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Innovative Originality, Profitability, and Stock Returns*

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Innovative Originality, Profitability, and Stock Returns

We propose that innovative originality is a valuable organizational resource, and that owing to limited investor attention and skepticism of complexity, greater innovative originality may be undervalued. We find that firms' innovative originality strongly predicts higher, more persistent, and less volatile profitability; and higher abnormal stock returns—findings that are robust to extensive controls. The return predictive power of innovative originality is stronger for firms with higher valuation uncertainty, lower investor attention, and greater sensitivity of future profitability to innovative originality. This evidence suggests that innovative originality acts as a 'competitive moat,' and is undervalued by the market.

JEL Classification: G11, G12, G14, O32

Keywords: Limited attention, Market efficiency, Processing fluency, Innovative originality, Complexity, Ambiguity aversion

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, complex and hard-to-process information. A type of information that is especially hard to evaluate is the originality of an innovation, which involves many dimensions of uncertainty that typically require extensive knowledge and expertise to evaluate. We therefore suggest that investors tend to neglect/underweight the information contained in proxies for innovative originality.

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 due to signal jamming. Hence stock prices would underweight innovative originality, which may contain favorable information about future profitability; and innovative originality is a positive predictor of future abnormal stock returns. To formalize this intuition and to motivate empirical analyses, we test the implications of a model of limited attention (see the Internet Appendix, Section D) about the direction and strength of the return predictive power of innovative originality. In the model,

[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).

innovative originality predicts high subsequent abnormal returns if it is positively associated with a firm's future profitability and a fraction of investors neglects innovative originality.[2]

Furthermore, the model predicts that this return predictive power is strengthened by valuation uncertainty, the fraction of inattentive investors, and the sensitivity of future profitability to innovative originality. 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 innovative originality. In addition, when prior uncertainty about the stock value (without any conditioning on innovative originality) is higher, heavier weight should optimally be placed on innovative originality by investors in forming posterior beliefs about value. So neglect of innovative originality causes greater mispricing. Similarly, the more sensitive a firm's future profitability is to innovative originality, the greater the mispricing induced by neglect of the signal.

Empirically, motivated by a popular view of innovation as recombinant search, we measure innovative originality by the breadth of knowledge used to innovate. Under this view, innovation comes from combining technological components in novel manners or reconfiguring existing combinations.[3] The discovery of the double helix structure of DNA by Francis Crick and James Watson illustrates the recombinant view. It was Crick's knowledge of X-ray crystallography that helped Watson understand the famous X-ray diffraction image of DNA (known as "Photo 51" discovered by Rosalind Franklin), which is crucial to their successful modeling of the double helix structure of DNA.[4] Since patents are widely used to measure innovation, we proxy a firm's innovative originality by the average range of knowledge built upon by its recently granted patents.

[2] As discussed in Section 3, models of ambiguity aversion provide a reinforcing argument for a positive innovative originality-return relation.
[3] See, e.g., Schumpeter (1934), Basalla (1988), Henderson and Clark (1990), Weitzman (1998), Ahuja and Katila (2001), and Singh and Fleming (2010).
[4] https://en.wikipedia.org/wiki/Francis_Crick#Crick1990, https://en.wikipedia.org/wiki/Photo_51, and https://www.youtube.com/watch?v=d7ET4bbkTm0 (36:03 to 36:47).

Intuitively, a patent that draws knowledge from a wide range of technology is more original because it tends to deviate from current technology trajectories to a greater extent (e.g., Balsmeier, Fleming, and Manso 2017). Innovative originality may also reflect the capability of a firm's managers and scientists to combine different technologies in an original way to create a sustainable competitive advantage.

To capture the range of knowledge built upon, we use the number of unique technological classes of patents cited by a firm's patents. If a firm's patents cite previous patents belonging to a wide set of technologies, its originality score will be high. Motivated by the view of innovation as recombinant search, the innovation/corporate finance literature has measured the originality of a patent by one minus the Herfindahl index of patents cited by the focal patent across different technological classes.[5] However, to better capture the cross-sectional variation in knowledge breadth that motivates this measure, we focus on the average number of unique technological classes of patents cited by a firm's recently granted patents (more details are provided in Section 1).

