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# Don't Hide Your Light Under a Bushel: Innovative Diversity and Stock Returns[*]

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# Don’t Hide Your Light Under a Bushel: Innovative Diversity and Stock Returns

We hypothesize that owing to limited investor attention and skepticism of complexity, innovative diversity (ID) of a firm’s patent portfolio will be undervalued. ID strongly predicts stock returns after controlling for firm characteristics and risk. High ID portfolios provide Carhart alphas of 56-81 basis points per month and stronger and less volatile operating performance. The Diversified Minus Concentrated (DMC) portfolio earns a high Sharpe ratio relative to well-known factors, and has high weight in the tangency portfolio in competition with standard factors and the innovative efficiency factor. Further tests suggest that limited investor attention contributes to the ID effect.

*JEL Classification:* G11, G12, G14, O32

*Keywords:* Limited attention, Market efficiency, Processing fluency, Innovative diversity, Patent portfolio

## 1. Introduction

To finance innovative activities effectively, investors need to value them, but this is hard to do, because this requires going beyond routine application of standardized procedures and metrics. Valuing innovation requires understanding of how the economic fundamentals of a firm or its industry are changing, and the inherent uncertainties in the long road from concept to implementation to actual profits. This suggests that the market may be inefficient in valuing innovation, and that we can gain insight into the nature of this predictability by considering the informational demands placed upon investors, and the constraints on investors' cognitive processing power.[1]

Extensive psychological evidence shows that individuals pay less attention to, and place less weight upon, information that is harder to process. Recipients tend to interpret signals that have lower processing fluency with greater skepticism, and view the subject matter of such signals as riskier [see, e.g., Alter and Oppenheimer 2006; Song and Schwarz (2008, 2009, 2010)]. This evidence accords with a popular view of corporate diversification in the business press that complex firms place high attentional demands upon analysts, and that analysts therefore value such firms pessimistically. Popular discussions therefore often present obtaining higher market valuations as a motivation for firms to sell divisions and refocus. This cognitive argument for why diversified firms should be underpriced applies much more strongly to diversity in a firm's *innovative* portfolio, since innovation places especially high cognitive burdens on analysts.

The complexity of a firm's innovative prospects can affect its misvaluation for two distinct reasons. First, people tend to view information that has low processing fluency more skeptically, so complexity should directly cause undervaluation. Second, as we document here, innovatively

[1] Some studies suggest that investors may overdiscount the cash flow prospects of R&D-intensive firms owing to high technical uncertainty associated with innovations, leading to underpricing (see, e.g., Hall 1993; Lev and Sougiannis 1996; Chan, Lakonishok, and Sougiannis 2001; Lev, Sarath, and Sougiannis 2005).

complex firms tend to have better future fundamentals, so if investors have limited attention, they will tend to underreact to this favorable information.[2,3] Both effects imply that more complex firms will on average earn higher abnormal returns.

In this study, we use the diversity of a firm's patent portfolio (innovative diversity, ID) as a proxy for the complexity of a firm's innovative activities. The valuation task is harder for a firm with a highly diversified portfolio of patents in different technological or business domains since a greater range of analytical expertise is needed, and because distinct analyses are needed for each domain.

We construct our main measure of a firm's innovative diversity by applying the well-known Herfindahl index (a measure of industry concentration) to the patents granted to the firm over the previous five years. Consistent with undervaluation of complexity, we find that on average analysts overestimate the earnings of low ID firms more than those of high ID firms. Furthermore, we find that insiders exploit the information contained in innovative diversity in their trading decisions; high ID firms on average have lower net stock sales by CEOs and non-CEO directors. We also find that high ID firms have higher and more stable future return on

[2] In principle, a more diversified patent portfolio could be associated with either better or worse future operating performance. Innovatively diverse firms may do worse if managerial attention becomes spread too thinly. On the other hand, innovative diversity may be associated with superior operating performance because: (i) diversity may reflect a talented management team that is skillful enough to handle an innovatively diverse portfolio; (ii) owing to the high uncertainty of R&D investment, spreading R&D efforts across different technological areas may increase the probability of finding the next path-breaking innovative product. Therefore, a firm with a well-diversified patent portfolio may have higher success probability and better operating performance; (iii) a diversified patent portfolio may diversify risk, thereby reducing the volatility of operating performance and expected costs associated with financial distress; and (iv) a well-diversified patent portfolio may help establish intellectual property rights, thereby deterring or defeating lawsuits about patent infringements.

[3] Neglect could take the form of not even being aware of the firm's innovative diversity, or of being aware of but not processing this information to make good use of it. There is evidence of investor underreaction to a different kind of favorable information about firms' innovative activities. Hirshleifer, Hsu, and Li (2012) find that firms with higher innovative efficiency (i.e., the ability to generate patents or patent citations per dollar of R&D investment), have higher subsequent operating performance and stock returns. Furthermore, Cohen, Diether, and Malloy (2012) find that firms that have successful past track records in converting R&D investment into sales and that invest heavily in R&D earn significantly higher abnormal returns and generate more patents, patent citations and new product innovations.

assets, cash flow, and profit margin.

To test whether the market fully impounds the information in innovative diversity, we perform portfolio sorts and examine the relation between firms' ID measures and future stock returns. At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing ID measures independently into three size groups (small "S", middle "M", or big "B") and three ID groups (low "L", middle "M", or high "H").[4] The intersection forms nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H). We then calculate monthly size-adjusted returns (equal- and value-weighted) of the low, middle, and high ID portfolios using the formulas (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively.

We find that the size-adjusted return increases monotonically with ID and the value-weighted (equal-weighted) return spread between the high and low ID portfolios is 51 (52) basis points per month with a *t*-statistic of 4.49 (4.69), which is economically substantial and statistically significant. The risk-adjusted return also increases monotonically with ID, and the spread between the high and low ID portfolios is large and significant. For example, the monthly value-weighted (VW) alphas estimated from the Carhart (1997) four-factor model for the low, middle, high, and high-minus-low ID portfolios are 7 ($t$ = 0.80), 28 ($t$ = 3.20), 56 ($t$ = 4.56), and 50 ($t$ = 4.28) basis points, respectively. The monthly equal-weighted (EW) alpha for the high ID portfolio is even higher: 81 ($t$ = 5.92) basis points. This evidence shows that high ID firms are undervalued relative to the Carhart model benchmark; the significant alpha for the hedge (i.e., high-minus-low) portfolio is mainly driven by the undervaluation of high ID firms.

Hirshleifer, Hsu, and Li (2012) document a significantly positive relation between innovative efficiency (i.e., patents or citations per dollar of research and development) and future abnormal

[4] We control for the size effect because larger firms with more resources are usually more diversified in product lines and market segments.

stock returns. To verify whether the ID effect is not just a correlate of the innovative efficiency effect, we add the innovative efficiency factor EMI (Efficient Minus Inefficient) to the Carhart model.[5]

The ID effect remains substantial and significant even after controlling for EMI. For example, the monthly VW and EW alphas estimated from this augmented model for the high ID portfolios are 44 ($t$ = 3.68) and 72 ($t$ = 5.46) basis points, respectively. The monthly VW and EW alphas for the high-minus-low ID portfolios are 32 ($t$ = 2.93) and 32 ($t$ = 2.74) basis points, respectively. This evidence indicates that the ID effect is incremental to the innovative efficiency effect.

To assess whether ID predicts the cross section of expected returns, and whether the ID effect is robust to a wider set of controls, we perform Fama-MacBeth (1973) cross-sectional return regressions that control for industry effects and different sets of well-known return predictors, including innovation-related controls such as innovative efficiency, patents, R&D intensity, R&D amount, significant R&D growth, and change in adjusted patent citations. The slopes on ID range from 0.12% to 0.20% with $t$-statistics between 2.22 and 5.54, which are economically and statistically significant, irrespective of the model specifications.

Relative to the mean return net of the one-month Treasury bill rate (excess return, 1.11% per month), it implies that a one standard deviation increase in ID predicts an average increase of 10.85% or higher in future stock returns, which is economically substantial. Furthermore, the predictive ability of ID remains substantial and is slightly increased when we additionally control for sales diversity. These findings indicate that innovative diversity contains distinct and

[5] Hirshleifer, Hsu, and Li (2012) argue that EMI reflects commonality in returns associated with innovative efficiency.

important information about future returns that is incremental to that of other innovation measures and firm characteristics.

If limited attention and skepticism about complexity drive the ID-return relation, then we would expect to see greater return predictability of ID among stocks with lower investor attention and among harder-to-value stocks. To test these hypotheses, we perform Fama-MacBeth return regressions in subsamples split by size or analyst coverage as proxies for investor attention to a stock (Hong, Lim, and Stein 2000) and in subsamples split by idiosyncratic volatility or firm age as proxies for valuation uncertainty (Kumar 2009).[6] We expect a stronger ID effect among firms with small market capitalization, low analyst coverage (AC), high idiosyncratic volatility (IVOL), and young age.

The subsample regressions are generally supportive of these predictions. For the attention subsamples, the ID-return relation is always significantly positive among SMALL and low AC firms, and is always insignificant (sometimes with negative point estimates) among BIG and high AC firms. The cross-subsample differences in the ID slopes are not always statistically significant, but their magnitudes are economically substantial. For the valuation uncertainty subsamples based on IVOL, the ID slopes are always positive and significant in the high IVOL subsample, but insignificant in the low IVOL subsample. For the age subsamples, the ID slopes in the young subsample are always positive and much larger than those in the old subsample.

An alternative explanation of the positive ID-return relation is related to the theory that overvaluation is caused by the combination of investor disagreement and short-sale constraints; we discuss this alternative hypothesis in detail in Section 4. If disagreement is the explanation for

[6] Other proxies of investor attention used in previous studies are related to these variables. For example, Fang and Peress (2009) report that media coverage increases with firm size and analyst coverage. Another approach is to run full-sample regressions with interaction terms between ID and these proxies. However, running regressions within subsamples split by one proxy at a time allows us to avoid multicollinearity since these proxies are highly correlated with each other. For example, the Spearman (Pearson) correlation between size and IVOL is –0.65 (–0.56).

the ID-return relation, then firms with low ID and high disagreement should earn abnormally low returns relative to standard benchmarks.

However, in the factor regression tests for ID portfolios discussed earlier, the alphas for low ID portfolio are non-negative (though not always significantly positive, and much lower than the alphas of the high ID portfolio).[7] This evidence suggests that neither high nor low ID firms are overvalued, and that high ID firms are undervalued both absolutely and relative to the low ID firms. This conclusion is in sharp contrast with the disagreement explanation, which would imply that both sets of firms would be overvalued.

To examine the value of ID for optimal investment portfolios, and to further examine if the ID-based return predictability is driven by risk, mispricing, or both, we construct a factor-mimicking portfolio for innovative diversity, DMC (Diversified Minus Concentrated), based on the ID measure following Fama and French (1993). The returns of the DMC factor are essentially the size-adjusted VW returns of the high-minus-low ID portfolio discussed earlier.

We find that DMC is not highly correlated with well-known factors such as the market, size, value, and momentum factors, the investment and ROE factors (Chen, Novy-Marx, and Zhang 2011), and the mispricing factor UMO (Undervalued Minus Overvalued; Hirshleifer and Jiang 2010). The correlations between DMC and these factors range from –0.12 to 0.22. Although the correlation between DMC and EMI is 0.42, DMC has a greater weight than EMI when we include both factors in the tangency portfolio (discussed later).

The average monthly return of the DMC factor is 0.51%, which is higher than that of the size factor (0.07%), the value factor (0.37%), the investment factor (0.36%), and EMI (0.26%). Furthermore, DMC offers an ex post Sharpe ratio, 0.25, which is higher than the market factor

[7] The alphas of the high ID portfolio are significantly positive. We can only estimate ID for the 54 to 57% of the firms in the Compustat universe that have sufficient patent data availability, so the alphas of firms sorted by ID need not average to zero.

(0.16) and all the above factors except UMO (0.27). Since the high level of the equity premium is a well-known puzzle for rational asset pricing theory (Mehra and Prescott 1985), the higher ex post Sharpe ratio associated with DMC is an even greater puzzle from this perspective.

Adding DMC to the Fama-French three factors increases the ex post Sharpe ratio of the tangency portfolio from 0.29 to 0.37 with a weight of 0.39 on DMC. Even when all of the above factors are included, the weight on DMC in the tangency portfolio is 0.17, which is substantially higher than that on any of the other factors except the market factor (0.19) and UMO (0.21). These findings indicate that the ID-return relation captures return predictability effects above and beyond those captured by other common factors.

Previous empirical research on the valuation of innovation focuses on innovative input (R&D), output (patents or citations), and efficiency (patents or citations per dollar of R&D).[8] However, this research does not examine the role of diversity in innovative activities. As discussed earlier, innovative diversity may affect innovation-driven firms' fundamentals and investors' view of these firms in important ways, so it is interesting to explore this aspect of innovation. Furthermore, we find that the ID effect is robust to controlling for all of the above known innovation-related effects. We also examine whether the ID effect is driven by risk or mispricing, and explore how this effect interacts with proxies for limited attention, valuation uncertainty, disagreement, and short-sale constraints.

A different stream of literature examines the valuation of diversification more generally.[9] A

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[8] Previous research has studied the valuation relevance of R&D reporting practices (Lev and Sougiannis 1996, Lev, Sarath, and Sougiannis 2005); the ability of R&D intensity to predict returns (Chan, Lakonishok, and Sougiannis 2001, Li 2011); the relation between R&D growth and stock returns and operating performance (Eberhart, Maxwell, and Siddique 2004, Lev, Sarath, and Sougiannis 2005); the link between patents and citations and stock returns, operating performance, and aggregate risk premium (Griliches 1990, Lerner 1994, Deng, Lev, and Narin 1999, Lanjouw and Schankerman 2004, Gu 2005, Hsu 2009); and the relation between innovative efficiency and stock returns and operating performance (Cohen, Diether, and Malloy 2012, Hirshleifer, Hsu, and Li 2012).

[9] Evidence concerning the diversification discounts or premia is provided by Lang and Stulz (1994) and Berger and Ofek (1995), among others. In addition, Lamont and Polk (2001) show that diversified firms trading at discount

key difference of our paper from this literature is that previous work tests for discounts or premia, induced by agency problems, that can exist—and are easiest to test for—in an informationally efficient market. In contrast, the hypothesis we study is whether there is inefficient underpricing of innovatively diversified firms. So our topic of study is fundamentally different from that of the diversification discount literature.

