Don't Hide Your Light Under a Bushel: Innovative Originality and Stock Returns*

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We propose that owing to limited investor attention and skepticism of complexity, firms with greater innovative originality (IO) will be undervalued. We find that IO strongly positively predicts firms’ profitability and abnormal stock returns, a finding that is robust to extensive asset pricing controls. We also find stronger return predictive power of IO for firms with higher valuation uncertainty, lower attention, and greater sensitivity of future profitability to IO, as suggested by a limited attention model. Although we do not rule out risk-based explanations, the most plausible interpretation of the evidence is that the market undervalues IO.

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To finance innovative activities effectively, investors need to value them. This is hard to do, as it requires going beyond routine application of standardized procedures and metrics. Valuing innovation requires understanding how the economic fundamentals of a firm or its industry are changing, and forecasting how a firm will navigate the long road from concept to implementation to actual profits. These considerations suggest that the market may be inefficient in valuing innovation, and that we can gain insight into the nature of such misvaluation 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. A type of information that is especially hard to evaluate is the originality of an innovation. We therefore suggest that investors will tend to underweight the information contained in proxies for innovative originality (IO).

Intuitively, we argue that inattentive investors neglect innovation-related signals, such as high IO, which may contain favorable information about future profitability.[2] In consequence, the stock price underweights this information. Hence IO is a positive predictor of future abnormal stock returns. To formalize this intuition and to motivate the empirical analysis, we build a model of limited attention (see the Appendix) and test its implications about the direction and strength of the return predictive power of IO. The model predicts that as long as a fraction of investors neglects the favorable information in IO, higher IO is associated with greater subsequent abnormal returns.

Furthermore, the model predicts that the strength of the return predictive power of IO increases with valuation uncertainty, the fraction of inattentive investors, and the sensitivity of future profitability to IO. Intuitively, the smaller the fraction of attentive investors, the less influence they have on the current price and hence the larger mispricing owing to neglect of IO.

[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; Aboody and Lev 1998; Chan, Lakonishok, and Sougiannis 2001; Lev, Sarath, and Sougiannis 2005).

[2] Neglect could take the form of not even being aware of the firm's innovative originality, 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. Cohen, Diether, and Malloy (2013) 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. Hirshleifer, Hsu, and Li (2013) 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 abnormal stock returns.

In addition, when the prior uncertainty about the value of the stock (without any conditioning on IO) is higher, heavier weight should optimally be placed on IO by investors in forming posterior beliefs about value. So neglect of IO causes greater mispricing. Similarly, the more sensitive a firm's future profitability is to IO, the greater the mispricing induced by neglect of the IO signal.

Models of ambiguity aversion provide a reinforcing argument for a positive IO-return relation. Such models (see, e.g., Dow and Werlang 1992; Chen and Epstein 2002; Cao, Wang, and Zhang 2005; and Bossaerts et al. 2010) imply that when investors perceive higher uncertainty about an investment opportunity, they view it more skeptically.[3] This is potentially consistent with psychological evidence showing that observers tend to interpret signals with lower processing fluency with greater skepticism, and view the subject matter of such signals as riskier (e.g., Alter and Oppenheimer 2006; Song and Schwarz 2008, 2009, 2010). More original innovations tend to deviate more from current technology trajectories, and hence involve greater uncertainty and complexity. This makes them harder to evaluate, inducing skepticism. We therefore argue that high IO leads to investor pessimism about firm value. This generates the same empirical prediction that high IO is associated with undervaluation, and hence is a positive predictor of future abnormal returns. However, the implication on the interaction of the return predictability of IO with the sensitivity of firms' future profitability to IO (discussed above) is unique to the limited attention model.

Empirically, we measure a firm's innovative originality by the breadth of knowledge used to innovate. This is motivated by a popular view of innovation as recombinant search (e.g., Schumpeter 1934; Basalla 1988; Henderson and Clark 1990; Weitzman 1998; Ahuja and Katila 2001; Singh and Fleming 2010). Under this view, innovation comes from combining technological components in novel manner or reconfiguring existing combinations. Since patent is a widely used measure of innovation, we proxy a firm's IO by its average patent citation diversity (APCD), i.e., the diversity of patents cited (by a patent) averaged across patents recently granted to a firm. If a firm's patents cite previous patents that belong to a wide set of technologies, its originality score will be high.

The diversity of citations made has been used to measure innovative originality in the innovation/corporate finance literature.[4] Intuitively, a patent that applies knowledge from a wide

[3] For example, in Cao, Wang, and Zhang (2005) conglomeration causes a price discount owing to the difficulty of evaluating complex firms.

[4] See, e.g., Trajtenberg, Henderson, and Jaffe (1997), Hall, Jaffe, and Trajtenberg (2001), Lerner, Sorensen, and

range of technology areas is more original because it tends to deviate from current technology trajectories to a greater extent. IO may also reflect the capability of a firm's managers and scientists to combine different technologies in an original way.

A literature in the strategy field argues that firms with more technologically diversified patents perform better in internal integration and cross-fertilization of knowledge and expertise. The organizational capability to create more novel technologies based on combinative and collaborative activities is a competitive advantage that other firms have difficulty in replicating or matching, and helps firms deal with rapid technological change.[5]

Empirically, we confirm that a firm's IO measure is significantly positively correlated with the average number of future citations its patents receive, a measure of innovation novelty in Seru (2014).[6] We also find that the IO measure predicts substantially and significantly higher future profitability. These findings further support the effectiveness of this measure in capturing innovative originality.

In addition, our IO proxy also reflects the complexity of a firm's innovation, since patents that apply or extend knowledge from a wide range of technology areas tend to require a correspondingly diverse range of investor expertise to fully evaluate these patents' importance. This complexity should also contribute to inattentive investors' neglect of this signal.[7]

To test the model prediction on the return predictive power of IO, we perform portfolio sorts and Fama-MacBeth (1973) cross-sectional regressions. The results are consistent with the model prediction. For portfolio analysis, we sort firms into three IO portfolios (low, middle, and high) at the end of each June based on IO in the previous year and construct a hedge portfolio that long the high and short the low IO portfolio. We compute their value-weighted (VW) returns over the next twelve months. The time-series average portfolio returns increase monotonically with IO,

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Strömberg (2011), and Custodio, Ferreira, and Matos (2013).

[5] Regarding competitive advantage, see, e.g., Levin et al. (1987), Henderson and Cockburn (1994), Gupta and Govindarajan (2000), Martin and Salomon (2003) and Subramaniam and Youndt (2005). Regarding technological change, see Gomez-Mejia et al. (2011).

[6] The Pearson correlation between the novelty measure of Seru (2014) and our IO measure is 0.22. The novelty measure of Seru (2014) utilizes ex-post information, as it is based upon subsequent citations received by a firm's patents. In contrast, our IO measure is based on ex-ante information, which is appropriate for tests of return predictability. Seru (2014) does not study whether innovation novelty predicts stock returns.

[7] The product uniqueness variable of Hoberg and Phillips (2012) suggests a different possible approach to measuring innovative originality. However, their measure reflects the difficulty of replicating a firm's *current* product lines, which are relatively easier to value, while our IO measure is based on patents, which is related to innovation that affects *future* product lines. As a forward looking measure, IO therefore captures the ongoing innovation that is susceptible to cognitive biases leading to misvaluation. This difference could explain why their product uniqueness measure does not predict abnormal returns, while our IO measure does.

and the monthly return spread between the high and low IO portfolios is economically substantial (29 basis points, t = 2.29). The pattern is the same even after industry- and characteristic-adjustment (by size, book-to-market, and momentum). For example, the monthly VW industry- and characteristic-adjusted return spreads are 23 and 28 basis points (t = 2.51 and 2.36), respectively.

To test whether IO predicts abnormal returns relative to standard risk factors, we compute alphas from different factor models for these IO portfolios. In particular, we use the Fama and French three-factor model augmented with the momentum (UMD) factor as in Carhart (1997) (henceforth, the Carhart model). We also augment the Carhart model with several other recently developed risk factors, such as the investment-minus-consumption (IMC) factor (Papanikolaou 2011), the liquidity (LIQ) factor (Pastor and Stambaugh 2003), and the robust-minus-weak (RMW) factor and the conservative-minus-aggressive factor (CMA) as in Fama and French (2015). The alphas also increase monotonically with IO, and the spreads between the high and low IO portfolios remain large and significant, regardless of the factor model we use.

For example, the monthly VW alphas estimated from the Carhart model for the low, middle, and high IO portfolios are −11, 16, and 24 basis points, respectively, and for the high-minus-low IO hedge portfolio is 35 basis points (t = 3.00). Similarly, when we add the IMC, LIQ, or the RMW and CMA factors to the Carhart model, the monthly alphas of the hedge portfolios are 35, 35, and 24 basis points, respectively, significant at the 1% or 5% level. This evidence shows that high IO firms are undervalued relative to standard risk factors; the significant alpha for the hedge portfolio is mainly driven by the undervaluation of high IO firms.

To verify that the IO effect is not just a manifestation of the innovative efficiency (IE) effect of Hirshleifer, Hsu, and Li (2013), we add the innovative efficient-minus-inefficient (EMI) factor that reflects commonality in returns associated with IE to the Carhart model. The IO effect remains substantial and significant even after controlling for EMI. For example, the monthly alpha estimated from this augmented model for the hedge portfolio is 25 basis points (t = 2.12). Furthermore, we report the results from double sorts on IE and IO. The monthly alphas from different factor models for the high-minus-low IO portfolios range from 0.53% to 0.73% and are significant at the 1% or 5% level among high IE firms. These results suggest that the IO effect is incremental to the IE effect. In addition, the phenomenon we explore is not limited to small

firms; the IO effect is stronger for larger firms (for reasons explained by the model, as discussed in Section III).

To assess whether the return predictive power of IO is robust to a wider set of controls, we perform Fama-MacBeth regressions that control for industry effects and different sets of well-known return predictors, including innovation-related controls such as innovative efficiency, patents, and R&D intensity. The IO effect remains economically and statistically significant, irrespective of the control variables we use.

We further test the model predictions on the conditioning return predictive power of IO through independent double sorts on IO and proxies of valuation uncertainty (VU), investor attention, and the sensitivity of future profitability to IO. We also perform Fama-MacBeth regressions in subsamples split by these conditioning variables. In particular, we proxy valuation uncertainty by an index of VU constructed as standardized opacity measure minus standardized age since younger or more opaque firms have higher valuation uncertainty (see Kumar 2009 and Hutton, Marcus, and Tehranian 2009). We proxy investor attention by an index of attention, which is constructed as standardized analyst-to-size (ATS) minus standardized post-earnings-announcement drift (PEAD) scaled by earnings surprise. Intuitively, firms with lower ATS or higher PEAD/earnings surprise receive lower investor attention (see Hirshleifer, Lim, and Teoh 2009).

Lastly, we measure the sensitivity of future profitability to IO by an index constructed as standardized size minus standardized book-to-market (BTM). Larger firms are better positioned to leverage original innovations more effectively owing to their abundant financing, research, and marketing resources (Schumpeter 1950; Acs and Audretsch 1987; Cohen, Levin, and Mowery 1987). Similarly, firms with low BTM typically are growth firms, whose values derive more from the originality of their innovation. Therefore, we expect future profitability of larger firms and firms with low BTM to be more sensitive to IO. Consistent with these hypotheses, we find empirically that the predictive ability of IO for profitability is stronger among firms with higher sensitivity in unreported tables.

The model predicts a stronger return predictive power of IO among firms with higher valuation uncertainty, lower investor attention, or higher sensitivity of future profitability to IO. Both portfolio analyses and subsample Fama-MacBeth regressions support these predictions. For example, the monthly VW alpha from the Carhart model of the hedge portfolio among high VU

firms is 1.07% (t = 3.07), which is substantial and significant. The monthly alphas remain large and highly significant even after we augment the Carhart model with additional factors. For example, the alphas from the Carhart model augmented with the RMW and CMA factors are 0.85% (t = 2.38). In contrast, among low VU firms, the alphas from different factor models are small and insignificant for the hedge portfolio, ranging from 0.10% to 0.19% per month.

This sharp contrast is present across subsamples split by the other proxies as well. The subsample Fama-MacBeth regressions show the same contrast in the IO slope after we control for many well-known return predictors and industry effects. Overall, these results support the predictions from the model based on limited attention. Moreover, the stronger return predictive power of IO among firms with higher sensitivity of future profitability to IO is not explained by skepticism of complexity.

As discussed earlier, the returns of the hedge portfolio is not fully explained by existing factor models. The correlations between the monthly returns of the hedge portfolio and those factor returns range from –0.42 with the size (SMB) factor to 0.44 with the RMW factor. In particular, the correlations with the IE factor, the momentum factor, the CMA factor, the investment-minus-consumption (IMC) factor, and the liquidity (LIQ) factor are small, ranging from –0.10 to 0.23. The correlation with the market factor is negative (–0.25), suggesting that investing in this portfolio can provide hedge against market downturns.