In particular, the range of knowledge captured by the number of unique technological classes may matter more in driving innovative originality than the distribution of patents cited among different classes captured by the Herfindahl index. When a patent cites only one patent from a certain class, knowledge from that class can still play a crucial role in making this focal patent original. Consider the case of Affymetrix, a pioneer of the development of DNA microarray techniques (see the Appendix). Knowledge about semiconductors, electricity, and optics is crucial for its innovative methods. However, the number of patents cited in these classes by Affymetrix's

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[5] See, e.g., Trajtenberg, Henderson, and Jaffe (1997), Hall, Jaffe, and Trajtenberg (2001), Lerner, Sorensen, and Strömberg (2011), and Custodio, Ferreira, and Matos (2013).

major patents is quite small.[6] The importance of these few patents cited is better captured by the number of unique technological classes than by one minus the Herfindahl index.

A literature in strategy 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 (sometimes called a competitive moat) that other firms have difficulty in replicating or matching, and helps firms deal with rapid technological change. In addition, when a firm is more experienced in integrating various knowledge sources, it is better at identifying and exploiting future innovation opportunities.[7]

Therefore, high innovative originality firms may generally outperform their competitors persistently due to the market power provided by original innovations. Consistent with this intuition, we find that high innovative originality firms have substantially and significantly higher future profitability up to five years (see the Internet Appendix, Section E). Furthermore, these firms have more persistent and stable future profitability. We also find that the influence of innovative originality on these aspects of future profitability is much stronger than that of innovative efficiency (Hirshleifer, Hsu, and Li 2013) and works (at least in part) through its effect on gross margin.

Greenwald et al. (2004) argue that value investors seldom place much weight on a firm's growth prospects in forming valuations as such prospects are only reliable within a protected franchise that offers sustainable competitive advantage. They argue that such advantage comes in

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[6] For example, Patent 6,965,020, which protects Affymetrix's major product line, GeneChip®, only cites *one* patent from each of the 'semiconductor' (Class 250) and 'optics' (Class 356) classes. It cites 30 patents from 19 unique classes (both primary and secondary) in total.

[7] See, e.g., Levin et al. (1987), Henderson and Cockburn (1994), Gupta and Govindarajan (2000), Martin and Salomon (2003), Subramaniam and Youndt (2005), Singh (2008), Makri, Hitt, and Lane (2010), Gomez-Mejia et al. (2011), and Berry (2014).

only a few forms (patents being one of the few), and that, perhaps for competitive reasons, firms tend to remain quiet about their 'moats.' This makes it hard for investors to differentiate companies that have genuine franchises from those that do not. This argument suggests that investors with limited attention—even value investors who are performing fundamental analysis—may tend to undervalue competitive moats.

To test the prediction on the return predictive power of innovative originality, we perform portfolio sorts and Fama-MacBeth (1973) cross-sectional regressions. The results are supportive. For portfolio analysis, the average portfolio returns increase monotonically with innovative originality, and the return spread between the high and low innovative originality portfolios is economically substantial. The pattern is robust to industry- and characteristic-adjustment (by size, book-to-market, and momentum) and recently developed risk benchmarks and mispricing factor models.[8] Furthermore, the innovative originality effect remains substantial and significant even after controlling for the patents- or citations-based innovative Efficient-Minus-Inefficient (EMI) factor that reflects commonality in mispricing associated with innovative efficiency (IE).

The theory predicts that innovative originality -induced mispricing should be more severe among harder-to-value firms. Consistent with this, independent double sorts show that the monthly value-weighted alphas for the high-minus-low innovative originality portfolio among firms with high valuation uncertainty (VU) index range from 0.82% (t = 2.38) to 1.08% (t = 3.10), depending on the factor model. The monthly industry- and characteristic-adjusted returns for this spread portfolio are also very large: 0.99% (t = 3.66) and 1.17% (t = 3.84), respectively. Furthermore,

[8] These models include the q-factor model (Hou, Xue, and Zhang 2015), the mispricing factor model (Stambaugh and Yuan 2017), the Fama and French three-factor model augmented with the momentum (UMD) factor as in Carhart (1997) (henceforth, the Carhart model), and the Carhart model augmented with one of the following factors: the Investment-Minus-Consumption (IMC) factor (Papanikolaou 2011), the liquidity (LIQ) factor (Pastor and Stambaugh 2003), the Undervalued-Minus-Overvalued (UMO) factor (Hirshleifer and Jiang 2010), the Robust-Minus-Weak (RMW) factor, and the Conservative-Minus-Aggressive (CMA) factor (Fama and French 2015).