Our paper is more closely related to the empirical literature on how limited investor attention and processing power affects security prices. Theoretical models imply that owing to limited attention, market prices will place insufficient weight on signals with low salience or that are hard to process (e.g., Hirshleifer and Teoh 2003, Peng and Xiong 2006, Hirshleifer, Lim, and Teoh 2011). Several studies provide evidence, consistent with theoretical models, suggesting that limited investor attention and processing power cause underreaction to value-relevant information and stock return predictability, and that such predictability is stronger when the information is less salient, when distracting information is present, when information arrives during low investor attention period, and when information is harder to process (see, e.g., Klibanoff, Lamont, and Wizman 1998, Huberman and Regev 2001, Barber and Odean 2008, Cohen and Frazzini 2008, DellaVigna and Pollet 2009, Hirshleifer, Lim, and Teoh 2009, Hou, Peng, and Xiong 2009, Da, Engelberg, and Gao 2011, Da, Gurun, and Warachka 2011, Da and Warachka 2011, Cohen and Lou 2012, Li and Yu 2012).

## 2. The data, the innovative diversity measures, and summary statistics

### *2.1. The data and the innovative diversity measures*

Our sample consists of firms in the intersection of Compustat, CRSP (Center for Research in

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have significantly higher subsequent returns than diversified firms trading at premium.

Security Prices), and the NBER patent database. We obtain accounting data from Compustat and stock returns data from CRSP. All domestic common shares trading on NYSE, AMEX, and NASDAQ with accounting and returns data available are included except financial firms, which have four-digit standard industrial classification (SIC) codes between 6000 and 6999 (finance, insurance, and real estate sectors). Following Fama and French (1993), we exclude closed-end funds, trusts, American Depository Receipts, Real Estate Investment Trusts, units of beneficial interest, and firms with negative book value of equity. To mitigate backfilling bias, we require firms to be listed on Compustat for two years before including them in our sample. For some of our tests, we also obtain analyst coverage and earning forecast data from the Institutional Brokers Estimate System (IBES), institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database, and directors' stock trading data from the Thompson Financial insider trading database (TFN).

Patent-related data are from the updated NBER patent database originally developed by Hall, Jaffe, and Trajtenberg (2001).[10] The database contains detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006: patent application date, grant date, assignee name, one-, two- and three-digit technological classes, the number of citations received by each patent, assignee's Compustat-matched identifier, and other details. Patents are included in the database only if they are eventually granted by the USPTO by the end of 2006.

To measure a firm's innovative diversity in year *t*, we apply the structure of the Herfindahl concentration index to a firm's patent portfolio as the following:

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

$$Innovative\ Diversity = 1 - \sum_{k=1}^{K} \left( \frac{n_k}{\sum_{k=1}^{K} n_k} \right)^2,$$

where $n_k$ is the number of patents granted in the $k^{\text{th}}$ technological class over the previous five ($t$ to $t$ – 4) or three ($t$ to $t$ – 2) years, and $K$ is the total number of three-digit technological classes. We focus on the three-digit technological classes in constructing the innovative diversity measures since the one- and two-digit technological classes are much broader and may be imprecise in describing the diversity of a firm's patent portfolio.[11]

We construct two ID measures for each firm from 1981 to 2006: ID1 (ID2) is one minus the Herfindahl index based on patents granted over the previous five (three) years across the three-digit technological classes. By construction, the ID measures range from 0 for the most concentrated to a supremum of 1 for the most diversified portfolio of patents. We use ID1, the more long-run measure, as our primary measure of innovative diversity, and use ID2 as a robustness check.

The NBER patent database tracks the change of patent ownership by using the data on mergers and acquisitions of public companies reported in the SDC (Securities Data Company) database. The patent database assumes that, when an organization is acquired/merged/spun-off, its patents automatically transfer to the new owner. In most of our tests, we construct the ID measures that include patents obtained through such transactions. As a robustness check, we also conduct tests using the ID measures excluding patents' ownership changes and obtain consistent results in Section 3.3.

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[11] There are in total 438 unique three-digit technological classes, 37 unique two-digit technological classes, and six unique one-digit technological classes in the patent database. Hall, Jaffe, and Trajtenberg (2001) group the 438 three-digit technological classes assigned by the USPTO into 37 two-digit technological classes such as communications (21), drugs (31), and biotechnology (33) and six one-digit technological classes including chemical (1), computers and communications (2), drugs and medical (3), electrical and electronics (4), mechanical (5), and others (6). We also construct ID measures based on the two-digit technological classes and find very similar patterns in unreported results.

*2.2. Summary statistics*

Table 1 reports the pooled mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum of the ID measures for selected innovation-intensive industries based on the two- or three-digit SIC codes following Chan, Lakonishok, and Sougiannis (2001). We observe significant variations in industrial innovative diversity. For example, the average (median) ID1 ranges from 0.39 (0.48) for the computer programming, software, and services industry to 0.70 (0.82) for the transportation equipment industry. In addition, the transportation equipment industry is the most diversified judged by both ID measures. These statistics suggest that it is important to control for industry effects in examining the relation between ID and subsequent stock returns.

At the end of June of year *t*, we form three ID portfolios based on the 30th and 70th percentiles of ID measured in year $t-1$ for both ID measures. Table 2 reports summary statistics of the ID portfolios and correlations between the ID measures and other characteristics. Panel A (B) reports the time-series mean of cross-sectional average (median) characteristics of the ID portfolios.[12]

The characteristics include the number of firms, size (market capitalization at the end of June of year *t*), book-to-market (BTM, the ratio of book equity of fiscal year ending in year $t-1$ to market equity at the end of year $t-1$), momentum (MOM, the previous eleven-month returns with a one-month gap between the holding period and the end of June of year *t*), ID (in year $t-1$), the number of three-digit technological classes, idiosyncratic volatility (IVOL, measured at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock

[12] The number of firms in the ID portfolios is the time-series average for both panels. We winsorize all variables at the 1% and 99% levels except the number of firms and technological classes.

returns on the Fama-French three factor returns over the previous 12 months with a minimum of 31 trading days), total skewness (TSKEW, measured at the end of June of year *t* using daily returns over the previous 12 months with a minimum of 31 trading days), idiosyncratic skewness (ISKEW, measured at the end of June of year *t* as the skewness of residuals from regressing daily stock returns on daily market factor returns and squared market factor returns), systematic skewness (SSKEW, the slope on the squared market factor returns from the regression for ISKEW), and expected idiosyncratic skewness (EISKEW).[13]

We also report summary statistics for R&D-to-market equity (RDME, R&D expenses in fiscal year ending in year $t-1$ divided by market equity at the end of year $t-1$), patents-to-assets (CTA, the number of patents issued to a firm in year $t-1$ divided by the firm's total assets at the end of year $t-1$), innovative efficiency (IE in year $t-1$) based on patent citations as in Hirshleifer, Hsu, and Li (2012), return on assets (ROA, income before extraordinary items plus interest expenses in year $t-1$ divided by lagged total assets), asset growth (AG, change in total assets in year $t-1$ divided by lagged total assets), investment (IA, capital expenditure in year $t-1$ divided by lagged total assets), net stock issues (NS, change in the natural log of the split-adjusted shares outstanding in year $t-1$), institutional ownership (IO, the fraction of firm shares outstanding owned by institutional investors in year $t-1$), one-year ahead ROA (FROA, ROA in year *t*), one-year ahead cash flow (FCF, net income minus accrual divided by average assets in year *t*), one-year ahead profit margin (FPM, operating income before depreciation divided by sales in year *t*), analyst forecast error (FE, the difference between the announced annual earnings per share in year $t+1$ and the average analyst forecast made one year before the announcement divided by the stock price at the end of the month when the forecast is made), CEO net stock

[13] The computation of TSKEW, ISKEW, and SSKEW follows Harvey and Siddique (2000) and Bali, Cakici and Whitelaw (2011). EISKEW is measured at the end of June of year *t* and its computation follows Boyer, Mitton, and Vorkink (2009).

sales (the shares sold by minus the shares bought by the CEO in year $t - 1$, divided by the average shares outstanding in year $t - 1$), and non-CEO director net stock sales (the shares sold by minus the shares bought by non-CEO directors in year $t - 1$, divided by the average shares outstanding in year $t - 1$).[14]

The ID portfolios are well diversified. For example, the average number of firms in the low, middle, and high ID1 portfolios is 428, 564, and 430, respectively. More diversified firms are on average much larger. For example, the average market capitalization of the low, middle, and high ID1 portfolios is $646 million, $1,067 million, and $3,920 million, respectively. The median market capitalization of the low, middle, and high ID1 portfolios is $105 million, $178 million, and $990 million, respectively. This is an economically meaningful set of firms to study as firms with non-missing ID measures cover 54% to 57% of the total U.S. market equity. On average, more diversified firms have slightly lower book-to-market. However, the median BTM for high ID firms is slightly higher than that for low ID firms. More diversified firms also have higher momentum.

There are significant variations in the ID measures across the ID portfolios. For example, the average and median ID1 (in year $t - 1$) for the low ID1 portfolio are 0.05 and 0, respectively. In contrast, the counterparts of these statistics are 0.87 and 0.87 for the high ID1 portfolio. This sharp contrast also holds for ID2.

The number of technological classes increases with the ID measures. For example, there are on average 1.27 and 32.44 three-digit technological classes in the patent portfolios for firms in the low and high ID1 portfolios, respectively. Unreported results show that there are on average 1.20 and 11.94 two-digit technological classes in the patent portfolios for firms in the low and

[14] The accruals for computing cash flow are changes in current assets plus changes in short-term debt and minus changes in cash, changes in current liabilities, and depreciation expenses. Our definition of insider sale follows Richardson, Teoh, and Wysocki (2004).

high ID1 portfolios, respectively. This evidence suggests that there are significant differences in the technological classes in the high ID firms' patent portfolios.[15]

Firms with higher ID have lower idiosyncratic volatility, total skewness, idiosyncratic skewness, and expected idiosyncratic skewness, but higher systematic skewness. Firms with higher ID also have slightly higher R&D-to-market equity and patents-to-assets and higher innovative efficiency.

ID is positively associated with contemporaneous ROA. The average ROA in year $t$ – 1 is positive for the high ID portfolios but negative for the low ID portfolios. For example, the average ROA is 5.57% for the high ID1 portfolio but is –0.54% for the low ID1 portfolio. The median ROA is positive for both low and high ID portfolios, but is higher for the high ID portfolios. For example, the median ROA is 7.52% for the high ID1 portfolio and 6.02% for the low ID1 portfolio.

ID is also associated with better *future* operating performance. The high ID portfolios also have higher average and median ROA, cash flow, and profit margin in the fiscal years ending in year $t$ and year $t$ + 1.[16] For example, the average profit margin in year $t$ is 0.01 (–0.49) for the high (low) ID1 portfolio. Furthermore, in unreported results, we find that high ID firms have higher and less volatile future operating performance, even after controlling for current and change in operating performance and other performance predictors including innovative efficiency. If investors underreact to this favorable information, we expect a positive relation between ID and future stock returns.

[15] For example, the two-digit classes assigned by Hall, Jaffe, and Trajtenberg (2001) include coating, gas, organic compounds, resins, miscellaneous chemical, communications, computer hardware and software, computer peripherals, information storage, drugs, surgery and medical instruments, biotechnology, miscellaneous drugs and medications, electrical devices, electrical lighting, measuring and testing, nuclear and X-rays, power systems, semiconductor devices, etc.

[16] For brevity, we only report in Table 2 the results for year $t$.

On average, high ID firms have slightly lower asset growth, same investment-to-asset ratio, slightly lower net stock issuance, and higher institutional ownership than low ID firms. High ID firms also have slightly lower median asset growth, slightly higher median investment-to-asset ratio, same net stock issuance, and higher institutional ownership than low ID firms.

Existing studies of analysts' earning forecasts find that they are on average overoptimistic, except at very short forecast horizons (see, e.g., Richardson, Teoh, and Wysocki 2004). On average analysts overestimate the earnings of high ID portfolios less than that of the high ID portfolios. For example, the average optimistic bias in the analyst forecast is 5.61% for the low ID1 portfolio and 2.52% for the high ID1 portfolio, both of which are lower than that for the whole sample (6.68%).

Greater complexity could lead to an opposing effect, increasing the forecast bias, if forecast optimism is due to analyst behavioral bias (rather than agency problems) and if complexity exacerbates this bias. On the other hand, the two arguments that are the focus of our paper act to reduce optimism. First, owing to limited processing, analysts may underweight the favorable information implicit in innovative diversity. Second, skepticism toward complexity dampens analysts' overoptimism and therefore, should reduce upward bias in forecasts. The finding that the optimism in the forecast bias is weaker for high ID firms suggests that the two effects hypothesized here outweigh the possible opposing effect.

Consistent with market misvaluation of innovative diversity, and with insiders having a better assessment of value than uninformed investors, we find that on average CEOs and non-CEO directors of high ID firms tend to sell less heavily than those of low ID firms. For example, average CEO net stock sales relative to shares outstanding is 0.21% for the high ID1 portfolio and 0.50% for the low ID1 portfolio; the average over all firms with non-missing net stock sales (regardless whether ID is missing or not) is 0.42%. Similarly, average non-CEO director net stock sales relative to shares outstanding is 0.34% for the high ID1 portfolio and 0.48% for the low ID1 portfolio; the average over all firms with non-missing net stock sales is 0.48%. Thus, the high-minus-low difference is substantial; insider net stock sales are more than 40% higher in the low ID1 portfolio than that in the high ID1 portfolio.

Table 2 Panel C reports the times-series average of cross-sectional correlations between the ID measures and the above characteristics. In addition, we also report the correlations between ID and stock illiquidity (ILLIQ, the absolute monthly stock return divided by monthly dollar trading volume computed in June of year *t* as in Amihud 2002) and lagged monthly stock return in June of year *t* (REV).[17] The timing of the ID measures and other characteristics follows Panels A and B. Pearson (Spearman rank) correlations are below (above) the diagonal.

ID1 is significantly positively correlated with ID2 with Pearson and Spearman correlations of 0.90 and 0.93, respectively. Consistent with Panels A and B, the ID measures correlate significantly positively with size, IE, ROA, SSKEW, and IO and significantly negatively with IVOL, TSKEW, ISKEW, EISKEW, and ILLIQ. However, the magnitude of the correlations between ID and these characteristics are small except with size (ranging from 0.42 to 0.48) and with IO (ranging from 0.32 to 0.36). In addition, the ID measures correlate with BTM, MOM, RDME, CTA, AG, IA, NS, and REV insignificantly.