The average monthly return of the hedge portfolio is 0.29%, which is substantially higher than that of SMB (0.07%), IMC (–0.15%), and CMA (0.15%) in absolute value, and is comparable to the value (HML) factor (0.37%), and the RMW factor (0.34%). Furthermore, the high-minus-low IO portfolio offers an ex post Sharpe ratio of 0.13, which is higher than SMB (0.02), HML (0.12), CMA (0.12), and IMC (–0.11), and is comparable to the market factor (0.16) and LIQ (0.17). Since the high level of the equity premium is a well-known puzzle for rational asset pricing theory (Mehra and Prescott 1985), the high ex post Sharpe ratio associated with the high-minus-low IO portfolio is also puzzling from this perspective.

Although the evidence above is consistent with a model motivated by limited attention, we do not rule out potential risk-based explanations. Our control for IMC addresses the possibility that the IO effect captures investment-specific technological change risk. Furthermore, the IO hedge portfolio has only tiny loading on IMC in the factor models we examine. The IO hedge portfolio also has very low correlation with other proxies for technology shocks that we examine.

We also argue that obsolescence risk does not seem a likely explanation for the IO-return relation (see Section III.C).

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 strand of research does not examine the role of originality in innovative activities. As discussed earlier, IO 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 return predictive power of IO is robust to controlling for all of the above known innovation-related effects. We also examine whether the IO effect can be explained by existing factor models, and explore the interaction of this effect with proxies for valuation uncertainty, investor attention, and the sensitivity of future profitability to IO as predicted by a model of limited attention.

Our paper is 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.[9]

[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, stock returns and operating performance (Cohen, Diether, and Malloy 2013; Hirshleifer, Hsu, and Li 2013).

[9] 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), and Li and Yu (2012).

I. The data, the innovative originality measure, and summary statistics

A. The data and the innovative originality measure

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

Patent-related data are mainly from the updated NBER patent database originally developed by Hall, Jaffe, and Trajtenberg (2001). The database contains detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006: patent grant date, primary three-digit technology classes, all citations received by each granted patent, assignee's Compustat-matched identifier, and other details. Only patents granted by the USPTO by the end of 2006 are included in the database. In addition, we collect the information on each patent's secondary three-digit technology classes from the Harvard Business School U.S. patent inventor database (Li et al. 2014). As a result, our combined dataset contains each patent's primary and secondary technology classes that are important for our analysis.

As mentioned earlier, we follow the literature and proxy a firm's IO by its average patent citation diversity. If a firm's patents cite previous patents that belong to a wide set of technologies, its originality score will be high. Specifically, we first compute a patent's originality score as the number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent. We then proxy a firm's IO in each year with the average originality score of all patents granted to the firm over the previous five years. Averaging across patents helps reduce the influence of extreme values and the correlation

between the IO measure and firm size. Furthermore, we choose a five-year rolling window since not all firms have patents granted every year. As a result, the firm-level IO measure is from 1981 to 2006.[10]

Since our IO measure relies on the list of citations made by the focal patent, to what extent the citation list is complete and relevant is worth discussions. We argue that the tendency of under- or over-citing is negligible based on the following reasons. First, patent applicants have a "duty of candor and good faith" to disclose all prior arts (especially previous publications and patents) that are material to patentability of the application.[11] As an application may be rejected by the USPTO if the duty of disclosure was violated, applicants have the incentive to cite all relevant patents in the filings (Caballero and Jaffe 1993). Even if a patent is granted, its validity could still be challenged if its citation list misses prior arts (Sampat 2010).

Second, patent applications are reviewed by patent examiners based on their novelty and non-obviousness, the two major requirements for patentability. Patent examiners conduct their own search for prior arts to reject applications that do not satisfy novelty and non-obviousness and require patent applicants to add any missing relevant citations. On average, 62% of citations made by granted patents are added upon request of patent examiners (Sampat 2010).

Third, over-citing prior arts is also inappropriate because the applicants have to describe how their applications are different from the cited prior arts to justify the "novelty" of their inventions. More importantly, such over-citing behavior does not exist in the data because 57% of self-citations of published patents, which are most likely to be over-cited by applicants, are inserted by patent examiners (Sampat 2010).

Fourth, even if there exists idiosyncratic errors in citations, they should not systematically bias our analyses since we average the originality score of all patents granted to a firm over the last five years.

Another concern of using patents data to measure IO is about how to deal with firms without patents granted over the last five years. Although certain firms may intentionally choose not to use patents to protect their invention, it is hard to separate them empirically from firms with no

[10] Another dimension of innovative originality is the diversity of a firm's patent portfolio (i.e., diversity of patents recently granted to a firm). Although we find similar return predictive power for this measure, it is highly correlated with firm size. Furthermore, it is bounded above by the number of patents granted to a firm, which is limited for many firms. Therefore, we focus on the diversity of patents cited, which has become standard in the literature as a proxy for innovative originality as discussed earlier.

[11] See http://www.uspto.gov/web/offices/pac/mpep/s2001.html.

invention to apply for patents and firms with unsuccessful patent applications, both of which should be categorized as low IO firms since only successful patent applications are recorded in the NBER patent database. However, the historical success rate for patent applications is around 50%-60% (see Kortum and Lerner 1998), suggesting that we cannot assume firms with no patents granted simply do not use patents to protect their intellectual property. Therefore, we include firms with positive R&D expenses but no patents granted over the last five years in our sample and assume these firms have the lowest IO. (Excluding these firms generate stronger results in portfolio sorts as discussed later.)

B. Summary statistics

Table I reports the summary statistics of the IO measures for firms in selected innovation-driven industries based on Fama and French (1997) 48 industry classifications. Although there is significant within-industry variation in IO, the cross-industry variation in IO is quite small. Specifically, the within-industry coefficient of variation (CV) for IO ranges from 0.48 for automobiles and trucks to 0.69 for business services, while the cross-industry CV is only 0.13 (0.10) based on mean (median) IO. Therefore, to make sure our results are not driven by any particular industry, we control for industry effects by adjusting stock returns directly instead of the IO measures as detailed later.

In Table II (Panel A), we report average IO and other characteristics that are known to predict stock returns for the three IO portfolios mentioned earlier (based on the 30th and 70th percentiles of lagged IO). We also assign firms with positive R&D expenses but no patents granted over the last five years to the low IO portfolio.[12] Intuitively, firms with positive R&D expenses have low innovative originality if they do not have any patents granted as explained earlier.

These portfolios are well diversified, with the average number of firms ranging from 409 to 1283. The cross-sectional variation in IO is large, ranging from 3.02 to 9.78 for these IO portfolios. The average size (market capitalization at the end of each June) of the low, middle, and high IO portfolios is $702 million, $4,334 million, and $2,033 million, respectively.

[12] The results are even stronger if we completely exclude firms with no patents granted. For example, the mean excess return and Carhart four-factor alpha for the high-minus-low IO portfolio are 0.32% and 0.37% per month, respectively, and are significant at the 1% level.

Furthermore, firms in our sample cover 71% of the total stock market capitalization. Therefore, it is economically meaningful to study these firms.

The 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 current month), and idiosyncratic volatility (IVOL, measured 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) do not vary much across the IO portfolios. There is no clear relation between IO and 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).

Firms with higher IO have higher 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 $t - 1$), higher innovative efficiency based on citations (IE in year $t - 1$), but lower R&D intensity (RDME, R&D expenses in fiscal year ending in year $t - 1$ divided by market equity at the end of year $t - 1$). We also report other characteristics, such as return on assets (ROA, income before extraordinary items plus interest expenses in year $t - 1$ divided by lagged total assets), return on equity (ROE, income before extraordinary items plus interest expenses in year $t - 1$ divided by lagged book equity), asset growth (AG, change in total assets in year $t - 1$ divided by lagged total assets), investment intensity (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 (InstOwn, the fraction of firm shares outstanding owned by institutional investors in year $t - 1$), 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 short-term reversal (REV, lagged monthly stock return in June of year t). However, these characteristics do not vary much across the IO portfolios except contemporaneous ROA and ROE. The high IO group has the second lowest contemporaneous ROA and ROE.

We report the time series average of cross-sectional correlations between IO and these characteristics in Panel B of Table II. Pearson (Spearman rank) correlations are below (above) the diagonal. Generally consistent with Panel A, IO does not strongly correlate with these firm characteristics. The Pearson (Spearman rank) correlations range from –0.07 (–0.08) with BTM to

0.13 (0.15) with IE. In particular, the Pearson (Spearman rank) correlation between IO and size is only –0.01 (0.05).

Overall, these low correlations suggest that our IO proxy is a firm characteristic that is distinct from other well-known return predictors.

II. Predictability of returns based upon innovative originality

We now test the first prediction of our model (see Proposition 1 in the Appendix) regarding the direction of the return predictive power of IO. The model predicts that as long as a positive fraction of investors neglect favorable information in IO, higher IO is associated with greater subsequent abnormal returns. Intuitively, inattentive investors neglect IO, which may contain favorable information about future profitability. In consequence, the stock price underweights this information. Hence IO is a positive predictor of future abnormal stock returns.

We first examine whether IO contains favorable information about a firm's future profitability to verify the key assumption of the model. We then use portfolio sorts and Fama-MacBeth regressions to test the return predictive power of IO.

A. IO and future profitability

Following Fama and French (2000), we conduct annual cross-sectional regressions of individual firms' future profitability on IO ranks and other control variables (profitability, change in profitability, market-to-book assets, advertising expenses, capital expenditure, R&D, IE, and industry effects). We use IO ranks to be consistent with the portfolio analysis of the IO-return relation. Specifically, we set a firm's IO rank to one, two, and three if the firm is assigned to the low, middle, and high IO portfolio, respectively. In addition, using rank variables avoids the situation that continuous variables tend to cluster in some ranges (Bernard and Thomas 1990), and mitigates the influence of outliers.

In Table III, we report the effect of IO on next-year's profitability and average profitability over the next five years for ROE and ROA in Panels A and B, respectively. As expected, IO (in ranks) is associated with significantly higher future profitability. On average, the difference in next-year's ROE (ROA) between the high and low IO portfolios is 4.02% (1.06%). The long-term benefit is even larger. The difference in average ROE (ROA) over the next five years between high and low IO firms is 8.38% (1.70%). These effects are economically substantial

since IO is negatively correlated with contemporaneous ROA and ROE (see Panel B of Table II).[13]

B. Unconditional return predictive power of IO—portfolio sorts

As explained earlier, at the end of June of year *t* from 1982 to 2007, we sort firms with non-missing IO into three IO portfolios (Low, Middle, and High) based on the 30th and 70th percentiles of IO in year $t - 1$. We also assign firms with no patents granted but with positive R&D spending over the last five years into the low IO portfolio. To examine the IO-return relation, we form a hedge portfolio that long the high IO portfolio and short the low IO portfolio. Since the USPTO fully discloses patents granted in the weekly *Official Gazette of the United States Patent and Trademark Office*, the IO measure in year $t - 1$ is publicly observable at the end of year $t - 1$. We allow a six-month lag in forming the IO portfolios only to make the results comparable to previous studies.

We hold these portfolios over the next twelve months and compute their value-weighted monthly returns to make sure the results are not driven by small firms. In Panel A of Table IV, we report average monthly returns in excess of one-month Treasury bill rate (excess returns) as well as industry- and characteristic-adjusted returns for these portfolios to make sure the IO effect is not driven by industry effects or well-known firm characteristics. The industry-adjusted returns are based on the difference between individual firms' returns and the returns of firms in the same industry (based on Fama and French 48 industry classifications). Following Daniel et al. (1997) (DGTW) and Wermers (2004), we compute characteristic-adjusted returns based on the difference between individual firms' returns and the DGTW benchmark portfolio returns (which are formed from 5-by-5-by-5 independent triple sorts on size, book-to-market, and momentum).

To examine the relation between IO and abnormal returns, we perform time-series regressions of the portfolios' excess returns on the Fama-French three factors (the market factor–MKT, the size factor–SMB, and the value factor–HML) and the momentum factor (UMD) in Panel B. We also report the alphas and factor loadings estimated from other factor models for robustness check. In particular, we augment the Carhart model with the IMC factor, the LIQ

[13] Although the slope on IE is insignificant in Table III, it becomes significantly positive without controlling for IO or if we use IE ranks instead of raw value.

factor, the RMW and CMA factors, or the EMI factor in Panels C, D, E, and F, respectively.[14] Controlling for these additional factors helps ensure that the IO effect is not driven by the investment-specific technology risk, the liquidity effect, the profitability and investment effects, or the innovative efficiency effect.