these results are mainly driven by the undervaluation of high innovative originality firms. In contrast, these returns are tiny and insignificant for low VU firms. Since R&D is a crucial input for generating innovation and to the extent that firms that invest heavily in R&D are also harder to value due to the uncertain nature of R&D investment, we expect the innovative originality effect to be stronger among high R&D firms. This is confirmed in the data. We also confirm that this innovative originality effect is stronger among firms with less investor attention (ATT) or higher sensitivity (Sen) of future profitability to innovative originality, as implied by the theory.

High innovative originality firms on average are larger. Other things equal, we expect large firms to receive greater investor attention, which tends to reduce misvaluation. However, large firms are also generally more complex, making them harder to value (e.g., Cohen and Lou 2012). It is not clear whether this additional attention outweighs complexity to make the valuation of the innovative originality of large firms more accurate. In fact, the return predictive power of innovative originality exists in both small and big firms and does not have a significant interaction with size.

To assess the robustness of the return predictive power of innovative originality, we perform Fama-MacBeth regressions that control for industry effects and different sets of well-known return predictors, including sales diversity and innovation-related variables such as IE, patents, and R&D. The innovative originality effect remains statistically significant, irrespective of the control variables used. Similar to the double sorts, we also perform Fama-MacBeth regressions in subsamples split by VU, ATT, and Sen. The same sharp contrast in the innovative originality effect exists across these subsamples.

Although the evidence is consistent with the limited attention theory, we do not completely rule out potential risk-based explanations (see further discussion in Section 3.5). Previous research on valuation of innovation focuses on innovative input, output, and efficiency.[9] However, this literature does not examine the role of innovative originality. Our paper is also closely related to the literature on how limited attention and processing power affect security prices.[10]

1. The Data, the Innovative Originality Measure, and Summary Statistics

1.1 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), and utility firms (SIC codes beginning with 49). 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 earnings forecast data from the Institutional Brokers Estimate System (IBES), and institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database.

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[9] See, e.g., Griliches (1990), Lerner (1994), Lev and Sougiannis (1996), Deng, Lev, and Narin (1999), Chan, Lakonishok, and Sougiannis (2001), Eberhart, Maxwell, and Siddique (2004), Lanjouw and Schankerman (2004), Gu (2005), Lev, Sarath, and Sougiannis (2005), Hsu (2009), Li (2011), Cohen, Diether, and Malloy (2013), and Hirshleifer, Hsu, and Li (2013).

[10] 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). Empirical studies provide supporting evidence (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 and Warachka 2011; Cohen and Lou 2012; Li and Yu 2012; Da, Gurun, and Warachka 2014).

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 application and grant dates, 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 proxy a firm's innovative originality (InnOrig) by the range of knowledge its innovations draw upon, specifically, the average number of unique technological classes of patents cited by its recently granted patents. Until November 2000, the USPTO did not disclose a patent application until it was approved. The gap between application and approval is on average two years. Failed patent applications were also not disclosed. Subsequent to the American Inventors Protection Act, which became effective on November 30, 2000, the USPTO began publishing patent applications 18 months after the filing date, even if the patents had not yet been granted. In contrast, the patent granting decision is published every Tuesday by the USPTO and is immediately available to the public. Therefore, we use recently granted patents instead of filed patent applications to measure a firm's InnOrig to ensure that investors can observe this originality measure at the time of portfolio formation and avoid look-ahead bias in our sample (1976-2006).

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 InnOrig in each year with the average originality score of all patents granted to the firm over the previous five years. A case example of innovative originality of Incyte in 1996 is provided in Section B of the Internet Appendix.[11] Averaging across patents helps reduce the influence of extreme values and the correlation between the InnOrig measure and firm size. Furthermore, we choose a five-year rolling window since not all firms have patents granted every year.[12] As a result, the firm-level InnOrig measure is available from 1980 to 2006. We begin our sample from 1981 as we need to control for the innovative efficiency measures, which are not available until 1981.