## 3. Predictability of returns based upon innovative diversity

### *3.1. Portfolio sorts*

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[17] REV captures the short-term return reversal effect as in Jegadeesh (1990) and Lehmann (1990).

We next examine the ability of the ID measures to predict portfolio returns and whether the ID effect is captured by other known return predictors. At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing ID measures independently into three size groups (small "S", middle "M", or big "B") based on the 30th and 70th percentiles of market capitalization measured at the end of June of year *t* and three ID groups (low "L", middle "M", or high "H") based on the 30th and 70th percentiles of ID in year $t$ – 1. The intersection forms nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) for each ID measure. Since the USPTO fully discloses patents granted in the weekly *Official Gazette of the United States Patent and Trademark Office*, the ID measures in year $t$ – 1 are publicly observable at the end of year $t$ – 1. However, we form the ID portfolios at the end of June of year *t* to make the portfolio results comparable to previous studies.

We hold these portfolios over the next twelve months (July of year *t* to June of year $t$ + 1) and compute their equal- and value-weighted monthly returns. We then calculate monthly size-adjusted returns of the low, middle, and high ID portfolios using the formulas (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively. Adjusting size is important since bigger firms are usually more diversified.

Table 3 shows that the average monthly size-adjusted portfolio return net of the one-month Treasury bill rate (excess returns) increases monotonically with ID for both ID measures. For example, the monthly value-weighted (VW) size-adjusted excess returns on the low, middle, and high ID1 portfolios are 74 ($t$ = 2.27), 93 ($t$ = 2.76), and 126 ($t$ = 3.77) basis points, respectively. Moreover, the difference in these returns between the high and low ID1 portfolios is large and statistically significant (51 basis points, $t$ = 4.49).

Similarly, the monthly equal-weighted (EW) size-adjusted excess returns on the low, middle, and high ID1 portfolios are 91 ($t$ = 2.70), 110 ($t$ = 3.08), and 142 ($t$ = 4.07) basis points, respectively. The difference in the returns between the high and low ID1 portfolios is also large and statistically significant (52 basis points, $t$ = 4.69). For ID2, the pattern is similar. For example, the VW (EW) return of the high-minus-low ID2 portfolio is 48 (51) basis points and is statistically significant at the 1% level.

We also examine whether the returns of the ID portfolios are captured by standard factors by regressing the time-series of size-adjusted portfolio excess returns on the Carhart (1997) four factor returns.[18] The Carhart model includes the market factor (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (MOM). MKT is the return on the value-weighted NYSE/AMEX/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. There is debate about the extent to which these factors capture risk versus mispricing, but controlling for them provides a more conservative test of whether the innovative diversity effect comes from mispricing, and ensures that the ID effect is not just a consequence of other well-known effects.

Table 3 shows that the risk-adjusted returns (alphas) also increase monotonically with ID and are always large and significantly positive for the high ID portfolios for both ID measures. The Carhart model can only fully explain the VW returns of the low ID portfolios. The VW Carhart alphas for the middle and high ID portfolios and the EW Carhart alphas for all the ID portfolios remain large and statistically significant at the 1% level. For example, the monthly VW Carhart alphas for the low, middle, and high ID1 portfolios are 7 ($t$ = 0.80), 28 ($t$ = 3.20), and 56 ($t$ =

[18] We obtain similar results (unreported) using the Fama-French (1993) three-factor model. The Carhart (1997) four factor returns and the one-month Treasury bill rate are obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

4.56) basis points, respectively. The monthly EW Carhart alphas for the low, middle, and high ID1 portfolios are 36 ($t$ = 3.37), 57 ($t$ = 5.33), and 81 ($t$ = 5.92) basis points, respectively. The difference in the VW (EW) alphas between the high and low ID1 portfolios is 50 (44) basis points with a $t$-statistic of 4.28 (3.70).

The pattern is essentially the same for ID2. For the high ID2 portfolios, the monthly VW (EW) Carhart alpha is 51 (77) basis points and significant at the 1% level. For the high-minus-low ID2 portfolios, the monthly VW (EW) Carhart alpha is 43 (40) basis points and significant at the 1% level.

Furthermore, for VW returns, the high and low ID portfolios have similar loadings on the Carhart four factors, indicating that the high returns provided by high ID firms do not seem to come from systematic risk. For EW returns, the high ID portfolios load significantly higher on the MKT and HML factors than the low ID portfolios. However, the EW alphas for the hedge portfolios are large and significant as discussed earlier. These results suggest that high ID firms are undervalued relative to low ID firms according to the Carhart model.

Hirshleifer, Hsu, and Li (2012) document that innovative efficiency (IE) is a positive predictor of abnormal stock returns. As shown in Table 2, IE and ID are significantly positively correlated. This association is reasonable. For example, talented scientists may be able to generate influential inventions that can be applied to many different technological areas, and managers capable of managing a diversified patent portfolio may be better at picking promising innovative projects.

To test whether the ID effect is robust to controlling for the IE effect, we augment the Carhart model with the innovative efficiency factor EMI (Efficient Minus Inefficient) of

Hirshleifer, Hsu, and Li (2012).[19] Table 4 shows that the ID effect remains statistically significant and economically substantial even after controlling for EMI. For example, the monthly VW and EW alphas for the high ID1 portfolio are 44 ($t$ = 3.68) and 72 ($t$ = 5.46) basis points, respectively. The monthly VW and EW alphas for the high-minus-low ID1 portfolios are also substantial and significant: 32 ($t$ = 2.93) and 32 ($t$ = 2.74) basis points, respectively. Similarly, the monthly VW (EW) alpha for the high ID2 portfolios is 40 (67) basis points with a $t$-statistic of 3.40 (5.11) and the monthly VW (EW) alpha for the high-minus-low ID2 portfolios is 27 (27) basis points with a $t$-statistic of 2.36 (2.16). These findings indicate that the ID effect is incremental to the innovative efficiency effect.

Overall, Tables 3 and 4 suggest that high ID firms are undervalued relative to low ID firms and that the ID effect is incremental both to well-known existing factors, and to the innovative efficiency factor, EMI.[20]

### *3.2. Predicting the cross-section of returns*

We next examine the ability of ID to predict the cross section of returns using monthly Fama-MacBeth regressions. This analysis allows us to control more extensively for other characteristics that can predict returns, to make sure that the positive ID-return relation as measured in portfolio sorts is not driven by other known return predictors or by industry characteristics. Following Fama and French (1992), we allow for a minimum six-month lag between stock returns and the accounting-related control variables to ensure the accounting variables are fully observable to investors. Specifically, for each month from July of year $t$ to

[19] For brevity, we report results from the citations-based EMI factor. In unreported results, we find that the ID effect is also robust to controlling for the patents-based EMI factor.

[20] In unreported results, we find the ID effect is also robust to controlling for the mispricing factor UMO (Undervalued Minus Overvalued; Hirshleifer and Jiang 2010).

June of year $t$ + 1, we regress monthly returns of individual stocks on ID of year $t$ – 1 and different sets of control variables. Table 5 shows the time-series average slopes and corresponding heteroscedasticity-robust $t$-statistics from the monthly cross-sectional regressions. In unreported results, we find very similar results using pooled regressions.

Model 1 controls for institutional ownership (IO), stock illiquidity (ILLIQ), short-term return reversal (REV), BTM, Size, momentum (MOM), and industry dummies based on Fama and French's (1997) 48 industries. IO and BTM are measured in year $t$ – 1. ILLIQ and REV are the previous month's stock illiquidity and stock return, respectively. Size is the log of market capitalization at the end of June of year $t$. In addition, BTM is also in the natural log form. All independent variables are defined in more details in Section 2. We winsorize all independent variables at the 1% and 99% levels to reduce the impact of outliers, and then standardize all independent variables to zero mean and one standard deviation to facilitate the comparison of economic effects.

The slopes on the ID measures are statistically significant and economically substantial. For example, Panel A of Table 5 shows that the slope on ID1 estimated from Model 1 is 0.20% ($t$ = 5.54), which is comparable to the slopes on BTM (0.25%, $t$ = 3.59) and stock illiquidity (0.20%, $t$ = 2.62) and is larger than the slope on momentum (0.18%, $t$ = 1.83). Consistent with previous studies, the slopes on REV and Size are significantly negative. The slope on IO is insignificant. This pattern is similar for ID2 as shown in Panel B.

In Model 2, we control for additional return predictors related to innovation (IE, CTA, and RDME), investment (AG and IA), financing (NS), and profitability (ROA) measured in year $t$ – 1.[21] IE is the natural log of one plus the citations-based IE measure following Hirshleifer, Hsu,

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[21] Adding RDME is a conservative test of the ID effect as the denominator of RDME automatically induces a positive relation between RDME and future stock returns. On the capital investment effect, see, e.g., Lyandres, Sun,

and Li (2012). CTA is the natural log of one plus patents granted in year $t$ – 1 divided by total assets in year $t$ – 1. RDME is the natural log of one plus R&D-to-market equity in year $t$ – 1.

The ID slopes remain economically and statistically significant. For example, in Panel A, the slope on ID1 estimated from Model 2 is 0.12% ($t$ = 2.41), which is comparable in magnitude to the slopes on AG (–0.18%, $t$ = –3.65), NS (–0.13%, $t$ = –3.07), ROA (0.17%, $t$ = 2.44), and ILLIQ (0.19%, $t$ = 2.06). It is also larger than the slopes on BTM (0.07%, $t$ = 1.00), MOM (0.09%, $t$ = 0.94), IA (0.01%, $t$ = 0.23), IE (0.07%, $t$ = 1.88), and CTA (–0.00%, $t$ = –0.06). The slopes on Size and REV remain significantly negative, and the slope on RDME is significantly positive. The slope on IE is not of high statistical significance because the sample with non-missing ID, IE, and other control variables is smaller, which may reduce the test power for the IE-return relation. The slope on IO remains insignificant. Also, the slopes on BTM and MOM become insignificant, probably owing to the reduced sample size. The patterns for ID2 reported in Panel B are generally similar.

As discussed in Section 2, the ID measures correlate significantly with idiosyncratic volatility (IVOL) and the skewness measures that are known to predict returns (e.g., Ang, Hodrick, Xing, and Zhang 2006, Harvey and Siddique, 2000, Kapadia 2006, Boyer, Mitton, and Vorkink 2009, Bali, Cakici, and Whitelaw 2011).[22] Therefore, in Models 3-6, we control for IVOL and one of the four skewness measures, in addition to the variables already included in Model 2.[23] The slopes on the ID measures remain substantial and statistically significant, and their magnitude is barely affected by the additional control variables. As a result, the ID-return

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., Ikenberry, Lakonishok, and Vermaelen (1995), Daniel and Titman (2006), Fama and French (2008), and Pontiff and Woodgate (2008). On the profitability effect, see, e.g., Fama and French (2006), and Chen, Novy-Marx, and Zhang (2011).

[22] Furthermore, Pastor and Veronesi (2009) and Garleanu, Panageas, and Yu (2012) suggest that new technologies are associated with productivity uncertainty and idiosyncratic risk.

[23] IVOL, TSKEW, SSKEW, and ISKEW are measured at the end of June of year $t$, while EISKEW is measured in the previous month.

relation is not due to the previously documented relation between stock returns and idiosyncratic volatility and skewness.

For example, Panel A shows that the slope on ID1 estimated from Model 3 remains the same (0.12%, $t$ = 2.45), which is comparable in magnitude to the slopes on AG (–0.16%, $t$ = –3.40) and NS (–0.15%, $t$ = –3.47). Relative to the mean excess return for this sample (1.11% per month), the ID1 slope implies that a one standard deviation increase in ID1 predicts that future stock returns will on average be 10.85% higher than their unconditional level. As in Model 2, the ID1 slope is higher than the slopes on BTM, MOM, IA, IE, and CTA.

The slope on IVOL is positive with marginal significance, which is consistent with the finding in Bali, Cakici, and Whitelaw (2011).[24] Consistent with the hypothesis that investors prefer positive skewness, the slope on TSKEW is negative (–0.08%, $t$ = –2.01). In addition, the slope on Size becomes marginally significant after we control for IVOL and TSKEW.

The ID1 slopes estimated from Models 4-6 are also significantly positive when we control for the other three skewness measures. The slope on ISKEW is negative with marginal significance, and the slope on SSKEW is positive and insignificant. The slope on EISKEW is negative and insignificant. Similar results are obtained when we use ID2 (Panel B) and other ID measures (unreported).

In unreported tables, we perform extensive robustness tests by including additional control variables such as sales diversity,[25] R&D capital (Chan, Lakonishok, and Sougiannis 2001), significant R&D growth (Eberhart, Maxwell, and Siddique 2004), change in adjusted patent citations (Gu 2005), R&D diversity, and the number of segments based on Compustat segment

[24] Computing IVOL based on daily returns over the last month generates similar results.
[25] Sales diversity is measured by one minus the Herfindahl index based on a firm's sales percentage across the Fama-French 48 industries over the previous five (three) years when ID is measured by ID1 (ID2). We use the segment sales data from Compustat segment files following Cohen and Lou (2012) among others.

files. The results all indicate a significantly positive ID-return relation. In addition, we also include squared ID in the regressions, and do not find any indication of nonlinearity in the ID effect.

Overall, these findings show that the predictive power of ID is distinct from, and robust to the inclusion of, other commonly known return predictors, innovation-related variables, and sales diversity.

### *3.3. Originally-assigned patents versus acquired patents*

Firms often undertake acquisitions to obtain growth opportunities and achieve technological synergies (e.g., Ang and Wu 2011, Bena and Li 2011, and Sevilir and Tian 2012). Ang and Wu (2011) and Sevilir and Tian (2012) document that investors recognize the value of acquired innovations, as reflected in higher deal premia, abnormal returns at deal announcement, and long-term returns associated with innovation-driven acquisitions. We therefore examine if the ID effect is driven by the documented acquiring-innovation effect.

To test this hypothesis, we compute the ID measures based on originally-assigned patents only (i.e., excluding patents obtained through reorganizations such as mergers, acquisitions, and spinoffs) and re-estimate the Fama-Macbeth regressions specified in Table 5 using these ID measures. As reported in Table 6, we find that the ID-return relation remains significantly positive with similar magnitudes. This evidence suggests that the ID-return relation identified earlier is not driven by patents obtained through mergers and acquisitions.

As an alternative test, we also estimate the models in Table 5 among firms that do not have any goodwill on book over the past three or five years since goodwill mainly reflects acquisition activities (goodwill data are only available after 1988). This approach is more conservative than the previous test as it excludes firms with any recent mergers or acquisitions, regardless whether the deal involves patents or not. We find that the ID-return relation in general remains significantly positive in untabulated results.