As mentioned in the introduction, the excess returns, industry- and characteristic-adjusted returns, and alphas from different factor models all increase monotonically with IO, implying a positive IO-return relation. Furthermore, the IO effect is economically and statistically significant. The risk-adjusted monthly returns of the hedge portfolio range from 0.24% to 0.35% and are significant at the 5% or 1% level. The hedge portfolio's loadings on the factors are small and insignificant except for MKT, SMB, RMW, and EMI. The significantly negative loading on MKT implies that high IO firms have lower market risk than low IO firms. The significantly negative loading on SMB and significantly positive loading on RMW are consistent with Table II, which shows that high IO firms are bigger and more profitable than low IO firms. The significantly positive loading on EMI implies that high IO firms are also more efficient in their R&D efforts.

Overall, these results suggest that high IO firms are undervalued relative to low IO firms, and the IO effect is incremental to industry effects, well-known characteristics, standard and recently developed risk factors, as well as the IE effect in Hirshleifer, Hsu, and Li (2013).

It is also noteworthy that these results are not driven by very small firms as shown in Table II. Furthermore, we construct value-weighted portfolios (which put more weight on larger firms) and rebalance them only once a year. Therefore, these abnormal returns are likely to survive typical transaction costs.

We next examine how the returns of the hedge portfolio vary over time and with the market. Figure 1 plots the return on the hedge portfolio and the market premium (MKT) on a per annum basis from July of 1982 to June of 2008. MKT is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio in excess of the one-month Treasury bill rate. We find that this portfolio reveals strong negative comovement with the market. The correlation between the hedge portfolio's returns and the market excess returns is –0.53 (–0.25) on an annual (monthly) basis.

[14] Following Fama and French (2015), the RMW and CMA factors are from 2 × 2 × 2 × 2 sorts on size, book-to-market, operating profitability, and investment.

The high-minus-low IO portfolio also provides a good hedge against market downturns. The market returns are negative in eight out of the 27 years. During these eight years, the hedge portfolio's returns are positive in all of them, particularly substantial during the high-tech collapse in 2000. Furthermore, the hedge portfolio's returns are negative only in eight out of the 27 years.

C. Unconditional return predictive power of IO—Fama-MacBeth regressions

We next examine the ability of IO 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 verify whether the positive IO-return relation as measured in portfolio sorts is driven by other known return predictors or by industry effects.

Following Fama and French (1992), we allow for a minimum six-month lag between the accounting-related control variables and stock returns to ensure that the accounting variables are fully observable to investors. Specifically, for each month from July of year t to June of year t + 1, we regress monthly returns of individual stocks on IO ranks of year t – 1, different sets of control variables, and industry fixed effects based on Fama and French 48 industry classifications. To be consistent with portfolio analysis and profitability regressions, IO ranks are set to one, two, and three if a firm is assigned to the low, middle, and high groups, respectively, in year t – 1.

Table V shows the time-series average slopes (in percentage terms) and corresponding heteroscedasticity-robust t-statistics from the monthly cross-sectional regressions for different model specifications. 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 48 industry classifications. 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 natural log of market capitalization at the end of June of year t; BTM is also in the log form. We winsorize all independent variables at the 1% and 99% levels to reduce the impact of outliers, and then standardize all control variables to zero mean and one standard deviation (except IO ranks) to facilitate the comparison of economic effects of all variables.

The slope on IO is statistically significant and economically substantial: 0.16% (t = 5.27). Since IO is in ranks, this slope implies a monthly return spread of 0.32% between high and low

IO firms controlling for all those variables listed above and industry effects. The magnitude is consistent with the results from portfolio sorts. The slopes on the other variables are consistent with previous studies.

In Model 2, we control for additional return predictors related to innovation (IE, CTA, and RDME), investment (AG and IA), financing (NS), profitability (ROA), idiosyncratic volatility (IVOL), and total skewness (TSKEW) measured in year $t - 1$.[15] IVOL is included as Pastor and Veronesi (2009) and Garleanu, Panageas, and Yu (2012) propose that new technologies are associated with idiosyncratic risk, and TSKEW is included as Kapadia (2006) argues that investors prefer high-tech stocks for their positive skewness. IE is the natural log of one plus the citations-based IE measure following Hirshleifer, Hsu, and Li (2013). 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 $t - 1$. We use the log transformation for those innovation variables to mitigate their skewness following Lerner (1994) and Aghion, Van Reenen, and Zingales (2013).

The IO slope remains economically meaningful and statistically significant: 0.08% (t = 2.22). The slopes on the control variables are generally consistent with previous studies. The insignificant slopes on MOM and CTA are probably owing to the reduced sample size. The slope on IVOL is significantly positive, which is consistent with Bali, Cakici, and Whitelaw (2011). Moreover, the IO slopes remain similar when we use other proxies of skewness such as systematic skewness (Harvey and Siddique 2000), idiosyncratic skewness (Bali, Cakici, and Whitelaw 2011), and expected idiosyncratic skewness (Boyer, Mitton, and Vorkink 2009) in unreported results.[16]

Lastly, we also control for sales diversity (SD) measured as the number of different sales segments defined by Fama-French 48 industries over the previous five years (year $t - 5$ to year $t - 1$). We use the segment sales data from Compustat segment files following Cohen and Lou

[15] On the capital investment effect, see, e.g., Lyandres, Sun, and Zhang (2008) and Polk and Sapienza (2009). On the asset growth effect, see, e.g., Cooper, Gulen, and Schill (2008). On the net stock issues 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). On the idiosyncratic volatility and skewness effects, see, e.g., Ang et al. (2006), Harvey and Siddique, (2000), Kapadia (2006), Boyer, Mitton, and Vorkink (2009), and Bali, Cakici, and Whitelaw (2011).

[16] Idiosyncratic skewness (ISKEW) is 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) is the slope on the squared market factor returns from the regression for ISKEW. Expected idiosyncratic skewness (EISKEW) is measured in the previous month.

(2012) among others. As shown in Model 3, the slope on IO remains the same magnitude with statistical significance. As a result, the IO effect is robust to controlling for sales diversity in product markets.

Overall, the results above show that the predictive power of innovative originality is distinct from, and robust to the inclusion of, other commonly known return predictors, innovation-related variables, industry effects, and sales diversity.

III. Conditional return predictive power of innovative originality

We next test the other three implications of our model regarding the strength of the return predictive power of IO (Propositions 2 through 4 in the Appendix). The model predicts that the IO effect should increase with valuation uncertainty, the fraction of inattentive investors, and the sensitivity of future profitability to IO. Intuitively, when the prior uncertainty about the value of the stock (without any conditioning on IO) is higher, heavier weight should optimally be placed on IO by investors in forming posterior beliefs about value. So neglect of IO causes greater mispricing among these firms. Similarly, the larger the fraction of inattentive investors, the more influence they have on the current price and hence the larger mispricing owing to neglect of IO.

In addition, the more sensitive a firm's future profitability is to IO (or the more favorable information contained in IO about a firm), the more that neglect of IO causes market value to deviate from true fundamental value. This prediction is implied by the limited attention argument but not by the argument based upon skepticism of complexity, and therefore helps to distinguish hypotheses.

To test these predictions, we perform independent double sorts on IO and proxies of valuation uncertainty (VU), investor attention, and the sensitivity of future profitability to IO. We also perform Fama-MacBeth regressions in subsamples split by these conditioning variables.

Following the literature, we measure valuation uncertainty by a composite index of firm age and opacity of financial reports.[17] Age is defined as the number of years listed on Compustat with non-missing price data. Opacity is defined as the three-year moving sum of the absolute

[17] Kumar (2009) also uses turnover and idiosyncratic volatility (IVOL) as additional proxies for valuation uncertainty. However, turnover has also been used as a proxy of investor attention in some studies (e.g., Gervais, Kaniel, and Mingelgrin 2001; Hou, Peng, and Xiong 2009). Since firms with lower turnover can be interpreted as having lower investor attention or lower valuation uncertainty, the overall prediction is unclear. We do not use IVOL to proxy VU as it is highly negatively correlated with firm size (see Panel B of Table II). Smaller firms have lower sensitivity of future profitability to IO, which could confound the prediction.

value of discretionary accruals, a proxy of earnings management. Younger firms or more opaque firms have higher valuation uncertainty. To construct the VU index, we first standardize all firms' age and opacity measure in each year to zero mean and one standard deviation. The VU index for each firm-year observation is then computed as standardized opacity minus standardized age. By construction, the higher the index, the higher VU is.

We measure investor attention by a composite index of the analyst-to-size (ATS) ratio and post-earnings-announcement drift (PEAD) scaled by earnings surprise.[18] Specifically, the attention index is standardized ATS minus standardized PEAD/earnings surprise. Firms with lower ATS or higher PEAD/earnings surprise receive lower investor attention. Therefore, by construction, attention increases with the index.

The number of analysts is a popular proxy of investor attention. PEAD is the pattern that, after positive (negative) earnings surprises, stocks on average experience a persistent increase (decrease) in cumulative abnormal stock returns (Ball and Brown 1968; Foster, Olsen, and Shevlin 1984). Under the standard behavioral interpretation, PEAD reflects correction of mispricing caused by inattentive investors' delayed reaction to earnings surprise (e.g., Bernard and Thomas 1989, 1990; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009). Ceteris paribus, PEAD increases in the fraction of inattentive investors. So we include PEAD/earnings surprise in the attention index. Scaling the number of analysts and PEAD ensures that these measures are comparable across firms with different amount of supply of information or different magnitude of earnings surprise.

In constructing the attention index, we exclude observations for which PEAD is in the opposite direction of the earnings surprise. PEAD refers to the cumulative abnormal returns (relative to matching size and book-to-market portfolio returns) over the 60 days after the earnings announcement date. We adopt a conservative procedure of skipping day 1 in analyzing investors' reactions to announcements (Hirshleifer, Lim, and Teoh 2009; Barinov, Park, and Yildizhan 2014). We compute earnings surprise as the difference between the actual earnings and earnings four quarters ago scaled by stock price based on the rolling seasonal random walk model (Livnat and Mendenhall 2006).

Lastly, we measure the sensitivity of future profitability to IO by a composite index of size and book-to-market (BTM). Specifically, the sensitivity index is constructed as standardized size

[18] We do not use Google search data since they are available only after 2003.

minus standardized BTM. It is well documented in the literature that larger firms are in a better position to extract the rents created by innovations because their financial stability enables them to more effectively convert inventions into product lines and revenues (e.g., Schumpeter 1950; Cohen, Levin, and Mowery 1987). Therefore, we expect the sensitivity of future profitability to IO to be stronger for larger firms, as these firms' financing, research, and marketing resources enable them to leverage original innovations more effectively. In addition, we also expect this sensitivity to be higher for low BTM firms since a larger portion of growth firms values is derived from IO. To verify these hypotheses, we confirm that the predictive ability of IO for profitability is stronger among larger firms and low BTM firms in unreported results.

Next we discuss the results from portfolio sorts first and then the subsample regressions. We then discuss potentially alternative explanations of our results.

A. Portfolio sorts

In Table VI, we test the interaction of the IO effect with valuation uncertainty, investor attention, and the sensitivity in Panels A, B, and C, respectively, using independent double sorts. At the end of June of year *t*, we conduct 3 by 3 double sorts on IO and each of those conditioning variables listed above except the attention index and the sensitivity index, for which we use NYSE tercile breakpoints as they involve size. As the number of analyst forecast is sparse before 1983, for the attention index, the portfolio sorts for attention index start in June of 1984. The three IO portfolios are formed as in Table IV. The conditioning variables are measured in year $t - 1$ except the sensitivity index, which are measured at the end of June of year *t*. To compare the IO effect across the subgroups, we also form a high-minus-low IO (hedge) portfolio in each subgroup. We hold these portfolios over the next twelve months (July of year *t* to June of year $t + 1$). All portfolios are value-weighted. Similar to Table IV, we report the average monthly excess returns, industry- and characteristic-adjusted returns, and alphas estimated from different factor models.

The results support the model predictions. The hedge portfolio's returns and alphas are substantial and significant in the high VU group (firms with VU index in the top tercile), but small and insignificant in the low VU group (firms with the VU index in the bottom tercile). Specifically, among high VU firms, the monthly excess returns, industry- and characteristic-adjusted returns of the hedge portfolio are 1.10%, 0.99%, and 1.17%, respectively, and are

significant at the 1% level. The monthly alphas from different factor models range from 0.85% (controlling for the Carhart four factors plus RMW and CMA) to 1.08% (controlling for the Carhart four factors plus LIQ) and are significant at the 1% level. In contrast, among low VU firms, these returns and alphas are small and insignificant, ranging from 0.07% to 0.19%.

Similarly, the IO effect is also much stronger among firms with lower investor attention or higher sensitivity of future profitability to IO (see Panels B and C). Specifically, the monthly alphas from different factor models for the hedge portfolios range from 0.56% (controlling for the Carhart four factors plus RMW and CMA) to 0.78% (controlling for the Carhart four factors plus LIQ) and are significant at the 1% or 5% level among low attention firms, and range from 0.25% (controlling for the Carhart four factors plus EMI) to 0.40% (controlling for the Carhart four factors) and are significant at the 10%, 5%, or 1% level among high sensitivity firms. But they are small and insignificant among firms with high attention or low sensitivity.