Compared to the Herfindahl index-based innovative originality measure proposed in Hall, Jaffe, and Trajtenberg (2001), our measure reflects the breadth of knowledge built upon by a firm's innovation more directly. The Herfindahl index (also known as the Herfindahl–Hirschman index, or HHI) mainly reflects the distribution of patents cited among different classes conditioning on the number of technological classes cited. This difference can be illustrated by a stylized example. Assume Patent 1 cites one patent from each of ten different technology classes, while Patent 2 cites one patent from each of five different classes. Since both patents cite an equal number of patents from different classes, they have very similar HHI-based innovative originality measures as proposed in Hall et al. (2001): 0.9 for Patent 1, and 0.8 for Patent 2. However, the range of knowledge drawn upon by Patent 1 doubles that of Patent 2: 10 versus 5.[13]

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[11] Incyte received 12 granted patents in the five-year period 1992-1996. The number of unique technology classes (*N*) of patents cited by these patents ranges from 1 to 6. By averaging *N* across these 12 patents, we obtain Incyte's InnOrig in 1996, 3.67.

[12] The choice of a five-year window for patent-based proxies is common in the literature (e.g., Deng, Lev, and Narin 1999; Rothaermel and Deeds 2004; Matolcsy and Wyatt 2008; Pandit, Wasley and Zach 2011).

[13] Section C of the Internet Appendix discusses the results using a modified HHI-based innovative originality measure.

Our InnOrig measure is significantly positively correlated with the average number of future citations a firm's patents receive, a measure of innovation novelty in Seru (2014).[14] The product uniqueness measure 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 InnOrig measure is based on patents, which is related to innovation that affects future product lines. As a forward-looking measure, InnOrig 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 InnOrig measure does.

Since InnOrig relies on the list of patents cited by the focal patent, its validity depends upon the extent the citation list is complete and relevant. 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 their applications.[15] 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; Roach and Cohen 2013). Even if a patent is granted, its validity could still be challenged if its citation list misses prior arts (Allison and Lemley 1998; 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

[14] The Pearson correlation between the two measures 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 InnOrig 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.

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

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. In fact, a substantial amount of patents cited by granted patents are added upon request of patent examiners: 62% in the sample of Sampat (2010) and 41% in the sample of Thompson (2006).

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 in fact 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 patent data to measure InnOrig 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 invention to apply for patents and firms with unsuccessful patent applications, both of which should be categorized as low InnOrig 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 InnOrig. (Excluding these firms generate stronger results in portfolio sorts as discussed later.) We also include firms with no R&D expenses over the last five years as a comparison group.

1.2 Summary statistics

Table 1 reports the pooled summary statistics of the InnOrig measure for firms (with non-zero patents granted over the last five years) in typical innovation-driven industries based on the Fama and French (1997) 48 industry classifications.[16] There is large cross-sectional variation in InnOrig within these industries. The 30th percentile is around 4, the 70th percentile is around 8, and the 95th percentile ranges from 10 to 18 across these industries. However, the time-series average of the cross-section of InnOrig across all firms with nonmissing InnOrig is more even (untabulated). The 30th, 70th, and 95th percentiles are 4, 6, and 11, respectively.

Although there is significant within-industry variation in InnOrig, the cross-industry variation in InnOrig is quite small. Specifically, the within-industry coefficient of variation (CV) for InnOrig 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) InnOrig. 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 InnOrig measure as detailed later.

In Table 2 (Panel A), we report average InnOrig and other characteristics (both raw value and percentile ranks) that are known to predict stock returns for the InnOrig portfolios formed (at the end of June of year *t*) based on the 30th and 70th percentiles of InnOrig in year $t - 1$. We also assign firms with positive R&D expenses but no patents granted over the last five years to the low InnOrig

[16] The variation in InnOrig across the Fama and French 48 industries is larger than that across these typical R&D-intensive industries. Therefore, we control for industry effects in all the tests.

portfolio.[17] Intuitively, firms with positive R&D expenses have low innovative originality if they do not have any patents granted as explained earlier. Firms with no R&D expenses over the last five years are assigned to the "No" group.