## 4. Distinguishing alternative explanations for the ID effect

To test the hypothesis that limited investor attention leads to a positive ID-return relation, we conduct Fama-MacBeth regressions within subsamples split by size or analyst coverage as a proxy for investor attention to a stock. Size is measured by market capitalization. Analyst coverage in year *t* is measured by the monthly number of analysts providing fiscal year earnings estimates averaged over year *t*.

In tests of the information-diffusion model of Hong and Stein (1999), Hong, Lim, and Stein (2000) report that the profitability of momentum strategies decreases with size and analyst coverage. The theoretical paper of Hirshleifer and Teoh (2003) proposes size and analyst coverage as proxies for investor attention. Evidence on stock return lead-lags suggests that information diffuses gradually across between large and small firms, and between firms that are followed by different numbers of analysts (Brennan, Jegadeesh, and Swaminathan 1993; Hong, Torous, and Valkanov 2007; Hou 2007; Cohen and Frazzini 2008).

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 diversity, and stronger return predictability.

To form the attention subsamples at the end of June of year *t*, we construct the small and big size subsamples based on the 30$^{th}$ and 70$^{th}$ percentiles of firms' size measured at the end of June of year *t*, and the low and high analyst coverage subsamples based on the 30$^{th}$ and 70$^{th}$

percentiles of firms' analyst coverage (AC) in year $t$ – 1. The small (big) subsample consists of firms with size below (above) the 30$^{th}$ (70$^{th}$) percentiles of size. Similarly, the low (high) AC subsample consists of firms with AC below (above) the 30$^{th}$ (70$^{th}$) percentiles of AC.[26] Within these subsamples, we then estimate Models 3-6 specified in Table 5 using monthly Fama-MacBeth cross-sectional regressions. For brevity, we report in Table 7 the time-series average slopes on ID only and corresponding heteroscedasticity-robust $t$-statistics from these subsample regressions.

Table 7 shows that the ID-return relation is significantly positive only among firms with small size and low AC. This relation is insignificant and sometimes negative among big and high AC firms. This sharp contrast is robust to alternative ID measures and model specifications. For example, the slopes on ID1 in the small subsamples range from 0.22% ($t$ = 2.41) for Model 5 to 0.27% ($t$ = 2.47) for Model 6. In contrast, the slopes on ID1 in the big subsamples are small, negative, and insignificant, ranging from –0.01% ($t$ = –0.20) for Model 4 to –0.00% ($t$ = –0.03) for Model 6. Furthermore, the differences in the ID1 slopes across the size subsamples are statistically significant at the 5% level. Although the cross-subsample differences in the ID slopes are not always statistically significant, their magnitudes are economically substantial. These contrasts tend to support the hypothesis that limited investor attention leads to the positive ID-return relation.

To further investigate the effect of limited attention on the ID-return relation, we perform Fama-MacBeth regressions within subsamples formed based upon valuation uncertainty (VU) proxies. Since previous literature has reported stronger behavioral biases among stocks with higher VU, we expect the ID-return relation to be stronger among firms with more valuation

[26] Forming the subsamples based on median size and median AC generates similar results in general.

uncertainty because they place a greater cognitive burden on investor attention.[27]

Following Kumar (2009), we employ two measures of VU: idiosyncratic volatility (IVOL) and firm age. Firm age is the number of years listed on Compustat with non-missing price data. We interpret firms with higher idiosyncratic volatility or younger age as having higher valuation uncertainty. At the end of June of year *t*, we form the low and high IVOL subsamples and the young and old subsamples based on the 30th and 70th percentiles of these measures. IVOL is measured at the end of June of year *t*, and age is measured at the end of year *t* – 1. Within each VU subsample, we conduct the same Fama-MacBeth regressions as were performed in the attention subsamples.

Consistent with the hypothesis that mispricing is stronger among firms with greater valuation uncertainty, Table 7 shows a stronger ID-return relation in the high IVOL and young subsamples. For example, the slopes on ID2 estimated from Model 3 in the high and low IVOL subsamples are 0.24% ($t$ = 2.58) and 0.02% ($t$ = 0.43), respectively. The difference is significant at the 5% level. Similarly, in Model 3, the slope on ID2 in the young subsample is 0.25% ($t$ = 2.39). In contrast, it is only –0.03% ($t$ = –0.56) in the old subsample. The difference is significant at the 5% level. These contrasts are generally robust to model specifications and alternative ID measures.

The evidence for the effects of firm age tends to be rather weakly supportive. The slopes on ID1 are not statistically significant in the young subsamples, but they are always positive, and the point estimates are substantially higher in economic terms than their counterparts in the old

[27] 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. Kumar (2009) reports greater individual investor trading biases among stocks with greater valuation uncertainty.

subsamples.

Kumar (2009) uses turnover as another proxy of valuation uncertainty. However, turnover has also been used as a proxy of investor attention in previous studies (e.g., Gervais, Kaniel, and Mingelgrin 2001; Hou, Peng, and Xiong 2009).[28] Since firms with lower turnover can be interpreted as having lower investor attention or lower valuation uncertainty, the overall prediction is not clear. If we interpret turnover as a proxy of valuation uncertainty, the limited attention hypothesis predicts a stronger ID effect among high turnover firms. However, if we interpret turnover as a proxy of investor attention, the limited attention hypothesis predicts a stronger ID effect among low turnover firms.[29]

An alternative explanation of the positive ID-return relation derives from the combination of disagreement and short-sale constraints (see, e.g. Miller 1977; Diether, Malloy, and Scherbina 2002). In this account, owing to short-sale constraints, only optimistic views of a firm are reflected in its stock price. Therefore, firms with high disagreement and strong short-sale constraints tend to be overvalued more. In our context, we would expect that firms with more diversified patent portfolios would tend to have less disagreement from investors since overvaluation of one component will tend to be offset by undervaluation of another component. We would expect less disagreement about firms with more diversified patent portfolios. This lower disagreement should be associated with less overvaluation. This channel also implies a positive ID-return relation.

To test this disagreement explanation, we examine how the ID-return relation varies across

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[28] Turnover is the average monthly turnover over the previous 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. Following the literature, e.g., LaPlante and Muscarella (1997) and Hou (2007), we divide the NASDAQ volume by a factor of two.

[29] In unreported results, we conduct the same Fama-MacBeth regressions as were performed in earlier analyses within the low and high turnover subsamples formed based on the 30$^{th}$ and 70$^{th}$ percentiles of turnover measured at the end of June of year *t*. We find that the slopes on ID1 are significantly positive in the low turnover subsample and are much larger than those in the high turnover subsample, while the slopes on ID2 are significantly positive in both turnover subsamples and are slightly larger in the high turnover subsample.

the subsamples split by disagreement measured by analyst dispersion, and split by short-sale constraints measured by institutional ownership or stock illiquidity.[30] Overall the evidence is not fully supportive; the results using short-sale constraint proxies are consistent with the disagreement explanation, but the results using the disagreement proxies are inconsistent with it.

Furthermore, in the factor regressions discussed in Section 3.1, we find that the low ID portfolios have non-negative alphas which are in some cases significantly positive. This, suggest that these firms are if anything *undervalued* rather than overvalued relative to the Carhart factor model, which is inconsistent with high overvaluation of low-ID firms as an explanation for the ID-return relation.

Taken together, the subsample regressions provide further support for the hypothesis that that the ID-return relation is driven primarily by limited investor attention.

## 5. The DMC (Diversified Minus Concentrated) factor

If the ID-return relation is caused by limited investor attention, it reflects market inefficiency. Several authors have suggested more generally that there is commonality in mispricing (e.g., Daniel, Hirshleifer, and Subrahmanyam 2001, Barberis and Shleifer 2003). If investors do not fully impound information about correlated shifts in innovative diversity or its profitability, we would expect commonality in the mispricing of innovative diversity.

One way in which this can occur is if a new technological opportunity arises, and a set of

[30] Analyst forecast dispersion (DISP) is computed at the end of year $t - 1$ as the average of the monthly coefficients of variations of analyst annual earnings per share (EPS) forecasts (the ratio of the standard deviation of the forecasts to the absolute value of mean forecast) in year $t - 1$. Institutional ownership (IO) is measured at the end of year $t - 1$, and illiquidity (ILLIQ) is measured at the end of June of year $t$. Both are defined in Section 2. Higher DISP reflects more disagreement about a firm's value. Higher IO and lower ILLIQ reflect weaker short-sale constraints, since IO is a standard proxy for the number of lendable shares and IO is significantly negatively related to illiquidity as reported in Table 2. As in the tests that examine attention and VU subsamples, we form the DISP, IO, and ILLIQ subsamples based on the 30th and 70th percentiles of corresponding measures at the end of June of year $t$. Within these subsamples, we conduct the same Fama-MacBeth regressions as were performed in the attention and VU subsamples.

firms increases diversity by extending their innovative activities to this new area. The comovement is introduced by the fact that the different firms are now all in this area. The associated commonality in returns will be even stronger if it is firms in the same industry or with similar initial technological expertise that tend to diversify into the new opportunity. For example, the recent rise of cloud computing has motivated many traditional technology powerhouses (e.g., IBM, Microsoft, Cisco, and Hewlett Packard) as well as new entrants (e.g., Apple, Google, and Amazon) to innovate in this new field.[31] So an association relation between comovement and diversity is induced both by fundamental shocks in the shared high-tech industry, and by shifts in investor sentiment toward cloud-related business models.

Another possible source of return commonality may arise from technological shifts favoring interdisciplinary versus focused R&D efforts, owing to a newly discovered synergy between previously disconnected technological areas. For example, with the rise of personalized medicine, Roche, a global pharmaceutical company, obtained patents and patent rights relating to a novel melanoma drug, Zelboraf, and its companion diagnostics which effectively identifies the patient subpopulation that is suitable for the drug treatment. The successful development of such a drug-diagnostic combination led to the recent approval by FDA. Favorable news about the success of personalized medicine will tend to be good news for all firms that have innovative diversity in the form of having both drug and diagnostic expertise.

To further analyze the ID effect, we construct a factor-mimicking portfolio for innovative diversity, DMC (Diversified Minus Concentrated), based on ID following the procedure in Fama and French (1993).[32] At the end of June of year *t* from 1982 to 2007, we sort firms with non-

[31] As of February 1, 2012, IBM, Microsoft, Cisco, Hewlett Packard, Apple, Google, and Amazon respectively own 1547, 1020, 641, 505, 94 (79 pending), 49 (48 pending), and 57 (5 pending) patents related to various aspects of cloud computing technology (see http://envisionip.wordpress.com/2012/02/01/).

[32] For brevity, we report the results for ID1 only. However, the results for ID2 are similar given the high correlations

missing ID independently into three size groups (small "S", middle "M", or big "B") based on the 30th and 70th percentiles of market capitalization measured at the end of June of year $t$ and three ID groups (low "L", middle "M", or high "H") based on the 30th and 70th percentiles of ID in year $t$ – 1. ID is one minus the Herfindahl index based on patents granted over the previous five years across the three-digit technological classes assigned by the USPTO.

We hold these portfolios over the next twelve months and compute monthly value-weighted returns of the nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H). We then calculate monthly size-adjusted returns of the low, middle, and high ID portfolios as (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively. The DMC factor returns are the difference in size-adjusted returns between the high and low ID portfolios. These return series reflect the return comovement associated with innovative diversity, regardless of whether such comovement is associated with any systematic risk or mispricing.

Figure 1 plots the DMC factor returns and the market factor (MKT) returns on a per annum basis from 1982 to 2008.[33] While the market factor return is negative in eight out of the 27 years, the DMC factor return is negative in only six years. Moreover, the DMC factor also seems to provide a good hedge against aggregate market downturns; the DMC factor returns are almost always positive in those years in which the stock market return is negative. For example, the returns for MKT 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 –10.94%, respectively. During those years, the corresponding DMC factor returns are 6.25%, 16.77%, 12.52%, 19.65%, 15.12%, 3.15%, 7.24%, and –1.21%, respectively. Furthermore, the DMC factor performed extremely well during the high-tech collapse in 2000, with a substantial return of 15.12%.

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between ID1 and ID2.

[33] The returns in 1982 and 2008 reflect only six months returns since the return series is from July of 1982 to June of 2008.

Panel A of Table 8 describes the means, standard deviations, time series *t*-statistics, and ex post Sharpe ratios of the monthly returns of DMC, MKT, the size factor (SMB), the value factor (HML), the momentum factor (MOM), the mispricing factor (UMO), the EMI factor, the investment factor (INV), and the ROE factor.[34] The average return of DMC is 0.51% per month, which is lower than that of MKT (0.68%), ROE (0.86%), MOM (0.83%), and UMO (0.87%); however, it is higher than the average returns of SMB (0.07%), HML (0.37%), EMI (0.26%), and INV (0.36%). Furthermore, the standard deviation of DMC is 2.01%, which is considerably lower than those of the other factors except EMI (1.80%) and INV (1.78%). Indeed DMC offers an ex post Sharpe ratio of 0.25, which is higher than that of all the other factors except UMO (0.27).[35]

Panel B reports the correlation between DMC and other familiar factors and shows generally low correlations. DMC has a correlation of 0.02 with MKT, –0.12 with SMB, 0.09 with HML, –0.09 with MOM, 0.09 with UMO, 0.22 with INV, and –0.11 with ROE, all of which are modest in magnitude. These findings suggest that by further adding the DMC factor to their portfolios, investors can perform substantially better than the market portfolio, or the Fama-French three factors in optimal combination. The correlation between DMC and EMI is 0.42, suggesting that innovatively diversified firms also tend to be more efficient in innovation.

In mean-variance portfolio theory, the tangency portfolio is the optimal portfolio of risky assets to select when a risk-free asset is available. Panel C summarizes the maximum ex post Sharpe ratios achievable by combining DMC with various other factors to form the tangency portfolio, and the optimal weights that different factors receive.

[34] The INV and ROE factors are from Chen, Novy-Marx, and Zhang (2011). We thank Lu Zhang for sharing the two factor returns.
[35] Ex post Sharpe ratio estimates are upward biased (MacKinlay 1995). However, adjusting for the bias would not change the qualitative nature of our conclusions.

The first row of Panel C shows that the monthly ex post Sharpe ratio of MKT is 0.16. When SMB is available as well (the second row), it receives negative weight in the optimal portfolio (–0.09), but that the maximum achievable Sharpe ratio remains 0.16. When HML is also available (the third row), it is weighted very heavily (0.51), and brings the Sharpe ratio to 0.29. The fourth row shows that adding DMC substantially increases the Sharpe ratio to 0.37. Moreover, the weight on DMC (0.39) is much higher than that on any of the other three factors (0.20 on MKT, 0.12 on SMB, and 0.30 on HML). The reason that DMC is so important for forming a mean-variance optimal portfolio is that it provides a substantial average return with a very low standard deviation, and has a very low (in some cases negative) correlation with the Fama-French three factors.