We also verify that these contrasts are not due to the difference in the IO measure spreads. The spread in IO does not vary much across these subsamples and are very similar to that in the one-way sort as shown in Table II. Furthermore, similar to the unconditional return predictive power of IO, the significant IO effect among high VU, low attention, high sensitivity firms is not driven by very small firms either. The average size of the low, middle, and high IO portfolios range from $316 to $895 million in the high VU index group, $4.63 to $14.36 billion in the low attention group, and $3.81 to $15.03 billion in the high sensitivity group (untabulated).

Overall, independent double sorts provide fairly strong evidence supporting the model predictions on the conditional return predictive power of IO. Although we show that the alphas remain large and significant even after controlling for EMI in the factor regressions, to further test the incremental IO effect relative to the IE effect, we report the results from 3 by 3 double sorts on IE and IO in Panel D. Intuitively, a firm will benefit from high IO only if the firm can achieve high IO at a reasonable cost or with a high level of innovative efficiency. Therefore, we expect the return predictive power of IO mainly exists in high IE firms. This is verified in Panel D. Specifically, the monthly alphas from different factor models for the hedge portfolios range from 0.53% (controlling for the Carhart four factors plus RMW and CMA) to 0.73% (controlling for the Carhart four factors plus EMI) and are significant at the 1% or 5% level among high IE firms.

B. Fama-MacBeth regressions

To further evaluate these hypotheses, we perform monthly Fama-MacBeth cross-sectional regressions across subsamples split by the conditioning variables as discussed above. We use the same method and model specifications as in the test of the unconditional IO effect. For brevity, we only report the slopes estimated from Model 2 in Table VII since the slope on sales diversity is small and insignificant (see Table V). The results also show a sharp contrast in the IO effect across the subsamples even after we control for many well-known return predictors and industry effects. Specifically, the slope on IO is 0.27%, 1.22%, 0.21% among high VU, low attention, and high sensitivity firms, respectively, and are significant at the 1% or 5% level. In contrast, their counterparts are only 0.01%, 0.02%, –0.04%, respectively, and are insignificant. Furthermore, the differences in the IO slopes across these subsamples are also substantial and statistically significant at the 1% or 5% level.

Taken together, consistent with the model predictions, both portfolio sorts and Fama-MacBeth regressions provide support for a more pronounced IO-return relation among firms with higher valuation uncertainty, lower investor attention, and higher sensitivity of future profitability to IO.

C. Potential alternative explanations

Although overall the evidence above is consistent with a model of limited attention, we do not rule out potential risk-based explanations. To address the possibility that IO captures information asymmetry, we examine whether our IO measure correlate with proxies for information asymmetry such as analyst coverage, analyst forecast dispersion, opacity of financial statements, and presence of bond rating. The correlations are very low.

In addition, since financing constraint is particularly important for R&D firms (e.g., Hall 1992, 2005, 2009; Himmelberg and Petersen 1994; Hall and Lerner 2010; Li 2011), one may wonder if our results are driven by financing constraints risk. However, we find that the IO effect is stronger among larger firms. Since size is inversely associated with information asymmetry and financing constraints (e.g., Gertler and Gilchrist 1994; Campello and Chen 2010), this evidence suggests that constraints risk cannot explain the IO effect. Furthermore, as discussed earlier, the correlation between our IO measure and size is very low.

To address the possibility that the IO effect captures investment-specific technological

change risk, as discussed earlier, we control for IMC in computing risk-adjusted returns and examine the loading of the IO hedge portfolio's returns on IMC.[19] The alphas are robust to controlling for IMC, and the loading on IMC is small and insignificant regardless whether we use IMC alone or combine IMC with the market factor or the Carhart model. For example, as shown in Table IV (Panel C), the loading of the IO hedge portfolio on IMC is –0.10 (t = –0.79). Furthermore, to capture technology-related risk we construct a portfolio that is long firms in high-tech industries and short firms in the other industries. The correlation between this mimicking portfolio's returns and the returns of the hedge portfolio is also very low and insignificant. In addition, the correlation between the IO hedge portfolio's return and the aggregate technology shock of Hsu (2009) is insignificant and negative.

Obsolescence is another particular kind of risk that stems from technological change (e.g., Greenwood and Jovanovic 1999; Hobijn and Jovanovic 2001; Laitner and Stolyarov 2003). Intuitively it would seem that high IO firms might be *less* susceptible to obsolescence risk, as high IO firms, by building upon advances in multiple fields will tend to have at least some investment in the winning technology (e.g., Garcia-Vega 2006; Gomez-Mejia et al. 2011) rather than having an all-or-nothing bet. So if anything, based on obsolescence risk we might expect a negative IO-return relation rather than the positive one that we find.

Lastly, one may wonder why firms would choose high IO if doing so leads to undervaluation. However, undervaluation need not be costly unless the firm needs to issue underpriced securities. So for a firm with enough cash to fund its investments, the benefits can easily exceed the costs (if any) associated with undervaluation. Indeed, we find that high IO firms have higher future profitability and more novel innovations, which is potentially consistent with high benefits. In consequence, managers who care about long-term value, not just short-term stock prices, may have an incentive (at least up to a point) to increase IO. This is similar to the point that firm managers may rationally invest in R&D even if this comes at the cost of temporary discount in stock price (Chan, Lakonishok, and Sougiannis 2001).

[19] Greenwood, Hercowitz, and Krusell (1997) suggest that investment-specific technological changes explain aggregate economic growth; later, Kogan and Papanikolaou (2010) and Papanikolaou (2011) propose investment-specific technological changes as a systematic risk priced in stock markets. We thank Papanikolaou for providing the IMC factor returns.

IV. Conclusion

Based upon the psychology of limited attention in which, under empirically realistic conditions, firms with greater innovative originality (measured by higher average patent citation diversity) will be undervalued by the market if IO is a favorable indicator of future fundamentals that is neglected by some investors. More original innovations tend to deviate more from current technology trajectory and have more uncertain prospects for success. In addition, the greater complexity associated with a higher IO measure also makes it harder to cognitively process this signal, resulting in skeptical appraisal. We further hypothesize that the effect of IO upon misvaluation will be stronger among firms with greater valuation uncertainty, lower investor attention, and stronger IO predictive ability for fundamentals.

Our tests support these hypotheses. We first confirm that firms with higher IO have higher future profitability. We then show that high IO firms on average experience higher subsequent abnormal stock returns, especially among firms with higher valuation uncertainty, lower investor attention, and stronger sensitivity of future profitability to IO. These findings are robust to industry adjustment, characteristic-adjustment, risk-adjustment methods, and to the inclusion of extensive controls including innovative efficiency and investment-specific technology risk. These results suggest that underreaction to the association between innovative originality 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 IO. The high Sharpe ratio of the high-minus-low IO portfolio also suggests that this relation is not entirely explained by rational pricing. Moreover, the stronger IO predictive ability among firms with greater sensitivity of future profitability to IO supports the limited attention explanation over an explanation based on skepticism of complexity.

Overall, our evidence is consistent with the predictions from a model of limited attention. Although we do not rule out risk-based explanations, the most plausible interpretation of the evidence is that the market underweights the information contained in innovative originality. Our evidence also suggests that innovative originality can be a useful input for firm valuation.

Appendix

A Model of Limited Investor Attention to Innovative Originality

This model considers the implications of a well-established psychological constraint, limited investor attention, on the ability of innovative originality (IO) to forecast abnormal returns. The basic argument is simple. As discussed in the main text, IO is a low-salience historical statistic about the firm's innovative activities; empirically, IO is a positive indicator of the average future citations received by a firm's patents and its profitability. Owing to low salience, a fraction of the investors neglect the favorable information about future profitability contained in high IO. In consequence, the stock price underweights this information, so high IO is associated with underpricing and low IO with overpricing. Hence IO is a positive predictor of future abnormal stock returns.

When the prior uncertainty about the value of the stock (without any conditioning on IO) is higher, heavier weight should optimally be placed on IO by investors in forming posterior beliefs about value. So neglect of IO causes greater mispricing. Hence the ability of IO to predict returns is stronger when prior valuation uncertainty is greater. Furthermore, we show that the ability of IO to predict returns is stronger when the fraction of attentive investors is lower, and when IO is a stronger positive predictor of fundamentals.

Attention requires effort, and the amount of information available exceeds our ability to process it. So attention must be selective (see, e.g., Kahneman 1973). Evidence from the experimental laboratory indicates that limited attention affects how both individual investors and financial professionals interpret public information (see the review of Libby, Bloomfield, and Nelson 2002). This suggests that limited attention may affect the valuation of public information in securities markets.

As in recent theoretical literature on limited attention, in our model some investors condition only on subsets of publicly available information signals in valuing a stock. Some investors attend to the implications of IO for the firm's future prospects, and some do not. Risk averse investors who are fully attentive to the relevant information item are willing to bear only a limited amount of risk in order to exploit mispricing. In consequence, equilibrium stock prices reflect a weighted average of the beliefs of investors who attend to different signals, with weights that depend on the relative numbers in each investor group and their risk tolerances. In

equilibrium, prices underreact to IO because of the subset of investors who do not incorporate this information into their expectations of future cash flows.

This model builds on a recent theoretical literature on how constraints on information processing affect investor behavior. The approach followed here is similar in spirit to that of Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011), who study the effects on market prices of investors neglecting relevant accounting information or strategic aspects of the disclosure and reporting environment. Here we examine the implications of limited attention for neglect of information relating to innovative activity of the firm. Other recent papers model the allocation of attentional resources (Gabaix and Laibson 2005; Peng 2005; and Hirshleifer, Lim, and Teoh 2008), how limited learning capacity affects asset price comovement (Peng and Xiong 2006) and the speed of price adjustment to fundamental shocks (Peng 2005; Peng and Xiong 2006), and how neglect of demographic information affects asset prices (DellaVigna and Pollet 2007).

AI. The economic setting

There are two types of investors: those who ignore the public information contained in innovative originality about future cash flows, and those who attend to all publicly available information. There are two dates. At date 1, innovative originality is publicly revealed. We denote the revealed level of IO by y. Those investors who attend to y update their prior beliefs accordingly. All consumption occurs at date 2. At date 2, the stock's terminal cash flows S_2 are realized.

Prices are set by trading in a securities market with no private information, so that a rational individual has nothing to learn from market price. An inattentive investor who is unaware of his/her signal neglect also thinks he/she has nothing to learn from market price. We therefore assume that inattentive investors do not update their beliefs based upon market price.[20]

In principle, a discrepancy between an investor's valuation and the market price could alert the investor to his information neglect. In general, however, the same constraints on processing

[20] As discussed in previous theoretical literature on limited attention in securities markets, observing the 'wrong' price is an event which, as perceived by the investor, is not supposed to occur in equilibrium. In the Perfect Bayesian Equilibrium concept of game theory setting the individual's posterior beliefs in such a situation equal to the prior belief can be consistent with equilibrium. Similar results would hold so long as some disagreement remains between the attentive and inattentive investors, i.e., inattentive investors do not always abandon their beliefs in favor of the information implicit in the market price.

power and memory that make it hard to attend to some public signal also make it hard to use price or other indicators to compensate optimally for the failure to attend to it. Since in reality people face many relevant signals, they try to leverage their attention by focusing on more important information items. However, we cannot know perfectly which are more important before processing them, which makes it hard to determine how to optimally compensate for information neglect. Section AIII discusses evidence suggesting that individuals fail to compensate fully for the consequences of limited attention in making decisions. So long as some fraction of inattentive investors have imperfect self-awareness, results similar to those derived here will obtain. Furthermore, even if individuals always attend to market price and draw inferences from this about their information neglect, similar results to those derived here could be obtained so long as there is noise in market price arising from liquidity trading. In such a setting, an individual who attends to a given public signal in effect has a sort of 'private' information, so individuals who attend to the public signals will profit at the expense of liquidity traders, in the spirit of the models of Grossman and Stiglitz (1976) and Diamond and Verrecchia (1981).

In general, attending to more information is costly. Since investors have finite cognitive resources, attending to some information implies less time and resources for other activities. We assume that there are two investor groups indexed by i who attend to different information sets. Fully attentive investors attend to all date 1 publicly available information including IO; investors with limited attention neglect IO.

We assume that investors have a mean-variance utility function,

$$E^i\left[C_2^i\right] - \left(\frac{A}{2}\right) V^i\left(C_2^i\right), \tag{1}$$

where C_2^i is terminal consumption, A is the coefficient of absolute risk aversion, V denotes variance, and i superscripts denote the expectation or variance as formed by group i. Specifically, we use an 'a' superscript to denote the attentive group which conditions on y, and a 'u' superscript to denote the inattentive group, which does not condition on y. (The 'u' superscript stands for "unconditional," as the inattentive group does not condition on the signal y.)