On average, there are 4671 firms in the sample, 2462 of which are in the "No" group. The three InnOrig portfolios (Low, Middle, and High) are well diversified, with the average number of firms ranging from 409 to 1283. The cross-sectional variation in InnOrig is large, ranging from 3.02 to 9.78 for the three InnOrig portfolios. The average size (market capitalization at the end of each June) of the low, middle, and high InnOrig portfolios is $702 million, $4,334 million, and $2,033 million, respectively. Furthermore, firms in the three InnOrig portfolios cover 67% 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 InnOrig portfolios. There is no clear relation between InnOrig and total skewness (SKEW, 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 InnOrig 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 citations- and patents-based innovative efficiency (CIE and PIE 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

[17] For the low InnOrig portfolio, average InnOrig is based on firms with at least one patent granted over the past five years, while the averages of other characteristics reported are based on all firms assigned to the portfolio.

year t – 1).[18] 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), short-term reversal (REV, lagged monthly stock return), number of sales segments (NSD, the number of sales segments based on Fama-French 48 industry classifications over year t – 5 to year t – 1), and one minus the Herfindahl index of segment sales (HHISD, based on Fama-French 48 industry classifications over year t – 5 to year t – 1). However, these characteristics do not vary much across the InnOrig portfolios except contemporaneous ROA and ROE. The high InnOrig group has the second lowest contemporaneous ROA and ROE.

We report the time series averages of cross-sectional correlations between InnOrig and these characteristics in Panel B of Table 2. Consistent with Panel A, InnOrig does not strongly correlate with these characteristics. In particular, the Pearson correlations between InnOrig and size, citations- and patents-based innovative efficiency, the number of sales segments, and the HHI-

[18] Citations-based innovative efficiency measure (CIE) in year t – 1 is adjusted patent citations received in year t – 1 by patents granted to a firm in years t – 2 to t – 6 scaled by the sum of R&D expenses in years t – 4 to t – 8. The adjusted citations in year t – 1 to patent k are citations to patent k in year t – 1 divided by the mean citations to patents of the same subcategory and grant year group in year t – 1. Patents-based innovative efficiency measure (PIE) in year t – 1 is patents granted to a firm in year t – 1 scaled by research and development (R&D) capital in year t – 3, computed as the five-year cumulative R&D expenses from year t – 7 to year t – 3 with a 20% annual depreciation.

based sales diversity are only –0.01, 0.13, 0.06, –0.03, and –0.03, respectively. The corresponding Spearman rank correlations are also very low.

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

1.3 Autocorrelations of innovative originality and mispricing

Our use of a rolling window to construct InnOrig follows the literature on the return predictive ability of R&D and patent-related variables, as mentioned earlier. InnOrig has moderate persistence beyond the first lag at the firm level. The cross-sectional average autocorrelations between InnOrig in year t and InnOrig in years $t-1$, $t-2$, $t-3$, $t-4$, and $t-5$ are 0.62, 0.43, 0.32, 0.23, and 0.08, respectively. Since we focus on InnOrig ranking in portfolio sorts, the average autocorrelations between InnOrig tercile ranks in year t and InnOrig tercile ranks in years $t-1$, $t-2$, $t-3$, $t-4$, $t-5$ are 0.52, 0.28, 0.12, –0.02, and –0.18, respectively. Correspondingly, the number of migrators within one year is quite low; there are on average 61 (56) firms that move to the top (bottom) tercile each year.

As discussed earlier, high InnOrig firms may outperform their competitors persistently due to the market power associated with original innovations. Generally, if a firm constantly adapts its innovation strategy by incorporating more diverse technology, then it is likely to rank persistently high in InnOrig and is protected against lagging behind. For example, Affymetrix persistently ranked high in InnOrig by constantly innovating based upon a wider range of technology than its competitors. Correspondingly, Affymetrix outperformed its competitors and was acquired by Thermo Fisher Scientific for approximately $1.3 billion in March 2016.

On the other hand, if a firm does not adapt to new technology trends or other firms' shifts in innovation strategy, then it is likely to lag behind and experience a drop in its InnOrig rank. An example of a firm with large shifts in InnOrig rank is Respironics, a leading manufacturer of medical devices used primarily for the treatment of respiratory disorders. When Respironics' InnOrig increased/dropped substantially relative to other firms, its profitability increased/declined correspondingly (see Section A of the Internet Appendix for more details). Since the raw value of Respironics' InnOrig did not change that much over time, these changes in Respironics' InnOrig rank may be partly owing to shifts in any given firm's innovation strategy or shifts in technology trends.