Mehra and Prescott (1985) point out that the high Sharpe ratio of the market factor already presents a difficult challenge for rational asset pricing theory. The improvement in the maximum Sharpe ratio from the inclusion of DMC is, therefore, a challenge to variation in risk premia as an explanation for the return predictability of ID.

Furthermore, DMC retains its substantial role in the tangency portfolio, with weights ranging from 0.24 to 0.32 when combined with EMI, MOM, UMO, INV, or ROE. Even when we include all the nine factors, the weight on DMC is 0.17, which is higher than that on any of the other eight factors except MKT (0.19) and UMO (0.21). These findings suggest that DMC captures substantial risk or mispricing effects above and beyond those captured by other commonly used factors.

## 6. Conclusion

We argue, based upon the psychology of limited attention and processing fluency, that firms with greater innovative diversity (defined as obtaining patents in a broader set of activities) will be undervalued by the market. This is based on two reinforcing psychological effects. First, individuals tend to interpret information with low processing fluency pessimistically. The greater complexity of innovatively diverse firms makes it harder to cognitively process the various kinds of information signals that are relevant for valuation, resulting in skeptical appraisal. Second, if innovative diversity is a favorable indicator of future fundamentals, then neglect of this indicator reduces valuations.

Consistent with these hypotheses, we find that high ID firms have less insider net stock sales. This is consistent with these firms being more undervalued, and with insiders having a more accurate assessment of value than outsiders. In addition, financial analysts are less overoptimistic about future earnings of high ID firms, consistent with analysts being skeptical when faced with innovative complexity.

Correspondingly, we find that firms with more diversified patent portfolios on average experience higher subsequent abnormal stock returns. These findings are robust to alternative innovative diversity (ID) measures, risk-adjustment methods, and to the inclusion of extensive controls including innovative efficency. We also find that high ID firms have higher and more stable future operating performance. These results suggest that underreaction to the association between innovative diversity and a firm's operating performance and/or the inherent skepticism toward complex information found in psychological studies of cognitive fluency may explain the return predictability of ID.

Further analyses show stronger ability of ID measures to predict returns among firms with lower investor attention, higher valuation uncertainty, and stronger short-sale constraints. These findings provide further support for psychological bias or constraints contributing to the ID-return relation. The high Sharpe ratio of the DMC (Diversified Minus Concentrated) factor that captures ID-related return comovement also suggests that this relation is not entirely explained by rational pricing. Finally, regardless of the source of the ID effect, the heavy weight of the DMC factor in the ex-post tangency portfolio indicates that innovative diversity captures pricing effects above and beyond those captured by the other well-known factors. Our evidence suggests that innovative diversity can be a useful input for firm valuation.

Overall, the evidence is consistent with limited attention causing undervaluation of innovative diversity. This could be the result of either a degree of investor neglect of the good news in innovative diversity, or of skepticism of complexity.

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**Table 1**
Innovative diversity measures of selected industries.

This table reports the pooled mean, standard deviation (Stdev), minimum (Min), $25^{th}$ percentile (P25), median (P50), $75^{th}$ percentile (P75), and maximum (Max) of the two innovative diversity (ID) measures for selected two- or three-digit SIC industries from 1981 to 2006. ID1 (ID2) is one minus the Herfindahl index based on patents granted over the previous five (three) years across three-digit technological classes assigned by the US Patent and Trademark Office (USPTO).

| | | | | | ID1 | | | |
|---|---|---|---|---|---|---|---|---|
| SIC | Industry | Mean | Stdev | Min | P25 | P50 | P75 | Max |
| 737 | Computer programming, software, services | 0.39 | 0.33 | 0.00 | 0.00 | 0.48 | 0.68 | 0.97 |
| 283 | Drugs & pharmaceuticals | 0.46 | 0.30 | 0.00 | 0.22 | 0.50 | 0.71 | 0.96 |
| 357 | Computers & office equipment | 0.54 | 0.34 | 0.00 | 0.34 | 0.63 | 0.82 | 0.98 |
| 38 | Measuring instruments | 0.50 | 0.32 | 0.00 | 0.22 | 0.57 | 0.76 | 0.98 |
| 36 | Electrical equipment excluding computers | 0.55 | 0.32 | 0.00 | 0.38 | 0.66 | 0.81 | 0.98 |
| 48 | Communications | 0.50 | 0.37 | 0.00 | 0.00 | 0.60 | 0.85 | 0.98 |
| 37 | Transportation equipment | 0.70 | 0.31 | 0.00 | 0.56 | 0.82 | 0.93 | 0.98 |
| | | | | | ID2 | | | |
| SIC | Industry | Mean | Stdev | Min | P25 | P50 | P75 | Max |
| 737 | Computer programming, software, services | 0.36 | 0.33 | 0.00 | 0.00 | 0.44 | 0.67 | 0.97 |
| 283 | Drugs & pharmaceuticals | 0.43 | 0.31 | 0.00 | 0.00 | 0.50 | 0.69 | 0.95 |
| 357 | Computers & office equipment | 0.52 | 0.34 | 0.00 | 0.18 | 0.61 | 0.81 | 0.98 |
| 38 | Measuring instruments | 0.47 | 0.33 | 0.00 | 0.00 | 0.50 | 0.74 | 0.98 |
| 36 | Electrical equipment excluding computers | 0.53 | 0.33 | 0.00 | 0.28 | 0.63 | 0.80 | 0.98 |
| 48 | Communications | 0.49 | 0.38 | 0.00 | 0.00 | 0.50 | 0.84 | 0.98 |
| 37 | Transportation equipment | 0.67 | 0.33 | 0.00 | 0.50 | 0.80 | 0.92 | 0.98 |

**Table 2**

Summary statistics and correlations.

At the end of June of year *t* from 1982 to 2007, we sort firms into three groups (low, middle, and high) based on the 30th and 70th percentiles of the ID measures in year *t* – 1. Panel A (B) reports the time-series mean of cross-sectional average (median) characteristics of the ID groups. Firms is the number of firms in each ID group. Size is market capitalization (in millions) at the end of June of year *t*. Book-to-market (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. Momentum (MOM) is the previous eleven-month returns (with a one-month gap between the holding period and the current month). ID1 (ID2) is one minus the Herfindahl index based on patents granted over the previous five (three) years across three-digit technological classes assigned by the USPTO. Class is the number of technological classes for a firm's patent portfolio over the previous five or three years. IVOL is computed at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months (with a minimum of 31 trading days). Total skewness (TSKEW) is computed at the end of June of year *t* using daily returns over the previous 12 months (with a minimum of 31 trading days). Idiosyncratic skewness (ISKEW) is computed at the end of June of year *t* as the skewness of residuals from regressing daily stock returns on daily market factor returns and squared market factor returns. The slope on the squared market factor returns is the systematic skewness (SSKEW). We compute expected idiosyncratic skewness (EISKEW) at the end of June of year *t* following Boyer, Mitton, and Vorkink (2009). RDME is R&D expenses in fiscal year ending in year *t* – 1 divided by market equity at the end of year *t* – 1. CTA is the number of patents issued to a firm in year *t* – 1 divided by the firm's total assets at the end of year *t* – 1. IE is the innovative efficiency measure based on patent citations as in Hirshleifer, Hsu, and Li (2012). ROA is income before extraordinary items plus interest expenses in year *t* – 1 divided by lagged total assets. Asset growth (AG) is the change in total assets in year *t* – 1 divided by lagged total assets. IA is capital expenditure in year *t* – 1 divided by lagged total assets. Net stock issues (NS) is the change in the natural log of the split-adjusted shares outstanding in year *t* – 1. 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 in year *t* – 1. FROA is ROA in year *t*. FCF is cash flow in year *t*. Cash flow is defined as net income minus accrual divided by average assets. FPM is profit margin in year *t*. Profit margin is defined as operating income before depreciation divided by sales. FE is analyst forecast error defined as the difference between the announced annual earnings per share in year *t* + 1 and the average analyst forecast made one year before the announcement divided by the stock price at the end of the month when the forecast is made. CEO NSS (net stock sales) is defined as the shares sold by minus the shares bought by firm CEOs in year *t* – 1, divided by the average shares outstanding in year *t* – 1. Director NSS (net stock sales) is defined as the shares sold by minus the shares bought by non-CEO directors in year *t* – 1, divided by the average shares outstanding in year *t* – 1. Panel C reports the times-series average of cross-sectional Pearson (Spearman rank) correlations between the ID measures and other characteristics below (above) the diagonal. Short-term reversal (REV) is monthly returns in June of year *t*. Stock illiquidity (ILLIQ) is defined as absolute stock return in June of year *t* divided by dollar trading volume in June of year *t*. We winsorize all variables at the 1% and 99% levels except the number of firms, technological classes, and CEO and director net stock sales.

**Panel A. Time-series average of cross-sectional mean**

| ID1 | Firms | Size | BTM | MOM | ID1 | Class | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | RDME | CTA | IE | ROA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 428 | 646 | 0.72 | 0.13 | 0.05 | 1.27 | 0.04 | 0.57 | 0.59 | -6.00 | 0.90 | 0.05 | 0.02 | 2.06 | -0.54% |
| Middle | 564 | 1067 | 0.68 | 0.15 | 0.59 | 4.70 | 0.03 | 0.49 | 0.51 | -5.43 | 0.77 | 0.06 | 0.03 | 2.96 | 0.18% |
| High | 430 | 3920 | 0.69 | 0.16 | 0.87 | 32.44 | 0.02 | 0.30 | 0.35 | -1.42 | 0.50 | 0.06 | 0.03 | 2.62 | 5.57% |
| ID2 | Firms | Size | BTM | MOM | ID2 | Class | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | RDME | CTA | IE | ROA |
| Low | 388 | 672 | 0.71 | 0.14 | 0.01 | 1.08 | 0.04 | 0.57 | 0.59 | -6.44 | 0.89 | 0.05 | 0.02 | 1.98 | -0.37% |
| Middle | 516 | 1095 | 0.67 | 0.15 | 0.56 | 3.97 | 0.03 | 0.48 | 0.50 | -5.12 | 0.76 | 0.06 | 0.04 | 3.15 | -0.42% |
| High | 391 | 4200 | 0.68 | 0.16 | 0.86 | 27.90 | 0.02 | 0.28 | 0.34 | -1.13 | 0.48 | 0.06 | 0.03 | 2.59 | 5.70% |

| ID1 | AG | IA | NS | IO | FROA | FCF | FPM | FE (%) | CEO NSS (%) | Director NSS (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.16 | 0.07 | 0.05 | 0.32 | -0.01 | 0.00 | -0.49 | -5.61 | 0.50 | 0.48 |
| Middle | 0.16 | 0.07 | 0.05 | 0.38 | 0.00 | 0.01 | -0.50 | -5.05 | 0.37 | 0.45 |
| High | 0.12 | 0.07 | 0.03 | 0.52 | 0.05 | 0.07 | 0.01 | -2.52 | 0.21 | 0.34 |
| ID2 | AG | IA | NS | IO | FROA | FCF | FPM | FE (%) | CEO sales (%) | Director sales (%) |
| Low | 0.16 | 0.07 | 0.05 | 0.32 | -0.01 | 0.00 | -0.50 | -5.14 | 0.49 | 0.45 |
| Middle | 0.16 | 0.07 | 0.05 | 0.39 | -0.01 | 0.01 | -0.55 | -5.16 | 0.38 | 0.45 |
| High | 0.12 | 0.07 | 0.03 | 0.53 | 0.06 | 0.07 | 0.02 | -2.51 | 0.22 | 0.34 |

**Panel B. Time-series average of cross-sectional median**

| ID1 | Firms | Size | BTM | MOM | ID1 | Class | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | RDME | CTA | IE | ROA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 428 | 105 | 0.56 | 0.04 | 0.00 | 1.00 | 0.03 | 0.45 | 0.48 | -4.93 | 0.84 | 0.02 | 0.00 | 0.03 | 6.02% |
| Middle | 564 | 178 | 0.54 | 0.06 | 0.61 | 3.27 | 0.03 | 0.40 | 0.43 | -4.29 | 0.69 | 0.03 | 0.01 | 0.57 | 6.09% |
| High | 430 | 990 | 0.57 | 0.10 | 0.87 | 16.88 | 0.02 | 0.25 | 0.31 | -1.08 | 0.40 | 0.03 | 0.01 | 0.77 | 7.52% |
| ID2 | Firms | Size | BTM | MOM | ID2 | Class | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | RDME | CTA | IE | ROA |
| Low | 388 | 108 | 0.55 | 0.05 | 0.00 | 1.00 | 0.03 | 0.45 | 0.48 | -5.22 | 0.82 | 0.02 | 0.00 | 0.05 | 6.13% |
| Middle | 516 | 191 | 0.54 | 0.06 | 0.56 | 3.04 | 0.03 | 0.40 | 0.43 | -4.00 | 0.68 | 0.03 | 0.01 | 0.63 | 5.95% |
| High | 391 | 1191 | 0.56 | 0.11 | 0.86 | 14.62 | 0.02 | 0.24 | 0.30 | -0.90 | 0.39 | 0.04 | 0.01 | 0.81 | 7.63% |

| ID1 | AG | IA | NS | IO | FROA | FCF | FPM | FE (%) | CEO NSS (%) | Director NSS (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.07 | 0.05 | 0.01 | 0.29 | 0.06 | 0.05 | 0.09 | -0.53 | 0.11 | 0.10 |
| Middle | 0.07 | 0.05 | 0.01 | 0.37 | 0.06 | 0.06 | 0.10 | -0.39 | 0.09 | 0.09 |
| High | 0.06 | 0.06 | 0.01 | 0.55 | 0.07 | 0.09 | 0.12 | -0.21 | 0.04 | 0.05 |
| ID2 | AG | IA | NS | IO | FROA | FCF | FPM | FE (%) | CEO NSS (%) | Director NSS (%) |
| Low | 0.07 | 0.05 | 0.01 | 0.29 | 0.06 | 0.05 | 0.09 | -0.56 | 0.11 | 0.11 |
| Middle | 0.07 | 0.05 | 0.01 | 0.37 | 0.06 | 0.06 | 0.10 | -0.39 | 0.09 | 0.09 |
| High | 0.06 | 0.06 | 0.01 | 0.56 | 0.07 | 0.09 | 0.13 | -0.19 | 0.04 | 0.05 |