Investors have an initial wealth endowment (i.e., claims to terminal consumption) of W, and zero shares of the risky security. There is also an exogenous per capita supply of the single risky

security of x_0 (i.e., supply per member of the decision-making population). (This is without loss of generality; the same results would apply if the investors were endowed with x_0 directly.)

At date 1, each individual can buy or sell the security in exchange for 'cash' (claims to terminal consumption) at price S_1. The position in the security he/she attains is denoted x^i. Let S_2, the terminal cash flow, be the true value of the stock, which is conclusively revealed to all at date 2. For brevity, we do not include any cost of attending to the information signal (for the attentive group) in the expression for terminal consumption since, conditional upon attending, such a cost is a constant that would not affect the optimal investment positions or any other expressions in the following derivations. So the consumption of an individual in attention group i is

$$C_2^i = W + x^i(S_2 - S_1). \tag{2}$$

Thus, an individual in attention group i solves for the x^i that maximizes the objective

$$x^i\left(E^i[S_2] - S_1\right) - \left(\frac{A}{2}\right)V^i\left(x^i S_2\right). \tag{3}$$

As a preliminary building block, we verify a standard finding that in equilibrium stock prices are a weighted average of investor expectations of terminal cash flows as adjusted by a risk premium. We start by calculating optimal investment positions. Differentiating the objective with respect to x^i, equating to zero and solving yields

$$x^i = \frac{E^i[S_2] - S_1}{AV^i(S_2)}. \tag{4}$$

Letting f^i denote the fraction of investors in attention group i, the security price is determined by the market clearing condition

$$\sum_i f^i x^i = x_0. \tag{5}$$

Substituting for x^i from (4), and solving for S_1 gives

$$S_1 = \frac{\sum_i \lambda^i E^i[S_2] - Ax_0}{\sum_i \lambda^i}, \tag{6}$$

where

$$\lambda^i \equiv \frac{f^i}{V^i(S_2)}. \tag{7}$$

By normality, the λ^i's are constants independent of the values of the signal realizations used by investors to condition beliefs. Of course, with normal distributions, an investor who fails to

condition on a signal will have higher variance than an investor who does condition on that signal.

This confirms that, in equilibrium, prices are a weighted average of the beliefs about terminal cash flows of different investors adjusted by a risk premium ($Ax_0/\sum_i \lambda^i$), with weight $\lambda^i/\sum_i \lambda^i$ on each group's belief. Both attention groups influence prices significantly owing to the finite risk-bearing capacity of each group. By (7), *ceteris paribus*, λ^i is increasing in f^i. Thus, the greater the fraction of investors who are inattentive to IO, the greater the weight that inattentive investors play in determining prices. Similar pricing equations are found in several behavioral models, such as Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011).

It also captures formally the idea, common to behavioral theories of anomalies, that arbitrage of market inefficiencies is imperfect. It can be argued that arbitrageurs such as hedge funds will profit by trading against mispricing, thereby growing in risk-bearing capacity. However, a literature in behavioral finance and accounting has argued that arbitrage is limited by market frictions, psychological effects, and dynamic considerations; see, e.g., Shleifer and Vishny (1997) and Hirshleifer (2001).

In this setting rational investors exploit a trading strategy that earns predictable abnormal returns relative to a fully rational asset pricing benchmark. Nevertheless, even though markets are perfect and there are no restrictions on either long positions or short-selling, fully attentive investors do not completely arbitrage away the mispricing generated by inattentive investors because doing so is risky.

AII. Innovative originality and return predictability

Suppose that, at date 1, fraction f^a of investors attend to IO, and fraction $f^u \equiv 1 - f^a$ ignore IO and remain at their prior belief. It is not essential for the main conclusions of this paper that these investors completely ignore IO. They could attend to some effects but ignore the positive implications of higher IO for future profits. For tractability, we assume multivariate normality of the stochastic variables. As a result, date 2 cash flows can be expressed as a linear function of y (date 1 IO, a normally distributed variable with mean $\bar{y}$ and standard deviation σ_y), and a noise term δ as

$$S_2 = \beta_0 + \beta_{Sy} y + \delta, \tag{8}$$

where $cov(\delta, y) = 0$.

Consistent with the empirical evidence (see Table III in the main text and Table IA.I in the Internet Appendix), we assume that IO is a positive predictor of future cash flows, i.e., $\beta_{Sy} > 0$. Therefore, high value at date 2 is associated with high IO at date 1. The strength of this relation is given by the regression coefficient $\beta_{Sy} \equiv cov(S_2, y)/\sigma_y^2$, where σ_y is the standard deviation of y.

We next examine the relation between the date 1 IO and expected future abnormal stock returns. For tractability, we examine price changes rather than percentage returns, as is standard in much of the literature on information in securities markets (see, e.g., Verrecchia (2001) and Peng (2005)). We begin by calculating, conditional on IO, the expected future value of the stock $E[S_2|y]$. Using standard properties of conditional expected values with multivariate normal distributions,

$$E^a[S_2] \equiv E[S_2|y] = E[S_2] + \beta_{Sy}(y - \bar{y}), \tag{9}$$

where $\bar{y}$ is the prior expectation of date 1 IO. So the sensitivity of $E[S_2|y]$ to the level of IO, $\frac{\partial(E[S_2|y])}{\partial y}$, is simply β_{Sy}.

We then examine how the current price, $S_1(y)$, relates to the level of IO. By a standard formula for normal distributions,

$$V(S_2|y) = (1 - \rho^2)V(S_2), \tag{10}$$

where ρ is the correlation between S_2 and y. Since $\beta_{Sy} = \rho\sigma_S/\sigma_y$, where σ_S is the standard deviation of S_2, our assumption that $\beta_{Sy} > 0$ implies that $\rho > 0$. In addition, we assume $\rho < 1$, i.e., the variation in future cash flows is not solely determined by the variation in IO. (ρ^2 is the R-square of the regression specified by (8).)

Substituting (7), (9), and (10) in (6), and recognizing that owing to limited attention, $E^u[S_2] = E[S_2]$ and $V^u(S_2) = V(S_2)$, gives

$$S_1(y) = \frac{\frac{f^a}{(1-\rho^2)}\left[E[S_2] + \beta_{Sy}(y - \bar{y})\right] + f^u E[S_2] - Ax_0 V(S_2)}{\frac{f^a}{(1-\rho^2)} + f^u}. \tag{11}$$

Let $W^a \equiv \frac{\lambda^a}{\lambda^a + \lambda^u}$ denote the weight of attentive investors in current price as defined in Section AI. It is clear from (11) that the sensitivity of the current price to y, $\frac{\partial S_1(y)}{\partial y}$, is simply $W^a\beta_{Sy}$,

which increases in W^a. The last term shows that greater $V(S_2)$ reduces current stock price and increases the risk premium. But this effect does not depend on the value of y, so it does not affect the cross-sectional prediction derived from varying y.

As discussed earlier, it is more tractable to define returns as price changes. Let R denote the price changes, $S_2 - S_1$. It follows from (9) and (11) that the expected return conditional on IO ($E[R]$) is

$$E[R] \equiv E[S_2|y] - S_1(y) = \frac{\beta_{Sy}(y-\bar{y})f^u}{\frac{f^a}{(1-\rho^2)} + f^u} + \frac{Ax_0 V(S_2)}{\frac{f^a}{(1-\rho^2)} + f^u}. \tag{12}$$

We label the first term the *expected future abnormal return*, which depends on the revealed level of IO (y). The second term relates to risk premium. So higher $V(S_2)$ causes a higher expected return on the stock owing to rational risk aversion, which does not depend on y. Therefore, the sensitivity of $E[R]$ to IO and the interactions of this sensitivity with other characteristics (discussed later) are the same as those for the future abnormal returns. For brevity, we only show the derivations based on $E[R]$ below.

From (12), we show that the sensitivity of expected returns (and future abnormal returns) to IO is

$$\frac{\partial E[R]}{\partial y} = \frac{\partial E[S_2|y]}{\partial y} - \frac{\partial S_1(y)}{\partial y} = \beta_{Sy}(1-W^a) = \frac{\beta_{Sy} f^u (1-\rho^2)}{(1-f^u\rho^2)}, \tag{13}$$

which is positive as long as $\beta_{Sy} > 0$ and $f^u > 0$, where the last equality in (13) follows from the definition of W^a. In other words, IO is a positive predictor of future abnormal returns if IO is positively associated with future value and if a non-zero fraction of investors neglect the favorable information in IO.

The sensitivity in (13) is decreasing in W^a, the influence of attentive investors' beliefs in the current price. This is intuitive since the weaker is the influence of attentive investors, the more the current price deviates from the efficient price that would prevail if all investors were attentive; and the more sensitive the abnormal return is to IO. Furthermore, W^a is increasing in the fraction of attentive investors, f^a, and decreasing in uncertainty about future cash flows as reflected in $V(S_2)$ or σ_S. (Note that $V(S_2) \equiv \sigma_S^2$.) More formally, W^a can be expressed as

$$W^a = \frac{\frac{f^a}{(1-\rho^2)V(S_2)}}{\frac{f^a}{(1-\rho^2)V(S_2)} + \frac{f^u}{V(S_2)}} = \frac{f^a}{1-f^u\rho^2}. \tag{14}$$

Hence the derivative of W^a with respect to f^a is

$$\frac{\partial W^a}{\partial f^a} = \frac{1-\rho^2}{(1-f^u\rho^2)^2} > 0, \tag{15}$$

and the derivative of W^a with respect to σ_S is

$$\frac{\partial W^a}{\partial \sigma_S} = \left[\frac{2f^a f^u \rho}{(1-f^u\rho^2)^2}\right]\left(\frac{\partial \rho}{\partial \sigma_S}\right) = \left[\frac{2f^a f^u \rho}{(1-f^u\rho^2)^2}\right]\left(\frac{-\beta_{Sy}\sigma_y}{\sigma_S^2}\right) = \frac{-2(1-f^u)f^u\rho^2}{(1-f^u\rho^2)^2\sigma_S} < 0, \tag{16}$$

where the second and third equalities follow from $\rho = \beta_{Sy}\sigma_y/\sigma_S$ and $\frac{\partial \rho}{\partial \sigma_S} = \frac{-\beta_{Sy}\sigma_y}{\sigma_S^2}$.

Intuitively, the smaller the fraction of attentive investors, the less influence they have on the current price and hence the larger mispricing owing to neglect of IO. In addition, when the prior uncertainty about the value of the stock (without any conditioning on IO) is higher, heavier weight should optimally be placed on IO by investors in forming posterior beliefs about value. So neglect of IO causes greater mispricing.

Since the sensitivity of expected returns (and future abnormal returns) to IO is decreasing in W^a as shown in (13), it is increasing in the uncertainty about S_2 and the fraction of inattentive investors (or decreasing in the fraction of attentive investors). More formally, taking the derivative of (13) with respect to σ_S and substituting $\frac{\partial W^a}{\partial \sigma_S}$ derived in (16) gives

$$\frac{\partial^2(E[R])}{\partial y \partial \sigma_S} = -\beta_{Sy}\frac{\partial W^a}{\partial \sigma_S} = \frac{2f^u(1-f^u)\rho^3}{\sigma_y(1-f^u\rho^2)^2}, \tag{17}$$

which is positive as long as $f^u > 0$. Similarly, taking the derivative of (13) with respect to f^u and substituting $\frac{\partial W^a}{\partial f^a}$ derived in (15) gives

$$\frac{\partial^2(E[R])}{\partial y \partial f^u} = -\beta_{Sy}\frac{\partial W^a}{\partial f^u} = \beta_{Sy}\frac{\partial W^a}{\partial f^a} = \frac{\beta_{Sy}(1-\rho^2)}{(1-f^u\rho^2)^2}, \tag{18}$$

which is positive as long as $\beta_{Sy} > 0$.

In sum, greater prior uncertainty about the stock payoff makes the return predictive power of IO stronger. This prior uncertainty will be higher in a more opaque information environment (e.g., younger firms, firms with more opaque financial reports). Furthermore, the strength of the

return predictive power based upon IO is increasing in f^u, the degree of inattention in the market, e.g., lower analyst following relative to the supply of information.

We also explore the interaction of this return predictive power of IO with β_{Sy}, the strength of the predictive relationship between IO and future cash flows. Taking the derivative of (13) with respect to β_{Sy} gives

$$\frac{\partial^2(E[R])}{\partial y \partial \beta_{Sy}} = \frac{f^u[1 - 3\rho^2 + f^u\rho^2(1+\rho^2)]}{(1 - f^u\rho^2)^2}, \tag{19}$$

which is positive if $f^u > \frac{3\rho^2-1}{\rho^4+\rho^2}$, i.e., the fraction of inattentive investors is large enough. A sufficient condition for this to hold for any non-zero f^u is $\rho^2 \leq 1/3$, i.e., the R-square from the regression of future cash flows on IO is less than or equal to 1/3. We verify that this sufficient condition holds in the data in untabulated results. Therefore, $\frac{\partial^2(E[R])}{\partial y \partial \beta_{Sy}} > 0$ for all $f^u > 0$. In other words, the model predicts that the strength of the return predictive power of IO increases with β_{Sy} as long as there are inattentive investors in the market.