However, for several reasons, persistence in InnOrig rank does not necessarily mean that conclusive corrective information about the cash flows of high InnOrig firms will arrive quickly. InnOrig is constructed based upon patent information instead of product information. Therefore, these patents may not generate cash flows for the firm quickly; the road from patent being granted to the patent-protected products generating cash flows could take years, and is subject to technical and market uncertainty. Some other examples in the innovation literature also suggest slow correction. For example, Lev and Sougiannis (1996) show that five-year accumulated R&D expenditures (scaled by market equity) positively predict abnormal stock returns in the subsequent year. Chambers et al. (2002) and Ciftci et al. (2011) find that five-year accumulated scaled R&D expenditures positively predict abnormal stock returns for up to ten years.

Furthermore, a firm can be persistently undervalued and have persistently high expected returns indefinitely. For example, Hong and Kacperczyk (2009) show that "sin" stocks (sin being a persistent trait) tend to be undervalued and have higher expected returns than otherwise-comparable stocks.

2. Innovative Originality and Future Profitability

In this section, we examine whether InnOrig contains favorable information about a firm's future profitability to verify the key assumption of the limited attention theory and the competitive advantage associated with InnOrig. In particular, we conduct annual Fama-MacBeth regressions to study the relation between InnOrig and different aspects of future profitability: the persistence and the volatility. To explore the channel of this association, we also examine the relation between InnOrig and gross margin.

2.1 InnOrig and persistence of future profitability

To explore the effect of InnOrig on the persistence of future profitability (measured by return on equity or return on assets), we examine the interaction between InnOrig and mean reversion of profitability. Specifically, following Fama and French (2000), we conduct annual cross-sectional regressions of next year's change in profitability on InnOrig, change in profitability, interaction between InnOrig and change in profitability, interaction between IE and change in profitability, and other control variables (profitability, market-to-book assets, advertising expenses, capital expenditure, R&D, innovative efficiency, and industry effects). We set missing values for InnOrig, IE, advertising expenses, and R&D expenses to zero. We also control for a dummy variable that equals one for firms with no R&D expenses over the last five years, and the interactions of this dummy with all the other control variables.[19] To reduce the influence of outliers and facilitate the interpretation, we winsorize all variables at the 1% and 99% levels and standardize all independent

[19] This dummy variable allows us to include firms with no valid InnOrig measures so that we can take advantage of the power of the full cross-section to make the coefficient estimates on the control variables more reliable. If we do not include these firms, the results are similar, albeit weaker for some of them, as expected.

variables (except the dummies) to zero mean and one standard deviation. For brevity, we omit the slopes on the industry dummies, the dummy for firms with no R&D and its interactions with other control variables in the tabulation of results. The focus is the slope on the interaction between InnOrig and change in profitability.

We report the results for ROE and ROA in Panels A1 and A2 of Table 3, respectively. In each panel, we control for citations-based IE (CIE) on the top and patents-based IE (PIE) at the bottom. The slopes on the interaction between InnOrig and change in profitability are significantly positive at the 1%, 5% or 10% level. The magnitude is substantial, regardless which type of IE we control for. For example, in the top row of Panel A1, the slope on $InnOrig_t*\Delta ROE_t$ is 1.97% (t = 3.49). Since the slope on ΔROE_t is –13.57%, this implies that a one standard deviation increase in InnOrig slows down the mean reversion of ROE by 14.52% relative to a firm with zero InnOrig and zero CIE. These results indicate that firms with high InnOrig exhibit significantly slower mean reversion, which is consistent with the intuition that high InnOrig allows firms to maintain competitive advantage and sustainable profitability.

In contrast, the effect of IE on the mean reversion of profitability is unclear. For example, in the top row of Panel A1, the slope on $CIE_t*\Delta ROE_t$ is –0.92% (t = –1.69); on the other hand, in the bottom row of the same panel, the slope on $PIE_t*\Delta ROE_t$ is 1.62% (t = 2.49). Combined with the insignificant slopes on IE and significant slopes on InnOrig (see the Internet Appendix, Section E) when we regress the level of future ROA/ROE on InnOrig and IE, these results illustrate the distinctiveness between IE and InnOrig in determining firms' fundamentals.