**Panel C. Time-series average of cross-sectional correlations**

| | ID1 | ID2 | Size | BTM | MOM | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | RDME | CTA | IE | ROA | AG | IA | NS | REV | ILLIQ | IO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID1 | 1 | 0.93 | 0.47 | 0.01 | 0.08 | -0.36 | -0.13 | -0.11 | 0.11 | -0.31 | 0.15 | 0.31 | 0.30 | 0.09 | -0.01 | 0.10 | -0.06 | 0.03 | -0.37 | 0.35 |
| ID2 | 0.90 | 1 | 0.48 | 0.01 | 0.07 | -0.36 | -0.14 | -0.12 | 0.12 | -0.31 | 0.15 | 0.28 | 0.28 | 0.09 | -0.01 | 0.10 | -0.06 | 0.02 | -0.39 | 0.36 |
| Size | 0.42 | 0.44 | 1 | -0.24 | 0.31 | -0.65 | -0.26 | -0.23 | 0.11 | -0.81 | -0.05 | 0.23 | 0.08 | 0.39 | 0.23 | 0.25 | 0.00 | 0.14 | -0.76 | 0.67 |
| BTM | 0.02 | 0.02 | -0.22 | 1 | -0.11 | -0.05 | 0.02 | 0.01 | 0.02 | 0.20 | -0.12 | -0.09 | -0.05 | -0.19 | -0.25 | -0.13 | -0.23 | 0.02 | 0.20 | -0.05 |
| MOM | 0.03 | 0.03 | 0.22 | -0.13 | 1 | -0.26 | 0.17 | 0.19 | -0.02 | -0.27 | -0.05 | 0.04 | 0.01 | 0.19 | 0.04 | 0.00 | -0.08 | 0.09 | -0.24 | 0.13 |
| IVOL | -0.27 | -0.28 | -0.56 | -0.02 | -0.12 | 1 | 0.30 | 0.27 | -0.14 | 0.67 | 0.19 | -0.11 | -0.04 | -0.41 | -0.13 | -0.16 | 0.21 | -0.10 | 0.50 | -0.52 |
| TSKEW | -0.10 | -0.10 | -0.22 | 0.02 | 0.20 | 0.32 | 1 | 0.96 | -0.03 | 0.33 | 0.05 | -0.06 | -0.02 | -0.22 | -0.14 | -0.14 | 0.01 | 0.06 | 0.21 | -0.27 |
| ISKEW | -0.08 | -0.09 | -0.19 | 0.02 | 0.21 | 0.30 | 0.98 | 1 | -0.10 | 0.29 | 0.04 | -0.05 | -0.02 | -0.21 | -0.14 | -0.14 | 0.00 | 0.06 | 0.19 | -0.25 |
| SSKEW | 0.08 | 0.10 | 0.10 | 0.03 | -0.03 | -0.12 | -0.03 | -0.08 | 1 | -0.13 | -0.02 | 0.04 | 0.02 | 0.07 | 0.02 | 0.04 | -0.04 | -0.01 | -0.09 | 0.12 |
| EISKEW | -0.28 | -0.29 | -0.76 | 0.16 | -0.20 | 0.64 | 0.32 | 0.29 | -0.12 | 1 | 0.12 | -0.14 | -0.05 | -0.39 | -0.21 | -0.25 | 0.10 | -0.10 | 0.65 | -0.61 |
| RDME | 0.06 | 0.06 | -0.16 | 0.07 | -0.08 | 0.22 | 0.06 | 0.06 | -0.03 | 0.20 | 1 | 0.43 | -0.07 | -0.20 | -0.10 | -0.13 | 0.09 | -0.04 | 0.03 | -0.01 |
| CTA | 0.07 | 0.06 | -0.04 | -0.13 | 0.01 | 0.08 | 0.04 | 0.03 | -0.02 | 0.08 | 0.23 | 1 | 0.29 | -0.01 | -0.03 | -0.01 | 0.01 | 0.00 | -0.18 | 0.20 |
| IE | 0.17 | 0.15 | -0.05 | -0.07 | 0.01 | 0.04 | 0.02 | 0.01 | -0.01 | 0.03 | -0.11 | 0.26 | 1 | 0.03 | 0.05 | 0.08 | 0.04 | 0.00 | -0.07 | 0.06 |
| ROA | 0.11 | 0.11 | 0.31 | 0.13 | 0.12 | -0.40 | -0.17 | -0.17 | 0.08 | -0.34 | -0.29 | -0.17 | -0.02 | 1 | 0.48 | 0.26 | -0.09 | 0.06 | -0.30 | 0.30 |
| AG | -0.04 | -0.04 | 0.11 | -0.19 | 0.00 | -0.05 | -0.07 | -0.07 | -0.01 | -0.08 | -0.13 | -0.04 | 0.08 | 0.10 | 1 | 0.40 | 0.30 | 0.01 | -0.18 | 0.15 |
| IA | 0.00 | 0.01 | 0.09 | -0.12 | -0.04 | -0.04 | -0.07 | -0.07 | 0.01 | -0.11 | -0.13 | -0.06 | 0.06 | 0.08 | 0.37 | 1 | 0.10 | 0.00 | -0.19 | 0.17 |
| NS | -0.06 | -0.06 | -0.07 | -0.16 | -0.06 | 0.19 | 0.04 | 0.03 | -0.06 | 0.16 | 0.02 | 0.02 | 0.06 | -0.25 | 0.41 | 0.14 | 1 | -0.04 | -0.02 | -0.03 |
| REV | 0.01 | 0.00 | 0.09 | 0.02 | 0.06 | -0.04 | 0.10 | 0.10 | -0.02 | -0.06 | -0.02 | -0.01 | 0.00 | 0.04 | -0.02 | -0.01 | -0.03 | 1 | -0.10 | 0.06 |
| ILLIQ | -0.13 | -0.13 | -0.40 | 0.14 | -0.15 | 0.31 | 0.10 | 0.09 | -0.01 | 0.34 | 0.05 | -0.01 | 0.00 | -0.13 | -0.09 | -0.06 | 0.01 | -0.05 | 1 | -0.55 |
| IO | 0.32 | 0.33 | 0.65 | -0.03 | 0.06 | -0.45 | -0.23 | -0.21 | 0.12 | -0.59 | -0.08 | -0.05 | -0.06 | 0.28 | 0.05 | 0.05 | -0.09 | 0.02 | -0.24 | 1 |

**Table 3**

Innovative diversity portfolio returns and risk factor models.

At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing innovative diversity (ID) measures independently into three size groups (small "S", middle "M", or big "B") based on the 30th and 70th percentiles of market capitalization measured at the end of June of year *t* and three ID groups (low "L", middle "M", or high "H") based on the 30th and 70th percentiles of ID in year $t - 1$. The ID measures are defined in Table 1 in more details. We hold these portfolios over the next twelve months and compute monthly value- and equal-weighted returns of the nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H). We then calculate monthly size-adjusted returns of the low, middle, and high ID portfolios as (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively. This table reports the average monthly size-adjusted excess returns (Exret, in percentage) to the ID portfolios and the intercepts (Alpha, in percentage) and risk factor loadings from regressing the size-adjusted excess returns to the ID portfolios on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess return is the difference between the size-adjusted ID portfolio returns and the one-month Treasury bill rate. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997).

Panel A. ID1 based on patents granted in the prior 5 years and 3-digit technological classes

| | Value-weighted portfolio returns | | | | | | Equal-weighted portfolio returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID1 | Exret | Alpha | MKT | SMB | HML | MOM | Exret | Alpha | MKT | SMB | HML | MOM |
| Low | 0.74 | 0.07 | 0.96 | 0.88 | -0.07 | -0.01 | 0.91 | 0.36 | 1.00 | 0.85 | -0.02 | -0.22 |
| | (2.27) | (0.80) | (42.83) | (14.67) | (-1.80) | (-0.18) | (2.70) | (3.37) | (33.00) | (15.22) | (-0.32) | (-5.44) |
| Middle | 0.93 | 0.28 | 0.98 | 0.84 | -0.18 | 0.01 | 1.10 | 0.57 | 1.04 | 0.90 | -0.10 | -0.23 |
| | (2.76) | (3.20) | (42.94) | (15.05) | (-5.00) | (0.25) | (3.08) | (5.33) | (33.25) | (14.81) | (-2.07) | (-6.00) |
| High | 1.26 | 0.56 | 1.00 | 0.82 | -0.02 | -0.03 | 1.42 | 0.81 | 1.05 | 0.91 | 0.12 | -0.25 |
| | (3.77) | (4.56) | (28.12) | (10.57) | (-0.28) | (-0.84) | (4.07) | (5.92) | (30.95) | (14.08) | (2.07) | (-5.61) |
| High-Low | 0.51 | 0.50 | 0.03 | -0.06 | 0.05 | -0.03 | 0.52 | 0.44 | 0.05 | 0.06 | 0.14 | -0.02 |
| | (4.49) | (4.28) | (1.20) | (-1.17) | (1.10) | (-0.86) | (4.69) | (3.70) | (1.77) | (1.47) | (3.08) | (-0.64) |

Panel B. ID2 based on patents granted in the prior 3 years and 3-digit technological classes

| | Value-weighted portfolio returns | | | | | | Equal-weighted portfolio returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID2 | Exret | Alpha | MKT | SMB | HML | MOM | Exret | Alpha | MKT | SMB | HML | MOM |
| Low | 0.76 | 0.08 | 0.99 | 0.81 | -0.05 | -0.02 | 0.88 | 0.37 | 1.00 | 0.80 | -0.03 | -0.25 |
| | (2.36) | (1.00) | (49.73) | (18.15) | (-1.45) | (-0.87) | (2.65) | (3.21) | (32.15) | (14.25) | (-0.51) | (-5.35) |
| Middle | 0.93 | 0.29 | 0.96 | 0.88 | -0.22 | 0.02 | 1.11 | 0.59 | 1.03 | 0.93 | -0.13 | -0.23 |
| | (2.68) | (3.00) | (37.26) | (12.69) | (-4.99) | (0.44) | (3.06) | (5.32) | (33.33) | (13.83) | (-2.49) | (-5.66) |
| High | 1.24 | 0.51 | 1.04 | 0.81 | 0.01 | -0.03 | 1.39 | 0.77 | 1.09 | 0.91 | 0.13 | -0.26 |
| | (3.68) | (4.31) | (31.99) | (12.57) | (0.10) | (-0.97) | (3.90) | (5.67) | (32.57) | (15.59) | (2.25) | (-6.51) |
| High-Low | 0.48 | 0.43 | 0.05 | 0.00 | 0.06 | -0.01 | 0.51 | 0.40 | 0.09 | 0.11 | 0.15 | -0.02 |
| | (4.26) | (3.65) | (1.82) | (0.04) | (1.32) | (-0.34) | (4.31) | (3.11) | (2.84) | (2.47) | (3.09) | (-0.46) |

**Table 4**

Innovative diversity portfolio returns and risk factor models augmented with the innovative efficiency factor (EMI).

At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing innovative diversity (ID) measures independently into three size groups (small "S", middle "M", or big "B") based on the 30th and 70th percentiles of market capitalization measured at the end of June of year *t* and three ID groups (low "L", middle "M", or high "H") based on the 30th and 70th percentiles of ID in year $t - 1$. The ID measures are defined in Table 1 in more details. We hold these portfolios over the next twelve months and compute monthly value- and equal-weighted returns of the nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H). We then calculate monthly size-adjusted returns of the low, middle, and high ID portfolios as (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively. The returns to the high-low ID portfolios are based on the size-adjusted returns. This table reports the intercepts (Alpha, in percentage) and risk factor loadings from regressing the monthly size-adjusted excess returns to the ID portfolios on factor returns. Heteroscedasticity-robust *t*-statistics are reported in parentheses. Excess return is the difference between the size-adjusted ID portfolio returns and the one-month Treasury bill rate. MKT, SMB, and HML are the market, size, and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). EMI (Efficient Minus Inefficient) is the innovative efficiency factor based on citations of Hirshleifer, Hsu, and Li (2012).

Panel A. ID1 based on patents granted in the prior 5 years and 3-digit technological classes

| | Value-weighted portfolio returns | | | | | | Equal-weighted portfolio returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID1 | Alpha | MKT | SMB | HML | MOM | EMI | Alpha | MKT | SMB | HML | MOM | EMI |
| Low | 0.12 | 0.96 | 0.87 | -0.09 | -0.01 | -0.14 | 0.40 | 1.00 | 0.85 | -0.03 | -0.23 | -0.10 |
| | (1.51) | (42.94) | (13.56) | (-2.43) | (-0.29) | (-2.50) | (3.79) | (31.79) | (14.69) | (-0.60) | (-5.44) | (-1.38) |
| Middle | 0.26 | 0.98 | 0.84 | -0.18 | 0.01 | 0.04 | 0.54 | 1.04 | 0.91 | -0.09 | -0.23 | 0.07 |
| | (2.97) | (42.93) | (14.67) | (-4.97) | (0.27) | (0.55) | (5.20) | (33.47) | (15.14) | (-1.84) | (-5.99) | (1.01) |
| High | 0.44 | 1.00 | 0.84 | 0.03 | -0.03 | 0.33 | 0.72 | 1.06 | 0.93 | 0.15 | -0.24 | 0.26 |
| | (3.68) | (28.87) | (11.59) | (0.55) | (-0.67) | (4.31) | (5.46) | (31.50) | (15.21) | (2.55) | (-5.66) | (3.48) |
| High-Low | 0.32 | 0.04 | -0.03 | 0.12 | -0.02 | 0.48 | 0.32 | 0.06 | 0.08 | 0.18 | -0.01 | 0.36 |
| | (2.93) | (1.25) | (-0.66) | (2.60) | (-0.60) | (6.76) | (2.74) | (1.83) | (2.12) | (3.97) | (-0.38) | (5.81) |