In addition, all the above derivations apply to date 1 mispricing as well, and hence to future abnormal returns. To see this, we define mispricing in the current stock price as the difference between S_1 and S_1^*, the price that would be set if all investors were attentive ($f^a = 1$). Setting f^a to 1 and f^u to 0 in (11) gives

$$S_1^* = E[S_2|y] - (1-\rho^2)Ax_0V(S_2). \tag{20}$$

Therefore, mispricing is

$$S_1^* - S_1 = E[R] - (1-\rho^2)Ax_0V(S_2), \tag{21}$$

where the equality follows from (12). In other words, expected returns are the sum of mispricing and the risk premium. It is clear that mispricing and $E[R]$ depend on IO in the same way since the second term in (21) does not vary with IO. Consequently, the interactions of this sensitivity with prior valuation uncertainty, investor attention, and the strength of the predictive relation between IO and future profits apply to mispricing and future abnormal returns as well.

The above analysis is summarized in the following propositions:

Proposition 1. If fraction $f^u > 0$ of investors neglect the favorable information in IO, then higher IO is associated with greater subsequent abnormal returns.

Proposition 2. The greater the valuation uncertainty as reflected in σ_S, the steeper the relation between IO and subsequent abnormal returns.

Proposition 3. The greater the fraction of inattentive investors, f^u, the steeper the relation between IO and subsequent abnormal returns.

Proposition 4. If the fraction of inattentive investors is large enough or if the correlation between IO and future cash flows is low enough, then the stronger the predictive relationship between IO and future profits as reflected in the regression coefficient, β_{Sy}, the steeper the relation between IO and subsequent abnormal returns.

AIII. Do investors fully compensate for limited attention?

A key assumption of our model is that individuals with limited attention trade based upon their beliefs. As a result, limited attention affects the equilibrium price. Casual observation suggests that investors often do make trades based on beliefs that do not fully reflect publicly available information. Intuitively, ignoring an information item and failing to adjust for the fact that the item has been neglected go hand in hand, as both kinds of neglect are natural results of limited cognitive capacity. A more detailed discussion and defense of the proposition that investors neglect information yet trade and influence price is provided in Hirshleifer, Lim, and Teoh (2011) Section 4.

There is extensive evidence from both psychology and experimental markets that people both neglect signals and do not adjust for the fact that they are neglecting them, such as studies that show that the form of presentation of information affects individuals' judgments and decisions (see, e.g., the review of Libby, Bloomfield, and Nelson 2002). Experimental studies have found that different presentations of equivalent information about a firm affect the valuations and trades of investors and experienced financial analysts. Presentation effects have been documented for various forms of accounting reporting and disclosure contexts. In principle, if an investor understood that owing to limited attention certain formats were hard to process, the investor could self-debias by, for example, mentally rearranging the format of presentation. However, such self-debiasing often does not occur.

There is other evidence that limited attention affects capital markets; indeed, Daniel, Hirshleifer, and Teoh (2002) argue that limited attention may underlie a wide range of anomalous patterns in securities market trading and prices. In an experimental setting, Gillette et al. (1999) document investor misreactions to public information arrival. Perhaps the most

striking indication of limited attention in public markets is that stock prices react to news that is already public information (Huberman and Regev 2001, and Ho and Michaely 1988). More broadly, Hong, Torous, and Valkanov (2007) report evidence that industry stock returns lead aggregate market returns, potentially consistent with gradual diffusion of information about fundamentals across markets. Hou and Moskowitz (2005) provide a measure of investor neglect of a stock, the lag in the relation between the return on the overall market and the stock's return. They find that stocks with long delay (which can be viewed as low-attention stocks) have stronger post-earnings announcement drift. Many short-horizon event studies confirm that stock markets react immediately to relevant news, but long-horizon event studies provide evidence suggesting that there is underreaction to various kinds of public news events (see, e.g., the review of Hirshleifer 2001). However, there has been a great deal of debate as to the appropriate methodology for testing market efficiency using long-run abnormal returns. There is also evidence suggesting that investors' and analysts' assessments are influenced by the format and salience with which public signals are presented. For example, Hand (1990) finds that the reannounced gains from debt-equity swaps in quarterly earnings announcements were significantly related to mean abnormal returns. Schrand and Walther (2000) provide evidence that managers strategically select the form of the prior-period earnings benchmark when announcing earnings. Prior period special gains were more likely to be mentioned than prior period special losses in the sample, apparently to lower the benchmark for current-period evaluation. Miller (2002) finds that firms at the end of periods of sustained earnings increases shift from long-term forecasts to short-term forecasts, thereby deferring the need to forecast adversely. Plumlee (2003) finds that analyst forecasts of effective tax rates impound the effects of complex tax-law changes less accurately than less complex changes.

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Table I
Innovative Originality of Selected Industries

This table reports the pooled mean, median, standard deviation (Stdev), coefficient of variation (CV), minimum (Min), 30th percentile (P30), 70th percentile (P70), and maximum (Max) of the innovative originality (IO) measure for firms in selected industries based on Fama-French 48 industry classifications (FF48). We report both within- and across-industries CV. The sample is from 1981 to 2006 and excludes financial firms. To compute a firm's IO, we first measure an individual patent's citation diversity as the number of three-digit technology classes (both primary and secondary classes) covered by patents cited by the focal patent (i.e., the "reference list" of the focal patent). The technology classes are assigned by the US Patent and Trademark Office (USPTO). We then measure a firm's IO in year *t* by the average of patent citation diversity across all patents granted to the firm over the past five years (year *t* – 4 to *t*).

Industry	Mean	Median	Stdev	CV	Min	P30	P70	Max
Medical equipment	7.38	6.04	4.91	0.67	1.00	4.47	8.35	43.92
Pharmaceutical products	6.59	5.50	4.41	0.67	1.00	4.33	7.00	42.47
Chemicals	6.53	5.80	3.83	0.59	1.00	4.61	7.25	38.00
Machinery	5.95	5.12	3.38	0.57	1.00	4.00	6.93	27.25
Electrical equipment	5.78	5.00	3.92	0.68	1.00	3.71	6.50	49.06
Automobiles and trucks	5.10	4.92	2.45	0.48	1.00	3.83	5.75	20.50
Business services	7.88	6.60	5.43	0.69	1.00	5.00	8.83	66.00
Computers	6.26	5.50	3.75	0.60	1.00	4.08	7.25	36.61
Electronic equipment	5.92	5.00	3.82	0.65	1.00	4.00	6.50	46.50
Measuring and control equipment	6.25	5.33	3.82	0.61	1.00	4.00	7.26	31.23
Coefficient of variation (CV)	0.13	0.10						

Table II
Summary Statistics and Correlations

At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing innovative originality (IO) measure into three groups (Low, Middle, High) based on the 30th and 70th percentiles of the IO measure in year *t* – 1. In addition, we assign firms with missing IO (i.e., no patents) but positive R&D over the last five years into the "Low" group. IO is defined in Table I. Panel A reports the time-series mean of cross-sectional average characteristics of firms in each IO group. Obs denotes the average number of firms in each group across years. 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 capitalization 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). 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). RDME is R&D expenses in fiscal year ending in year *t* – 1 divided by market capitalization 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 patent citations-based innovative efficiency measure as in Hirshleifer, Hsu, and Li (2013). ROA (return on assets) is defined as income before extraordinary items plus interest expenses in year *t* – 1 divided by lagged total assets. ROE (return on equity) is defined as income before extraordinary items plus interest expenses in year *t* – 1 scaled by lagged book equity (common equity plus deferred tax). 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 (InstOwn) denotes the fraction of firm shares outstanding owned by institutional investors in year *t* – 1. 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* and is in units of bps. We winsorize all variables at the 1% and 99% levels except the number of firms and IO. Panel B reports the times-series average of cross-sectional Pearson (Spearman rank) correlations between IO and other characteristics below (above) the diagonal.

Panel A. Summary statistics

Rank	Obs	IO	Size	BTM	MOM	IVOL	TSKEW	RDME	CTA	IE	ROA	ROE	AG	IA	NS	InstOwn	REV	ILLIQ
Low	1283	3.02	702	0.68	0.13	0.04	0.64	6.76%	0.84%	0.18	-2.84%	-4.17%	0.18	0.07	0.07	0.29	0.53%	0.00
Middle	550	5.37	4334	0.70	0.15	0.03	0.39	6.03%	2.84%	0.68	3.05%	5.56%	0.14	0.07	0.04	0.45	0.63%	0.00
High	409	9.78	2033	0.64	0.15	0.03	0.47	5.90%	3.45%	0.81	0.29%	1.10%	0.16	0.07	0.05	0.40	0.66%	0.00

Panel B. Correlation coefficient

	IO	Size	BTM	MOM	IVOL	TSKEW	RDME	CTA	IE	ROA	ROE	AG	IA	NS	InstOwn	REV	ILLIQ
IO	1	0.05	-0.08	0.01	-0.01	-0.01	0.05	0.11	0.15	-0.02	-0.03	0.02	0.05	0.04	0.03	0.00	-0.05
Size	-0.01	1	-0.24	0.31	-0.65	-0.26	-0.05	0.23	0.33	0.39	0.38	0.23	0.25	0.00	0.67	0.14	-0.75
BTM	-0.07	-0.07	1	-0.12	-0.04	0.02	-0.12	-0.09	-0.05	-0.20	-0.11	-0.25	-0.13	-0.23	-0.06	0.02	0.20
MOM	0.00	0.04	-0.12	1	-0.26	0.17	-0.05	0.04	0.06	0.19	0.19	0.04	-0.01	-0.08	0.11	0.09	-0.24
IVOL	0.04	-0.16	0.09	-0.12	1	0.30	0.19	-0.11	-0.23	-0.41	-0.43	-0.13	-0.16	0.21	-0.52	-0.10	0.50
TSKEW	0.01	-0.07	0.06	0.20	0.32	1	0.05	-0.06	-0.12	-0.22	-0.19	-0.14	-0.14	0.01	-0.28	0.06	0.22
RDME	0.01	-0.03	0.08	-0.08	0.23	0.06	1	0.43	0.05	-0.20	-0.25	-0.10	-0.13	0.09	-0.01	-0.04	0.03
CTA	0.09	-0.01	-0.10	0.01	0.08	0.04	0.22	1	0.61	0.00	-0.03	-0.03	-0.01	0.01	0.20	0.00	-0.18
IE	0.13	0.02	-0.06	0.02	-0.08	-0.04	-0.06	0.36	1	0.08	0.08	0.04	0.13	-0.01	0.28	0.01	-0.26
ROA	-0.06	0.09	0.01	0.12	-0.40	-0.17	-0.28	-0.17	0.02	1	0.85	0.48	0.26	-0.09	0.29	0.06	-0.30
ROE	-0.06	0.11	0.02	0.13	-0.45	-0.17	-0.31	-0.17	0.03	0.85	1	0.32	0.18	-0.14	0.26	0.06	-0.28
AG	0.03	0.00	-0.18	0.00	-0.05	-0.07	-0.13	-0.04	0.04	0.10	0.16	1	0.40	0.30	0.14	0.01	-0.18
IA	0.04	0.01	-0.12	-0.04	-0.04	-0.07	-0.13	-0.05	0.06	0.08	0.08	0.37	1	0.10	0.16	0.00	-0.19
NS	0.04	-0.04	-0.11	-0.06	0.19	0.04	0.02	0.02	0.00	-0.25	-0.21	0.41	0.14	1	-0.03	-0.04	-0.02
InstOwn	-0.03	0.17	-0.11	0.04	-0.45	-0.24	-0.08	-0.05	0.09	0.27	0.27	0.05	0.05	-0.08	1	0.04	-0.56
REV	0.00	0.01	0.02	0.06	-0.04	0.10	-0.02	-0.01	0.00	0.04	0.04	-0.02	-0.01	-0.03	0.01	1	-0.10
ILLIQ	-0.01	-0.05	0.20	-0.15	0.31	0.10	0.05	-0.01	-0.07	-0.13	-0.15	-0.09	-0.06	0.01	-0.24	-0.05	1

Table III
Innovative Originality and Future Profitability

This table reports the average slopes (in %) and their time series heteroscedasticity-robust *t*-statistics in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions of profitability in year $t + 1$ and average profitability in year $t + 1$ to $t + 5$ on innovative originality (IO) and other control variables in year *t* from 1981 to 2006. Profitability is measured by return on equity (ROE), defined as income before extraordinary items plus interest expenses scaled by lagged book equity (common equity plus deferred tax), or return on assets (ROA), defined as income before extraordinary items plus interest expenses scaled by lagged total assets. IO and IE are defined in Table I. IO is set to one, two, and three if a firm belongs to the Low, Middle, and High IO groups as defined in Table II, respectively. ΔROE (ΔROA) is the change in ROE (ROA) between year *t* and year $t - 1$. MTB is market-to-book assets. AdvEx is advertising expense divided by lagged book equity. CapEx is capital expenditure divided by lagged book equity. R&D is R&D expenditure divided by lagged book equity. All regressions include industry dummies based on the Fama and French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize all independent variables (except IO ranks) to zero mean and one standard deviation. Financial firms are excluded. R-square is the time-series average of the R-squares from the annual cross-sectional regressions.

