remains. These findings show that the IE effect on returns is incremental to existing return predictors and cannot be explained by known factors (risk or mispricing).

Further analyses show that proxies for investor inattention and valuation uncertainty are associated with stronger ability of IE measures to predict returns. These findings provide further support for psychological bias or constraints contributing to the IE-return relation. The high Sharpe ratios of the two Efficient Minus Inefficient (EMI) factors also suggest this relation is not entirely explained by rational pricing. Finally, regardless of the source of the effect, the heavy weight of the EMI factors in the tangency portfolio suggests that innovative efficiency captures pricing effects above and beyond those captured by the other well-known factors and other innovation effects, which focus on either innovative input or output separately.

The fact that the mispricing factor partly helps explain the innovative efficiency effect suggests that there is commonality in mispricing across firms associated with innovative efficiency. Such commonality could arise, for example, if investors do not fully impound news about the correlated shifts in innovative efficiency that are driven by technological shifts. This is consistent with behavioral models in which there is commonality in mispricing (Daniel, Hirshleifer, and Subrahmanyam, 2001; Barberis and Shleifer, 2003).

As a policy matter, if capital markets fail to reward firms that are more efficient at innovation, there will be potential misallocation of resources in which firms that are highly effective at innovation are undercapitalized relative to firms that are less effective at innovating. Our findings suggest that investors should direct greater attention to innovative efficiency and that innovative efficiency can be a useful input for firm valuation.

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