Panel B. ID2 based on patents granted in the prior 3 years and 3-digit technological classes

| | Value-weighted portfolio returns | | | | | | Equal-weighted portfolio returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID2 | Alpha | MKT | SMB | HML | MOM | EMI | Alpha | MKT | SMB | HML | MOM | EMI |
| Low | 0.13 | 0.99 | 0.80 | -0.07 | -0.03 | -0.16 | 0.41 | 1.00 | 0.79 | -0.04 | -0.25 | -0.12 |
| | (1.80) | (49.10) | (16.50) | (-2.10) | (-1.05) | (-3.08) | (3.67) | (31.15) | (14.04) | (-0.82) | (-5.33) | (-1.65) |
| Middle | 0.27 | 0.97 | 0.89 | -0.21 | 0.02 | 0.05 | 0.55 | 1.04 | 0.94 | -0.11 | -0.23 | 0.10 |
| | (2.84) | (36.98) | (12.25) | (-5.06) | (0.49) | (0.75) | (5.15) | (33.64) | (14.04) | (-2.26) | (-5.63) | (1.25) |
| High | 0.40 | 1.04 | 0.83 | 0.04 | -0.03 | 0.31 | 0.67 | 1.09 | 0.92 | 0.16 | -0.26 | 0.27 |
| | (3.40) | (32.38) | (13.88) | (0.79) | (-0.83) | (4.44) | (5.11) | (33.22) | (16.64) | (2.75) | (-6.56) | (3.59) |
| High-Low | 0.27 | 0.05 | 0.03 | 0.11 | 0.00 | 0.47 | 0.27 | 0.09 | 0.13 | 0.20 | -0.01 | 0.39 |
| | (2.36) | (2.00) | (0.96) | (2.77) | (0.01) | (7.23) | (2.16) | (2.89) | (3.15) | (4.11) | (-0.24) | (5.73) |

**Table 5**

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

This table reports the average slopes (in percentage) and their time series heteroscedasticity-robust $t$-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions of individual stocks' returns from July of year $t$ to June of year $t + 1$ on innovative diversity (ID) in year $t - 1$ and different sets of control variables. All the other independent variables are defined in Table 2. Size, BTM, IE, CTA, and RDME are in the natural log form. In particular, IE is the natural log of one plus citations-based innovative efficiency measure in year $t - 1$, and CTA is the natural log of one plus patents granted divided by total assets in year $t - 1$. RDME is the natural log of one plus RDME in year $t - 1$. ILLIQ is the previous month's stock illiquidity. The return reversal (REV) is the previous month's stock return. IVOL, Size, TSKEW, SSKEW, and ISKEW are measured at the end of June of year $t$. EISKEW is measured in the previous month. The other control variables are measured in fiscal year ending in year $t - 1$. All models control for industry effects based on the Fama-French 48 industries. All independent variables are normalized to zero mean and one standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1982 to June of 2008. R-square (in percentage) is the time-series average of the R-square from the monthly cross-sectional regressions for each model.

Panel A. ID1 based on patents granted in the prior 5 years and 3-digit technological classes

| Model | ID1 | IO | ILLIQ | REV | BTM | Size | MOM | AG | IA | IE | CTA | RDME | NS | ROA | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.20 | 0.07 | 0.20 | -0.84 | 0.25 | -0.29 | 0.18 | | | | | | | | | | | | | 9.74 |
| | (5.54) | (1.19) | (2.62) | (-9.61) | (3.59) | (-2.72) | (1.83) | | | | | | | | | | | | | |
| 2 | 0.12 | 0.08 | 0.19 | -0.87 | 0.07 | -0.27 | 0.09 | -0.18 | 0.01 | 0.07 | 0.00 | 0.29 | -0.13 | 0.17 | | | | | | 12.91 |
| | (2.41) | (1.37) | (2.06) | (-10.79) | (1.00) | (-2.62) | (0.94) | (-3.65) | (0.23) | (1.88) | (-0.06) | (3.84) | (-3.07) | (2.44) | | | | | | |
| 3 | 0.12 | 0.09 | 0.16 | -0.88 | 0.09 | -0.17 | 0.09 | -0.16 | 0.00 | 0.07 | 0.00 | 0.25 | -0.15 | 0.19 | 0.24 | -0.08 | | | | 13.74 |
| | (2.45) | (1.67) | (1.52) | (-11.08) | (1.38) | (-1.72) | (0.97) | (-3.40) | (0.02) | (1.85) | (-0.01) | (3.61) | (-3.47) | (2.97) | (1.81) | (-2.01) | | | | |
| 4 | 0.12 | 0.09 | 0.16 | -0.88 | 0.09 | -0.18 | 0.09 | -0.16 | 0.00 | 0.07 | 0.00 | 0.25 | -0.15 | 0.19 | 0.23 | | -0.07 | | | 13.73 |
| | (2.45) | (1.70) | (1.53) | (-11.09) | (1.36) | (-1.74) | (0.96) | (-3.39) | (0.01) | (1.84) | (-0.00) | (3.63) | (-3.46) | (2.96) | (1.76) | | (-1.82) | | | |
| 5 | 0.12 | 0.10 | 0.16 | -0.87 | 0.08 | -0.19 | 0.08 | -0.16 | 0.00 | 0.07 | 0.00 | 0.25 | -0.14 | 0.20 | 0.21 | | | 0.08 | | 13.82 |
| | (2.46) | (1.77) | (1.55) | (-11.10) | (1.26) | (-1.84) | (0.87) | (-3.40) | (-0.00) | (1.79) | (-0.05) | (3.63) | (-3.38) | (3.05) | (1.60) | | | (1.61) | | |
| 6 | 0.13 | 0.08 | 0.20 | -0.84 | 0.05 | -0.24 | 0.05 | -0.13 | 0.04 | 0.07 | -0.01 | 0.26 | -0.17 | 0.17 | 0.35 | | | | -0.13 | 13.20 |
| | (2.22) | (1.35) | (1.58) | (-8.78) | (0.59) | (-1.94) | (0.41) | (-2.44) | (0.88) | (1.52) | (-0.13) | (3.07) | (-3.31) | (2.26) | (2.30) | | | | (-1.14) | |

Panel B. ID2 based on patents granted in the prior3 years and 3-digit technological classes

| Model | ID2 | IO | ILLIQ | REV | BTM | Size | MOM | AG | IA | IE | CTA | RDME | NS | ROA | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.20 | 0.06 | 0.15 | -0.82 | 0.24 | -0.28 | 0.19 | | | | | | | | | | | | | 10.24 |
| | (5.20) | (1.11) | (2.46) | (-9.30) | (3.54) | (-2.58) | (1.96) | | | | | | | | | | | | | |
| 2 | 0.12 | 0.06 | 0.10 | -0.85 | 0.06 | -0.27 | 0.11 | -0.15 | 0.00 | 0.06 | 0.00 | 0.31 | -0.14 | 0.18 | | | | | | 13.50 |
| | (2.65) | (1.12) | (1.41) | (-10.38) | (0.74) | (-2.59) | (1.19) | (-3.01) | (0.12) | (1.57) | (-0.05) | (3.95) | (-3.17) | (2.79) | | | | | | |
| 3 | 0.13 | 0.09 | 0.03 | -0.85 | 0.09 | -0.14 | 0.11 | -0.13 | 0.00 | 0.06 | 0.00 | 0.25 | -0.16 | 0.21 | 0.33 | -0.08 | | | | 14.40 |
| | (2.89) | (1.58) | (0.51) | (-10.63) | (1.38) | (-1.44) | (1.15) | (-2.66) | (-0.06) | (1.55) | (-0.07) | (3.54) | (-3.78) | (3.50) | (2.51) | (-1.85) | | | | |
| 4 | 0.13 | 0.09 | 0.03 | -0.85 | 0.09 | -0.15 | 0.11 | -0.13 | 0.00 | 0.06 | 0.00 | 0.25 | -0.16 | 0.21 | 0.32 | | -0.06 | | | 14.38 |
| | (2.89) | (1.63) | (0.51) | (-10.64) | (1.36) | (-1.48) | (1.13) | (-2.65) | (-0.07) | (1.55) | (-0.07) | (3.56) | (-3.76) | (3.49) | (2.46) | | (-1.56) | | | |
| 5 | 0.13 | 0.09 | 0.04 | -0.85 | 0.08 | -0.15 | 0.10 | -0.13 | 0.00 | 0.06 | -0.01 | 0.25 | -0.16 | 0.22 | 0.30 | | | 0.05 | | 14.45 |
| | (2.83) | (1.65) | (0.54) | (-10.66) | (1.29) | (-1.49) | (1.06) | (-2.63) | (-0.09) | (1.51) | (-0.12) | (3.59) | (-3.67) | (3.59) | (2.36) | | | (1.10) | | |
| 6 | 0.12 | 0.08 | 0.07 | -0.81 | 0.05 | -0.17 | 0.07 | -0.11 | 0.02 | 0.07 | -0.01 | 0.26 | -0.19 | 0.23 | 0.48 | | | | -0.12 | 13.87 |
| | (2.19) | (1.33) | (0.80) | (-8.53) | (0.73) | (-1.42) | (0.57) | (-2.04) | (0.55) | (1.46) | (-0.13) | (3.04) | (-3.59) | (3.15) | (3.22) | | | | (-1.04) | |

**Table 6**

Fama-MacBeth regressions of stock returns on innovative diversity and other variables – original assignees only.

In this table, we compute innovative diversity (ID) measures based on original assignees only. This table reports the average slopes (in %) and their time series heteroscedasticity-robust *t*-statistics in parentheses for Models 3-6 specified in Table 5 from monthly Fama and MacBeth (1973) cross-sectional regressions of individual stocks' returns from July of year *t* to June of year *t* + 1 on innovative diversity (ID) in year *t* – 1 and different sets of control variables. All variables are defined in Tables 2 and 5. All independent variables are normalized to zero mean and one standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1982 to June of 2008. R-square (in percentage) is the time-series average of the R-square from the monthly cross-sectional regressions for each model.

Panel A. ID1 based on patents granted in the prior 5 years and 3-digit technological classes

| Model | ID1 | IO | ILLIQ | REV | BTM | Size | MOM | AG | IA | IE | CTA | RDME | NS | ROA | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 0.09 | 0.05 | 0.08 | -0.86 | 0.09 | -0.11 | 0.04 | -0.15 | 0.00 | 0.05 | 0.03 | 0.23 | -0.11 | 0.18 | 0.29 | -0.07 | | | | 14.20 |
| | (2.20) | (0.89) | (1.20) | (-10.93) | (1.44) | (-1.17) | (0.40) | (-3.53) | (-0.09) | (1.32) | (0.64) | (3.52) | (-2.68) | (3.00) | (2.32) | (-1.86) | | | | |
| 4 | 0.09 | 0.05 | 0.08 | -0.86 | 0.09 | -0.11 | 0.04 | -0.15 | 0.00 | 0.05 | 0.03 | 0.23 | -0.11 | 0.18 | 0.28 | | -0.07 | | | 14.19 |
| | (2.20) | (0.91) | (1.21) | (-10.93) | (1.42) | (-1.20) | (0.39) | (-3.53) | (-0.10) | (1.32) | (0.65) | (3.54) | (-2.67) | (2.99) | (2.28) | | (-1.71) | | | |
| 5 | 0.09 | 0.06 | 0.09 | -0.85 | 0.08 | -0.12 | 0.03 | -0.15 | -0.01 | 0.05 | 0.03 | 0.23 | -0.11 | 0.18 | 0.26 | | | 0.07 | | 14.28 |
| | (2.20) | (1.01) | (1.27) | (-10.95) | (1.31) | (-1.32) | (0.29) | (-3.53) | (-0.18) | (1.32) | (0.59) | (3.54) | (-2.59) | (3.03) | (2.17) | | | (1.42) | | |
| 6 | 0.10 | 0.05 | 0.11 | -0.82 | 0.03 | -0.17 | 0.00 | -0.12 | 0.03 | 0.06 | 0.02 | 0.25 | -0.14 | 0.17 | 0.43 | | | | -0.14 | 13.59 |
| | (1.96) | (0.81) | (1.45) | (-8.64) | (0.43) | (-1.54) | (-0.02) | (-2.45) | (0.61) | (1.36) | (0.36) | (3.10) | (-2.71) | (2.44) | (2.97) | | | | (-1.22) | |

Panel B. ID2 based on patents granted in the prior 3 years and 3-digit technological classes

| Model | ID2 | IO | ILLIQ | REV | BTM | Size | MOM | AG | IA | IE | CTA | RDME | NS | ROA | IVOL | TSKEW | ISKEW | SSKEW | EISKEW | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 0.11 | 0.04 | 0.04 | -0.85 | 0.06 | -0.10 | 0.05 | -0.13 | 0.00 | 0.04 | 0.02 | 0.23 | -0.13 | 0.18 | 0.33 | -0.07 | | | | 14.82 |
| | (2.61) | (0.68) | (0.54) | (-10.50) | (0.95) | (-1.10) | (0.54) | (-2.81) | (0.04) | (1.09) | (0.33) | (3.41) | (-3.07) | (3.11) | (2.60) | (-1.82) | | | | |
| 4 | 0.11 | 0.04 | 0.04 | -0.85 | 0.06 | -0.11 | 0.05 | -0.13 | 0.00 | 0.04 | 0.02 | 0.23 | -0.13 | 0.18 | 0.32 | | -0.06 | | | 14.80 |
| | (2.61) | (0.72) | (0.54) | (-10.51) | (0.93) | (-1.13) | (0.53) | (-2.81) | (0.03) | (1.09) | (0.34) | (3.43) | (-3.05) | (3.11) | (2.55) | | (-1.57) | | | |
| 5 | 0.11 | 0.05 | 0.04 | -0.84 | 0.06 | -0.11 | 0.04 | -0.13 | 0.00 | 0.04 | 0.01 | 0.23 | -0.12 | 0.19 | 0.31 | | | 0.04 | | 14.87 |
| | (2.55) | (0.80) | (0.58) | (-10.52) | (0.87) | (-1.16) | (0.45) | (-2.79) | (-0.03) | (1.07) | (0.30) | (3.43) | (-2.93) | (3.18) | (2.47) | | | (0.91) | | |
| 6 | 0.10 | 0.04 | 0.08 | -0.82 | 0.01 | -0.14 | 0.01 | -0.11 | 0.02 | 0.05 | 0.01 | 0.25 | -0.17 | 0.21 | 0.51 | | | | -0.13 | 14.27 |
| | (2.11) | (0.64) | (0.93) | (-8.38) | (0.18) | (-1.19) | (0.11) | (-2.07) | (0.50) | (1.16) | (0.16) | (2.99) | (-3.09) | (2.98) | (3.42) | | | | (-1.11) | |

**Table 7**

Fama-MacBeth regressions of stock returns on innovative diversity and other variables: subsample analysis.