Panel A: Effect of IO on future ROE										
Profitability	IO	ROE	ΔROE	MTB	AdvEx	CapEx	R&D	IE	Intercept	R^2
Next year	2.01	38.02	-14.27	4.84	1.36	2.11	-5.15	0.29	-4.32	0.26
	(3.35)	(15.07)	(-8.06)	(5.48)	(4.10)	(2.28)	(-6.32)	(0.72)	(-1.00)	
Next five years	4.19	41.87	-16.44	2.69	0.91	1.87	-8.28	0.74	-16.75	0.23
	(8.21)	(19.22)	(-10.27)	(2.17)	(2.04)	(1.52)	(-11.33)	(1.49)	(-3.89)	
Panel B: Effect of IO on future ROA										
Profitability	IO	ROA	ΔROA	MTB	AdvEx	CapEx	R&D	IE	Intercept	R^2
Next year	0.53	13.36	-2.60	0.46	0.29	0.16	-1.45	0.02	0.73	0.51
	(5.72)	(19.40)	(-9.80)	(2.26)	(2.56)	(0.77)	(-5.69)	(0.27)	(0.40)	
Next five years	0.85	11.04	-2.64	0.27	0.44	0.33	-2.10	0.08	-2.02	0.47
	(9.14)	(17.84)	(-11.42)	(1.37)	(5.22)	(1.58)	(-7.94)	(1.08)	(-1.27)	

Table IV
Return Predictive Power of Innovative Originality – Portfolio Analysis

At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing innovative originality (IO) into three IO portfolios (Low, Middle, and High) based on the 30th and 70th percentiles of IO in year *t* – 1. In addition, we assign firms with missing patents but positive R&D over the last five years into the low IO portfolio. We also construct a high-minus-low (High–Low) portfolio by holding a long (short) position in the high (low) IO portfolio and hold these portfolios over the next twelve months (July of year *t* to June of year *t* + 1). In Panel A, we report their monthly returns in excess of one-month Treasury bill rate (Exret) as well as their industry- and characteristic-adjusted returns. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms' returns and the returns of firms in the same industry (based on Fama-French 48 industry classifications). Following Daniel, Grinblatt, Titman, and Wermers (DGTW 1997) and Wermers (2004), the portfolio characteristic-adjusted returns (Char-adjret) are based on the difference between individual firms' returns and the DGTW benchmark portfolio returns. In Panel B, we report the alphas and factor loadings from the regression of the time-series of portfolio excess returns on the Fama-French three factors (the market factor–MKT, the size factor–SMB, and the value factor–HML) plus the momentum factor (UMD). In Panel C, we report the alphas from the regression of the time-series of portfolio excess returns on these Carhart four factors plus the investment-minus-consumption (IMC) factor (Papanikolaou 2011), the innovative efficient-minus-inefficient (EMI) factor (Hirshleifer, Hsu, and Li 2012), the liquidity (LIQ) factor (Pastor and Stambaugh 2003), or the robust-minus-weak factor (RMW) and the conservative-minus-aggressive factor (CMA) as in Fama and French (2015). All returns and alphas are value-weighted and in percentage.

	Panel A. Excess returns and adjusted returns			Panel B. Alphas and loadings from four-factor model (4F)				
IO	Exret	Ind-adjret	Char-adjret	Alpha	MKT	SMB	HML	UMD
Low	0.51	-0.14	-0.09	-0.11	1.02	0.24	-0.20	-0.01
	(1.74)	(-1.97)	(-0.36)	(-1.44)	(44.48)	(7.50)	(-5.17)	(-0.34)
Middle	0.73	0.03	0.07	0.16	0.97	-0.15	-0.17	-0.02
	(2.83)	(0.76)	(0.31)	(2.49)	(53.59)	(-6.07)	(-5.75)	(-1.10)
High	0.80	0.09	0.19	0.24	0.95	0.01	-0.13	-0.04
	(3.09)	(1.86)	(0.76)	(2.74)	(44.26)	(0.21)	(-3.08)	(-1.64)
High-Low	0.29	0.23	0.28	0.35	-0.07	-0.23	0.07	-0.03
	(2.29)	(2.51)	(2.36)	(3.00)	(-2.34)	(-5.04)	(1.23)	(-1.19)

Panel C. Alphas and loadings from 4F plus IMC							Panel D. Alphas and loadings from 4F plus LIQ					
IO	Alpha	MKT	SMB	HML	UMD	IMC	Alpha	MKT	SMB	HML	UMD	LIQ
Low	-0.11	1.02	0.25	-0.19	-0.01	0.08	-0.12	1.02	0.24	-0.21	-0.01	0.02
	(-1.33)	(44.46)	(7.64)	(-5.10)	(-0.36)	(0.93)	(-1.51)	(44.29)	(7.45)	(-5.02)	(-0.31)	(0.55)
Middle	0.17	0.97	-0.15	-0.16	-0.02	0.05	0.17	0.97	-0.15	-0.17	-0.02	-0.01
	(2.48)	(52.98)	(-5.86)	(-5.44)	(-1.07)	(0.68)	(2.55)	(53.86)	(-6.07)	(-5.56)	(-1.11)	(-0.64)
High	0.24	0.95	0.01	-0.14	-0.04	-0.02	0.23	0.95	0.01	-0.14	-0.04	0.02
	(2.71)	(43.47)	(0.18)	(-3.04)	(-1.62)	(-0.19)	(2.54)	(44.20)	(0.21)	(-3.10)	(-1.61)	(0.75)
High-Low	0.35	-0.08	-0.24	0.06	-0.03	-0.10	0.35	-0.07	-0.23	0.07	-0.03	0.00
	(2.87)	(-2.37)	(-5.03)	(1.06)	(-1.17)	(-0.79)	(2.90)	(-2.32)	(-4.99)	(1.18)	(-1.16)	(0.11)

Panel E. Alphas and loadings from 4F plus RMW and CMA								Panel F. Alphas and loadings from 4F plus EMI					
IO	Alpha	MKT	SMB	HML	UMD	RMW	CMA	Alpha	MKT	SMB	HML	UMD	EMI
Low	-0.04	1.01	0.20	-0.17	-0.01	-0.21	-0.15	-0.05	1.02	0.23	-0.23	-0.01	-0.20
	(-0.56)	(46.54)	(5.39)	(-2.71)	(-0.25)	(-2.72)	(-1.74)	(-0.59)	(44.06)	(6.90)	(-5.88)	(-0.57)	(-4.75)
Middle	0.17	0.97	-0.19	-0.23	-0.02	-0.02	0.11	0.09	0.97	-0.14	-0.14	-0.01	0.20
	(2.68)	(56.14)	(-6.73)	(-4.32)	(-1.33)	(-0.39)	(1.84)	(1.45)	(54.37)	(-6.03)	(-5.24)	(-0.89)	(5.53)
High	0.20	0.95	0.04	-0.26	-0.04	0.21	-0.01	0.20	0.95	0.01	-0.12	-0.04	0.11
	(2.19)	(42.44)	(1.00)	(-3.40)	(-1.70)	(2.45)	(-0.14)	(2.23)	(43.03)	(0.42)	(-2.62)	(-1.50)	(1.95)
High-Low	0.24	-0.06	-0.16	-0.09	-0.04	0.43	0.14	0.25	-0.07	-0.21	0.11	-0.02	0.31
	(1.99)	(-2.01)	(-2.93)	(-1.00)	(-1.27)	(3.43)	(1.21)	(2.12)	(-2.15)	(-4.56)	(1.84)	(-0.92)	(4.66)

Table V
Return Predictive Power of Innovative Originality – Fama-MacBeth Regressions

This table reports the average slopes (in %) and their time series heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions. For each month from July of year *t* to June of year *t* + 1, we regress monthly returns of individual stocks on IO ranks of year *t* – 1, different sets of control variables, and industry fixed effects. IO ranks are defined as in Table III. Model 1 controls for size, book-to-market (BTM), momentum (MOM), institutional ownership (InstOwn), stock illiquidity (ILLIQ), short-term return reversal (REV), and industry dummies based on Fama and French 48 industries. Size is the log of market capitalization at the end of June of year *t*. BTM is also in the natural log form. InstOwn and BTM are measured in year *t* – 1. ILLIQ and REV are the previous month's stock illiquidity and stock return, respectively. In Model 2, we control for additional return predictors related to innovation (IE, CTA, and RDME), investment (AG and IA), net stock issues (NS), return-on-assets (ROA), idiosyncratic volatility (IVOL), and total skewness (TSKEW) measured in year *t* – 1. IE is the natural log of one plus the citations-based innovative efficiency measure following Hirshleifer, Hsu, and Li (2013). 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. In Model 3, we further control for sales diversity (SD) measured as the number of different sales segments defined by Fama-French 48 industries over the previous five years (year *t* – 5 to year *t* – 1). All independent variables (except IO and SD) 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 is the time-series average of the R-squares from the monthly cross-sectional regressions.

	Model 1		Model 2		Model 3	
	Slope	*t*-statistic	Slope	*t*-statistic	Slope	*t*-statistic
IO	0.16	(5.27)	0.08	(2.22)	0.08	(2.18)
Size	-0.27	(-2.67)	-0.14	(-1.60)	-0.13	(-1.49)
BTM	0.38	(6.01)	0.20	(3.28)	0.20	(3.30)
MOM	0.11	(1.13)	-0.02	(-0.19)	-0.02	(-0.19)
InstOwn	0.10	(1.80)	0.12	(2.18)	0.11	(2.15)
ILLIQ	0.34	(4.79)	0.19	(2.02)	0.18	(2.00)
REV	-0.96	(-10.36)	-1.00	(-12.09)	-1.00	(-12.06)
AG			-0.26	(-5.11)	-0.26	(-5.05)
IA			-0.03	(-0.58)	-0.02	(-0.37)
IE			0.11	(3.25)	0.11	(3.22)
CTA			0.02	(0.71)	0.02	(0.69)
RDME			0.18	(3.56)	0.19	(3.67)
NS			-0.08	(-1.42)	-0.08	(-1.48)
ROA			0.13	(2.13)	0.12	(2.06)
IVOL			0.32	(2.52)	0.32	(2.52)
TSKEW			-0.09	(-2.43)	-0.09	(-2.36)
SD					-0.01	(-0.23)
R^2	0.08		0.11		0.11	

Table VI
Conditioning Return Predictive Power of Innovative Originality – Portfolio Analysis

At the end of June of each year *t*, we conduct independent double sorts on innovative originality (IO) and proxies of valuation uncertainty (VU), investor attention, the sensitivity of future profitability to IO, and innovative efficiency (IE). In Panel A, we proxy VU by a composite index of firm age and opacity of financial reports (standardized opacity minus standardized age). In Panel B, we proxy attention by a composite index of analyst-to-size (ATS) and post-earnings-announcement drift (PEAD) scaled by earnings surprise (standardized ATS minus standardized PEAD/earnings surprise). In Panel C, we proxy the sensitivity by a composite index of size and book-to-market (BTM) (standardized size minus standardized BTM). IE and IO are defined as in Table I. The IO portfolios are formed as in Table IV. The IE and VU portfolios are based on tercile breakpoints. The attention and sensitivity portfolios are based on NYSE tercile breakpoints. The Low (High) index portfolio refers to the bottom (top) 30%. We also construct a high-minus-low IO portfolio in each index or IE group and hold these portfolios for the next 12 months. For each portfolio, we report monthly value-weighted excess return (Exret), industry-adjusted returns (Ind-adjret), characteristic-adjusted returns (Char-adjret), and alphas from different factor models as defined as in Table IV. All returns and alphas are in percentage. The sample period is from 1982 to 2007 except for attention index, which starts from 1983 due to sparsity of analyst forecast data before 1983.