2.2 Innovative originality and volatility of future profitability

In addition, if high InnOrig allows a firm to maintain sustainable profitability, we expect that high InnOrig is associated with less volatile future profitability. Therefore, following Kothari, Laguerre, and Leone (2002), we conduct annual cross-sectional regressions of volatility of profitability over the next five years on InnOrig, the volatility of profitability over the past five years, and other control variables.[20] The methodology of treating missing variables is the same as above. Similarly, for brevity, we omit the slopes on the industry dummies, the dummy for firms with no R&D and its interactions with other control variables. The focus is the slope on InnOrig.

We report the results for ROE and ROA in Panels B1 and B2 of Table 3, respectively. In each panel, we control for citations-based IE (CIE) on the top and patents-based IE (PIE) at the bottom. The slope on InnOrig is always significantly negative at the 1% level and substantial. For example, in the top row of Panel B1, the slope on InnOrig is –2.79% (t = –4.62). This implies that a one standard deviation increase in InnOrig reduces the volatility of next five years' ROE by 11.37% (relative to the average volatility of ROE over next five years at 24.53%) controlling for citations-based IE and other variables. Similarly, in the top row of Panel B2, the slope on InnOrig is –0.68% (t = –7.19). This implies that a one standard deviation increase in InnOrig reduces the volatility of next five years' ROA by 10.37% (relative to the average volatility of ROA over next five years at 6.56%) controlling for citations-based IE and other variables. The magnitude of these effects controlling for patents-based IE is almost identical as indicated by the very similar slopes on InnOrig in the bottom rows of Panels B1 and B2.

In contrast, the effect of IE on volatility of future profitability is often tiny and positive. For example, the slope on citations-based IE in Panel B1 is only 0.65% (t = 1.22). These results confirm

[20] Using a five-year window allows us to estimate the volatility more accurately. On the other hand, this also imposes stronger restriction on the data, which requires a firm to have at least 10-year data in order to be included in these regressions. Therefore, the results are subject to survivorship bias to some extent. However, when we use a three-year window to estimate volatility, the results are similar.

that the relations between InnOrig or IE and firm's fundamentals differ substantially. This evidence is consistent with the idea that more original innovation is a means by which firms can build moats that protect firms from competition, resulting in higher, more persistent, and more stable subsequent profitability.

2.3 Innovative originality and future gross margin

As discussed earlier, highly original innovation may help create unique and superior products, which allow firms to charge a price premium and maintain sustainable competitive advantage. Therefore, in this subsection, we examine the relation between InnOrig and future gross margin (GM), measured by sales minus cost of goods sold, scaled by sales. To reduce the noise in this measure, we set GM to 1 (or –1) if it exceeds 1 (or –1) following the literature (see, e.g. Kothari, et. al. 2002). We find that InnOrig is associated with significantly higher persistence and lower volatility of future gross margins.

Specifically, to illustrate the effect of InnOrig on the persistence in GM, we conduct annual Fama-MacBeth regressions of next year's gross margin on InnOrig, gross margin in current year and over the past four years, interaction of InnOrig with current GM and GM over the past four years, and other controls. Similar to Table 3, we set missing values for InnOrig, IE, advertising expenses, and R&D expenses to zero. We also control for a dummy variable that equals one for firms with no R&D expenses over the last five years, and the interactions of this dummy with all the other control variables. For brevity, in the tabulation of results we omit the slopes on these terms, GM over the past four years and their interaction with InnOrig, and the industry dummies. To reduce the influence of outliers and facilitate the interpretation, we winsorize all variables at the 1% and 99% levels and standardize all independent variables (except the dummies) to zero mean and one standard deviation.

The focus is the slope on the interaction between InnOrig and GM. As shown in Panel A of Table 4, the slope on $InnOrig_t*GM_t$ is significantly positive at the 5% level, regardless which type of IE we control for. The magnitude is also substantial. For example, in the top row of Panel A, the slope on $InnOrig_t*GM_t$ is 0.71%. Since the slope on GM_t is 23.90%, this implies that a one standard deviation increase in InnOrig increases the persistence in GM by 3% relative to a firm with zero InnOrig.[21] These results are consistent with the intuition that high InnOrig allows firms to maintain competitive advantage and sustainable high gross margin.