This table reports the average slopes (in %) of innovative diversity (ID) and their time series heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions of individual stocks' returns from July of year *t* to June of year *t* + 1 on innovative diversity (ID) and different sets of control variables in subsamples split by the 30th and 70th percentiles of different variables. The ID measures are defined in Table 1. Models 3-6 are specified in Table 5. Size is market capitalization at the end of June of year *t*. Analyst coverage (AC) is the average monthly number of stock analyst reports on earnings estimates in year *t* – 1. IVOL is computed at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months (with a minimum of 31 trading days). Firm age denotes the number of years listed on Compustat with non-missing price data at the end of year *t* – 1. Dispersion is the average of monthly standard deviation of analyst earning forecasts divided by the absolute value of consensus analyst earning forecast in year *t* – 1. Institutional ownership (IO) denotes the fraction of firm shares outstanding owned by institutional investors in year *t* – 1. Stock illiquidity (ILLIQ) is defined as absolute stock return in June of year *t* divided by dollar trading volume in June of year *t*. The return data are from July of 1982 to June of 2008.

| | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|
| | ID1 | ID2 | ID1 | ID2 | ID1 | ID2 | ID1 | ID2 |
| Small | 0.24 | 0.19 | 0.24 | 0.20 | 0.22 | 0.18 | 0.27 | 0.20 |
| | (2.61) | (2.24) | (2.64) | (2.26) | (2.41) | (2.09) | (2.47) | (2.01) |
| Big | -0.01 | 0.04 | -0.01 | 0.04 | -0.01 | 0.05 | 0.00 | 0.05 |
| | (-0.19) | (0.94) | (-0.20) | (0.93) | (-0.14) | (1.12) | (-0.03) | (0.94) |
| Small-Big | 0.25 | 0.15 | 0.25 | 0.15 | 0.23 | 0.13 | 0.27 | 0.15 |
| | (2.43) | (1.54) | (2.47) | (1.58) | (2.24) | (1.34) | (2.25) | (1.35) |
| Low AC | 0.21 | 0.21 | 0.21 | 0.22 | 0.20 | 0.20 | 0.19 | 0.21 |
| | (2.45) | (2.54) | (2.46) | (2.59) | (2.41) | (2.35) | (2.01) | (2.18) |
| High AC | 0.02 | 0.06 | 0.02 | 0.05 | 0.02 | 0.06 | 0.04 | 0.08 |
| | (0.30) | (0.99) | (0.25) | (0.92) | (0.35) | (1.09) | (0.56) | (1.15) |
| Low-High AC | 0.19 | 0.16 | 0.19 | 0.16 | 0.18 | 0.13 | 0.16 | 0.14 |
| | (1.85) | (1.61) | (1.89) | (1.69) | (1.78) | (1.38) | (1.33) | (1.22) |
| High IVOL | 0.18 | 0.24 | 0.18 | 0.25 | 0.19 | 0.24 | 0.19 | 0.25 |
| | (1.95) | (2.58) | (1.96) | (2.63) | (2.01) | (2.56) | (1.76) | (2.18) |
| Low IVOL | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.02 |
| | (-0.07) | (0.43) | (-0.09) | (0.42) | (-0.08) | (0.53) | (0.09) | (0.51) |
| High-Low IVOL | 0.18 | 0.22 | 0.19 | 0.23 | 0.19 | 0.22 | 0.19 | 0.22 |
| | (1.76) | (2.12) | (1.78) | (2.17) | (1.83) | (2.07) | (1.54) | (1.78) |
| Young | 0.10 | 0.25 | 0.10 | 0.24 | 0.10 | 0.20 | 0.07 | 0.26 |
| | (1.09) | (2.39) | (1.10) | (2.35) | (1.05) | (1.94) | (0.64) | (2.11) |
| Old | 0.02 | -0.03 | 0.02 | -0.03 | 0.02 | -0.03 | 0.04 | -0.05 |
| | (0.33) | (-0.56) | (0.33) | (-0.58) | (0.29) | (-0.52) | (0.57) | (-0.76) |
| Young-Old | 0.09 | 0.28 | 0.09 | 0.28 | 0.08 | 0.23 | 0.03 | 0.31 |
| | (0.84) | (2.35) | (0.84) | (2.33) | (0.82) | (1.95) | (0.29) | (2.23) |

| | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|
| | ID1 | ID2 | ID1 | ID2 | ID1 | ID2 | ID1 | ID2 |
| High Dispersion | -0.09 | -0.07 | -0.08 | -0.06 | -0.08 | -0.07 | -0.07 | -0.07 |
| | (-0.90) | (-0.68) | (-0.87) | (-0.65) | (-0.84) | (-0.71) | (-0.73) | (-0.67) |
| Low Dispersion | 0.06 | 0.12 | 0.06 | 0.12 | 0.06 | 0.13 | 0.06 | 0.12 |
| | (0.98) | (1.91) | (0.99) | (1.89) | (1.05) | (1.97) | (0.92) | (1.89) |
| High-Low Dispersion | -0.15 | -0.19 | -0.15 | -0.19 | -0.15 | -0.20 | -0.13 | -0.19 |
| | (-1.37) | (-1.62) | (-1.35) | (-1.59) | (-1.37) | (-1.70) | (-1.18) | (-1.61) |
| Low IO | 0.19 | 0.23 | 0.19 | 0.24 | 0.19 | 0.23 | 0.22 | 0.23 |
| | (2.08) | (2.27) | (2.13) | (2.31) | (2.13) | (2.25) | (2.09) | (1.85) |
| High IO | 0.06 | 0.09 | 0.06 | 0.09 | 0.07 | 0.10 | 0.05 | 0.07 |
| | (1.07) | (1.68) | (1.08) | (1.68) | (1.22) | (1.89) | (0.78) | (1.12) |
| Low-High IO | 0.13 | 0.15 | 0.13 | 0.15 | 0.12 | 0.13 | 0.16 | 0.16 |
| | (1.29) | (1.33) | (1.33) | (1.37) | (1.23) | (1.21) | (1.48) | (1.22) |
| High ILLIQ | 0.31 | 0.17 | 0.31 | 0.17 | 0.31 | 0.18 | 0.29 | 0.15 |
| | (3.35) | (2.02) | (3.34) | (2.02) | (3.39) | (2.14) | (2.70) | (1.45) |
| Low ILLIQ | -0.02 | 0.03 | -0.02 | 0.03 | 0.00 | 0.05 | -0.03 | 0.02 |
| | (-0.23) | (0.44) | (-0.22) | (0.48) | (0.01) | (0.70) | (-0.43) | (0.22) |
| High-Low ILLIQ | 0.32 | 0.14 | 0.32 | 0.14 | 0.31 | 0.14 | 0.32 | 0.13 |
| | (2.86) | (1.32) | (2.86) | (1.29) | (2.74) | (1.23) | (2.45) | (1.01) |

**Table 8**
Summary statistics of monthly factor returns and Sharpe ratios.

The DMC (Diversified Minus Concentrated) factor returns are the difference in size-adjusted returns between the high and low ID1 portfolios as explained in Table 3. DMC is one minus the Herfindahl index based on patents granted over the previous five years across three-digit technological classes assigned by the USPTO. MKT is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. SMB and HML are the returns on two factor-mimicking portfolios associated with the size effect and the book-to-market effect, respectively. MOM denotes the momentum factor. EMI is the innovative efficiency factor based on patent citations from Hirshleifer, Hsu, and Li (2012). INV and ROE are the investment and profitability factors from Chen, Novy-Marx, and Zhang (2011). UMO (Undervalued Minus Overvalued) is the mispricing factor of Hirshleifer and Jiang (2010). Panel A reports the mean, standard deviation (Stdev), *t*-statistics, and ex post Sharpe ratio (SR) for these factors. Panel B reports the Pearson correlation coefficients among these factors. Panels C reports 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. $\Omega$ 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

| | DMC | MKT | SMB | HML | MOM | UMO | EMI | INV | ROE |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.51 | 0.68 | 0.07 | 0.37 | 0.83 | 0.87 | 0.26 | 0.36 | 0.86 |
| Stdev | 2.01 | 4.31 | 3.26 | 3.05 | 4.27 | 3.26 | 1.80 | 1.78 | 3.72 |
| *t*-stat | 4.49 | 2.77 | 0.37 | 2.15 | 3.43 | 4.74 | 2.60 | 3.60 | 4.06 |
| Ex post SR | 0.25 | 0.16 | 0.02 | 0.12 | 0.19 | 0.27 | 0.15 | 0.20 | 0.23 |

Panel B: Correlation matrix of factor-mimicking portfolios

| | DMC | MKT | SMB | HML | MOM | UMO | EMI | INV | ROE |
|---|---|---|---|---|---|---|---|---|---|
| DMC | 1.00 | | | | | | | | |
| MKT | 0.02 | 1.00 | | | | | | | |
| SMB | -0.12 | 0.19 | 1.00 | | | | | | |
| HML | 0.09 | -0.48 | -0.42 | 1.00 | | | | | |
| MOM | -0.09 | -0.10 | 0.12 | -0.09 | 1.00 | | | | |
| UMO | 0.09 | -0.61 | -0.28 | 0.66 | 0.32 | 1.00 | | | |
| EMI | 0.42 | 0.06 | -0.03 | -0.15 | -0.04 | -0.06 | 1.00 | | |
| INV | 0.22 | -0.29 | -0.11 | 0.38 | 0.17 | 0.54 | -0.06 | 1.00 | |
| ROE | -0.11 | -0.32 | -0.45 | 0.40 | 0.29 | 0.52 | -0.11 | 0.13 | 1.00 |

Panel C: Ex post tangency portfolio

| Portfolio weights | | | | | | | | | Tangency portfolio | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MKT | SMB | HML | DMC | EMI | MOM | UMO | INV | ROE | Mean | Std | Ex post SR |
| 1.00 | | | | | | | | | 0.68 | 4.31 | 0.16 |
| 1.09 | -0.09 | | | | | | | | 0.73 | 4.65 | 0.16 |
| 0.34 | 0.15 | 0.51 | | | | | | | 0.43 | 1.51 | 0.29 |
| 0.20 | 0.12 | 0.30 | 0.39 | | | | | | 0.45 | 1.22 | 0.37 |
| 0.18 | 0.11 | 0.28 | 0.27 | 0.16 | | | | | 0.41 | 1.09 | 0.38 |
| 0.18 | 0.07 | 0.26 | 0.32 | | 0.16 | | | | 0.52 | 1.16 | 0.45 |
| 0.26 | 0.08 | 0.00 | 0.24 | | | 0.41 | | | 0.67 | 1.25 | 0.54 |
| 0.18 | 0.08 | 0.20 | 0.28 | | | | 0.26 | | 0.44 | 1.10 | 0.40 |
| 0.16 | 0.17 | 0.14 | 0.31 | | | | | 0.23 | 0.52 | 1.04 | 0.50 |
| 0.19 | 0.11 | 0.03 | 0.17 | 0.10 | 0.01 | 0.21 | 0.05 | 0.13 | 0.58 | 0.99 | 0.58 |

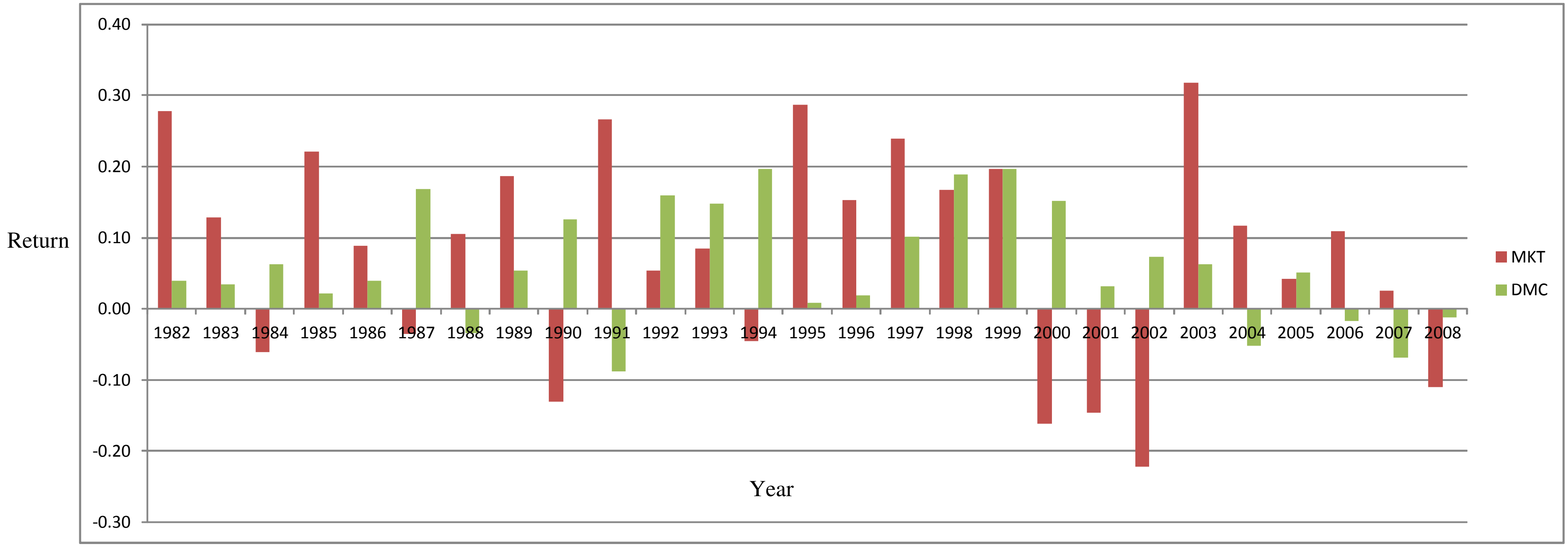


**Fig. 1.** DMC (Diversified Minus Concentrated) factor and market factor returns over time. This figure plots the returns (on a per annum basis) for the DMC factor and the market factor from July 1982 to June 2008. We show 6-month returns for 1982 and 2008. MKT is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio minus the one-month Treasury bill rate. At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing innovative diversity (ID) measures independently into three size groups (small "S", middle "M", or big "B") based on the 30$^{th}$ and 70$^{th}$ percentiles of market capitalization measured at the end of June of year *t* and three ID groups (low "L", middle "M", or high "H") based on the 30$^{th}$ and 70$^{th}$ percentiles of ID in year *t* – 1. ID is one minus the Herfindahl index based on patents granted over the previous five years across three-digit technological classes assigned by the USPTO. We hold these portfolios over the next twelve months and compute monthly value-weighted returns of the nine size-ID portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H). We then calculate monthly size-adjusted returns of the low, middle, and high ID portfolios as (S/L + M/L + B/L)/3, (S/M + M/M + B/M)/3, and (S/H + M/H + B/H)/3, respectively. The DMC factor returns are the difference in size-adjusted returns between the high and low ID portfolios.