Panel A. Return predictive power of IO and valuation uncertainty (VU)

		Excess returns and adjusted returns			Alphas from different factor models				
VU	IO	Exret	Ind-adjret	Char-adjret	4F	4F + IMC	4F + LIQ	4F + RMW + CMA	4F + EMI
Low	Low	0.66	-0.04	0.03	-0.07	-0.08	-0.07	-0.19	0.03
		(2.68)	(-0.67)	(0.13)	(-0.61)	(-0.71)	(-0.64)	(-1.72)	(0.26)
	Middle	0.74	0.03	0.06	0.13	0.12	0.14	0.08	0.08
		(3.06)	(0.50)	(0.29)	(1.66)	(1.61)	(1.77)	(1.07)	(1.06)
	High	0.73	0.05	0.12	0.12	0.10	0.12	-0.08	0.12
		(3.17)	(0.79)	(0.56)	(0.98)	(0.88)	(1.01)	(-0.69)	(1.05)
	High-Low	0.07	0.09	0.09	0.18	0.18	0.19	0.11	0.10
		(0.51)	(1.02)	(0.67)	(1.23)	(1.21)	(1.26)	(0.74)	(0.65)
High	Low	0.23	-0.45	-0.43	-0.23	-0.17	-0.19	0.15	-0.18
		(0.47)	(-2.15)	(-0.99)	(-0.96)	(-0.73)	(-0.79)	(0.61)	(-0.75)
	Middle	0.89	0.10	0.22	0.40	0.43	0.44	0.67	0.34
		(1.95)	(0.44)	(0.51)	(1.43)	(1.56)	(1.57)	(2.28)	(1.21)
	High	1.32	0.54	0.74	0.84	0.87	0.89	1.00	0.80
		(2.60)	(2.02)	(1.52)	(2.77)	(2.73)	(2.82)	(3.08)	(2.84)
	High-Low	1.10	0.99	1.17	1.07	1.04	1.08	0.85	0.98
		(3.88)	(3.66)	(3.84)	(3.07)	(2.93)	(3.10)	(2.38)	(3.01)

Panel B. Return predictive power of IO and investor attention (ATT)

		Excess returns and adjusted returns			Alphas from different factor models				
ATT	IO	Exret	Ind-adjret	Char-adjret	4F	4F + IMC	4F + LIQ	4F + RMW + CMA	4F + EMI
Low	Low	0.40	-0.23	-0.26	-0.22	-0.21	-0.29	-0.16	-0.16
		(1.22)	(-1.89)	(-0.91)	(-1.26)	(-1.22)	(-1.57)	(-0.88)	(-0.85)
	Middle	0.71	0.09	0.11	0.16	0.17	0.16	0.16	0.00
		(2.35)	(1.02)	(0.39)	(1.20)	(1.25)	(1.25)	(1.21)	(-0.01)
	High	0.99	0.32	0.37	0.51	0.50	0.49	0.40	0.49
		(2.89)	(2.35)	(1.08)	(2.49)	(2.49)	(2.34)	(1.97)	(2.36)
	High-Low	0.60	0.55	0.63	0.73	0.72	0.78	0.56	0.65
		(2.36)	(3.03)	(2.57)	(2.66)	(2.64)	(2.71)	(2.03)	(2.27)
High	Low	0.85	0.17	0.14	0.17	0.18	0.18	0.33	0.15
		(2.02)	(0.76)	(0.37)	(1.03)	(1.10)	(1.10)	(1.98)	(0.91)
	Middle	0.87	0.20	0.07	0.03	0.03	0.08	0.06	-0.03
		(2.14)	(0.93)	(0.21)	(0.13)	(0.17)	(0.36)	(0.32)	(-0.13)
	High	0.98	0.16	0.32	0.41	0.41	0.44	0.44	0.35
		(2.46)	(0.79)	(0.87)	(2.15)	(2.15)	(2.22)	(2.29)	(1.89)
	High-Low	0.13	-0.01	0.17	0.24	0.23	0.25	0.11	0.20
		(0.64)	(-0.06)	(0.79)	(1.27)	(1.22)	(1.25)	(0.58)	(1.04)

Panel C. Return predictive power of IO and sensitivity of future profitability to IO (Sen)

		Excess returns and adjusted returns			Alphas from different factor models				
Sen	IO	Exret	Ind-adjret	Char-adjret	4F	4F + IMC	4F + LIQ	4F + RMW + CMA	4F + EMI
Low	Low	0.66	0.00	0.02	-0.17	-0.13	-0.17	0.08	-0.14
		(1.88)	(-0.02)	(0.06)	(-1.00)	(-0.88)	(-1.04)	(0.60)	(-0.89)
	Middle	0.88	0.22	0.12	0.10	0.10	0.16	0.03	0.08
		(2.92)	(1.43)	(0.43)	(0.55)	(0.54)	(0.86)	(0.17)	(0.46)
	High	0.77	0.09	0.14	-0.06	-0.09	-0.02	-0.14	-0.07
		(2.36)	(0.54)	(0.47)	(-0.33)	(-0.47)	(-0.11)	(-0.78)	(-0.37)
	High-Low	0.11	0.09	0.12	0.11	0.05	0.15	-0.22	0.07
		(0.52)	(0.50)	(0.64)	(0.52)	(0.24)	(0.75)	(-1.10)	(0.31)
High	Low	0.42	-0.23	-0.13	-0.14	-0.13	-0.14	-0.10	-0.04
		(1.43)	(-3.06)	(-0.48)	(-1.30)	(-1.24)	(-1.35)	(-0.93)	(-0.41)
	Middle	0.72	0.02	0.07	0.19	0.19	0.19	0.20	0.12
		(2.77)	(0.42)	(0.28)	(2.81)	(2.78)	(2.77)	(2.86)	(1.83)
	High	0.75	0.06	0.18	0.26	0.26	0.25	0.22	0.21
		(2.86)	(0.99)	(0.70)	(2.51)	(2.50)	(2.31)	(2.04)	(1.96)
	High-Low	0.33	0.29	0.30	0.40	0.39	0.39	0.32	0.25
		(2.11)	(2.76)	(2.05)	(2.56)	(2.49)	(2.48)	(1.97)	(1.64)

Panel D. Return predictive power of IO and innovative efficiency (IE)

		Excess returns and adjusted returns			Alphas from different factor models				
IE	IO	Exret	Ind-adjret	Char-adjret	4F	4F + IMC	4F + LIQ	4F + RMW + CMA	4F + EMI
Low	Low	0.57	-0.10	-0.05	-0.05	-0.04	-0.03	0.03	0.04
		(1.87)	(-1.22)	(-0.17)	(-0.46)	(-0.39)	(-0.33)	(0.29)	(0.43)
	Middle	0.80	0.04	0.14	0.12	0.13	0.17	0.16	0.14
		(2.96)	(0.46)	(0.55)	(1.17)	(1.22)	(1.54)	(1.50)	(1.27)
	High	0.67	0.01	0.03	0.11	0.12	0.12	0.09	0.16
		(2.23)	(0.15)	(0.11)	(0.71)	(0.73)	(0.74)	(0.57)	(1.00)
	High-Low	0.10	0.12	0.08	0.16	0.16	0.15	0.06	0.11
		(0.65)	(1.00)	(0.48)	(1.00)	(0.97)	(0.90)	(0.36)	(0.71)
High	Low	0.39	-0.26	-0.31	-0.07	-0.04	-0.12	0.20	-0.27
		(0.91)	(-1.30)	(-0.82)	(-0.36)	(-0.17)	(-0.58)	(0.90)	(-1.38)
	Middle	0.89	0.06	0.16	0.44	0.45	0.40	0.51	0.23
		(2.74)	(0.48)	(0.53)	(2.55)	(2.59)	(2.27)	(2.70)	(1.40)
	High	1.17	0.32	0.48	0.63	0.64	0.55	0.73	0.46
		(3.06)	(1.94)	(1.28)	(3.05)	(3.05)	(2.63)	(3.41)	(2.34)
	High-Low	0.78	0.57	0.80	0.70	0.67	0.67	0.53	0.73
		(2.92)	(2.29)	(2.92)	(2.79)	(2.60)	(2.56)	(2.03)	(2.84)

Table VII
Conditioning Return Predictive Power of Innovative Originality – Fama-MacBeth Regressions

This table reports the average slopes (in %) and their time series heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions as in Model 2 of Table V within subsamples split by valuation uncertainty (VU), investor attention (ATT), and the sensitivity of future profitability to IO in Panels A, B, and C, respectively. All variables are defined as in Table V.

Panel A. Return predictive power of IO and valuation uncertainty (VU)

VU	IO	Size	BTM	MOM	InstOwn	ILLIQ	REV	AG	IA	IE	CTA	RDME	NS	ROA	IVOL	TSKEW
Low	0.01	-0.08	0.13	0.14	-0.06	-0.07	-0.56	-0.14	-0.17	0.10	0.01	0.07	-0.01	0.07	0.26	-0.09
	(0.19)	(-0.69)	(1.38)	(1.26)	(-0.88)	(-0.57)	(-5.75)	(-1.94)	(-1.82)	(1.76)	(0.12)	(1.21)	(-0.21)	(0.85)	(1.82)	(-1.38)
High	0.27	-0.29	0.21	-0.03	0.17	0.45	-1.19	-0.28	0.24	0.16	0.12	0.28	-0.15	0.20	0.45	-0.19
	(2.66)	(-1.55)	(1.69)	(-0.15)	(1.48)	(2.04)	(-7.28)	(-2.95)	(2.07)	(1.62)	(1.35)	(2.33)	(-1.25)	(2.00)	(2.11)	(-1.92)
High-Low	0.26	-0.21	0.08	-0.17	0.23	0.52	-0.63	-0.14	0.41	0.05	0.11	0.21	-0.14	0.13	0.19	-0.09
	(2.20)	(-1.10)	(0.57)	(-1.05)	(1.80)	(2.11)	(-4.05)	(-1.16)	(2.85)	(0.46)	(1.14)	(1.76)	(-0.99)	(1.13)	(0.89)	(-0.86)

Panel B. Return predictive power of IO and investor attention (ATT)

ATT	IO	Size	BTM	MOM	InstOwn	ILLIQ	REV	AG	IA	IE	CTA	RDME	NS	ROA	IVOL	TSKEW
Low	1.22	-1.36	2.77	0.33	1.81	-14.05	-0.24	0.56	0.53	-0.28	1.06	1.21	-0.74	0.27	2.98	2.90
	(2.18)	(-0.71)	(1.05)	(0.58)	(1.38)	(-0.81)	(-0.72)	(0.95)	(0.64)	(-0.96)	(0.94)	(0.68)	(-2.21)	(1.07)	(1.23)	(0.88)
High	0.02	0.03	0.65	0.25	0.23	0.52	-1.04	-0.19	-0.02	0.13	0.10	0.03	-0.04	0.22	0.57	-0.16
	(0.23)	(0.18)	(4.06)	(1.64)	(1.98)	(1.99)	(-7.31)	(-1.57)	(-0.14)	(1.16)	(1.25)	(0.21)	(-0.33)	(1.38)	(2.61)	(-1.83)
Low-High	1.20	-1.40	2.12	0.07	1.58	-14.58	0.80	0.75	0.55	-0.41	0.96	1.19	-0.69	0.05	2.41	3.05
	(2.14)	(-0.72)	(0.80)	(0.14)	(1.20)	(-0.84)	(2.22)	(1.28)	(0.66)	(-1.41)	(0.85)	(0.67)	(-2.09)	(0.18)	(1.01)	(0.93)

Panel C. Return predictive power of IO and sensitivity of future profitability to IO (Sen)

Sen	IO	Size	BTM	MOM	InstOwn	ILLIQ	REV	AG	IA	IE	CTA	RDME	NS	ROA	IVOL	TSKEW
Low	-0.04	-0.18	-0.05	0.04	-0.08	0.21	-1.06	-0.25	0.07	0.13	0.02	0.22	-0.02	0.25	0.48	-0.12
	(-0.45)	(-1.31)	(-0.65)	(0.43)	(-1.06)	(1.26)	(-10.21)	(-2.48)	(0.60)	(1.88)	(0.36)	(2.77)	(-0.16)	(2.59)	(3.09)	(-1.63)
High	0.21	0.04	0.17	0.00	0.15	2.05	-1.07	-0.34	0.02	0.16	0.04	0.21	-0.11	0.29	0.13	-0.14
	(2.84)	(0.22)	(1.73)	(0.03)	(1.71)	(2.42)	(-8.52)	(-3.58)	(0.22)	(2.91)	(0.55)	(2.55)	(-1.25)	(2.66)	(0.57)	(-1.75)
High-Low	0.24	0.22	0.21	-0.04	0.23	1.84	-0.01	-0.08	-0.05	0.03	0.02	-0.01	-0.09	0.04	-0.35	-0.01
	(2.27)	(1.09)	(1.88)	(-0.34)	(2.14)	(2.12)	(-0.08)	(-0.60)	(-0.31)	(0.34)	(0.25)	(-0.09)	(-0.60)	(0.29)	(-1.58)	(-0.12)

Figure 1. High-minus-Low IO Portfolio Returns versus Market Excess Returns

Figure 1 plots the return on the high-minus-low IO portfolio and the market premium (MKT) on a per annum basis from July of 1982 to June of 2008. MKT is the return on the value-weighted NYSE/AMEX/NASDAQ portfolio in excess of the one-month Treasury bill rate. There are only six months in 1982 and 2008.