We also examine the effect of InnOrig on volatility of future GM. The model specification is the same as in Panel B of Table 3. In Panel B of Table 4, we show that high InnOrig also reduces volatility of future GM significantly. The slope on InnOrig is always significantly negative at the 1% level and substantial. For example, in the top row of Panel B, the slope on InnOrig is –0.28% (t = –3.42). This implies that a one standard deviation increase in InnOrig reduces the volatility of next five years' GM by 5.53% (relative to the average volatility of GM over next five years at 5.06%) controlling for citations-based IE and other variables. In contrast, the slope on CIE and PIE are significantly positive.

Overall, these results suggest that high InnOrig firms are able to achieve higher, more persistent, and less volatile profitability (at least in part) through the effect of InnOrig on gross margin.

[21] Although the slope on $InnOrig_t$ itself is negative, –0.16 (t = –1.37), the gross effect of InnOrig on GM_{t+1} is equal to (–0.16 + 0.71*GM_t), which is positive as long as (standardized) GM_t > 0.23, which applies to about 40% of the sample firms. We note that not all original innovations enhance gross margin or product price: some firms' original inventions are used to improve operational efficiency (such as enhancing turnover or reducing SG&A) that will enhance ROA and ROE but not gross margin or product price.

3. Return Predictive Power of Innovative Originality

We next test whether InnOrig predicts returns. Limited attention predicts that as long as a positive fraction of investors neglect favorable information in InnOrig, higher InnOrig is associated with greater subsequent abnormal returns. A similar implication follows from skepticism of complexity and models of ambiguity aversion.[22]

After evaluating this prediction in the full sample, we then test the other three implications regarding the strength of the return predictive power of InnOrig (see Propositions 2 through 4 in Section D of the Internet Appendix). The limited attention hypothesis predicts that the InnOrig effect should increase with valuation uncertainty, the fraction of inattentive investors, and the sensitivity of future profitability to InnOrig. Intuitively, when the prior uncertainty about the value of the stock (without any conditioning on InnOrig) is higher, heavier weight should optimally be placed on InnOrig by investors in forming posterior beliefs about value. So neglect of InnOrig 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 InnOrig.

In addition, the more sensitive a firm's future profitability is to InnOrig (or the more favorable information contained in InnOrig about a firm), the more that neglect of InnOrig causes market

[22] 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. For example, in Cao et al. (2005), conglomeration causes a price discount owing to the difficulty of evaluating complex firms. 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 InnOrig leads to investor pessimism about firm value. This generates the same empirical prediction that high InnOrig is associated with undervaluation, and hence is a positive predictor of future abnormal returns.

value to deviate from true fundamental value. In particular, the limited attention argument requires InnOrig to be an important predictor of firms' future profitability, as we verify in Tables 3 and 4. Ignoring/underreacting to this important signal in valuation will lead to mispricing, especially for firms whose future profitability is more sensitive to InnOrig. So the cash flow channel predicts a stronger ability of InnOrig to predict returns among firms with high sensitivity.

To test these hypotheses, we conduct portfolio sorts first to illustrate the abnormal returns and then Fama-MacBeth regressions to illustrate the robustness of the effect to other return predictors.

3.1 Portfolio sorts

3.1.1 Single sort

At the end of June of year *t* from 1982 to 2007, we sort firms with non-missing InnOrig into three InnOrig portfolios (Low, Middle, and High) based on the 30th and 70th percentiles of InnOrig 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 InnOrig portfolio.[23] As an alternative for comparison, we also assign firms with no R&D expenses and patents over the last five years in the "No" group. To examine the InnOrig-return relation, we form a hedge portfolio that takes a long position in the high InnOrig portfolio and a short position in the low InnOrig portfolio. Since the USPTO fully discloses patents granted in the weekly *Official Gazette of the United States Patent and Trademark Office*, the InnOrig measure in year t – 1 is publicly observable at the end of year t – 1. We allow a six-month lag in forming the InnOrig portfolios only to make the results comparable to previous studies.

[23] 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 InnOrig portfolio are 0.32% and 0.37% per month, respectively, and are significant at the 1% level.

We hold these portfolios over the next twelve months (July of year *t* to June of year *t* + 1) and compute their value-weighted monthly returns to make sure the results are not driven by small firms. In Panel A of Table 5, 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 that the InnOrig 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).

In Panel B, to examine the relation between InnOrig 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 (UMD) factor as in Carhart (1997) (henceforth, the Carhart 4F model). We also report alphas from other factor models for robustness check. In particular, we augment the Carhart model with the Investment-Minus-Consumption (IMC) factor, the liquidity (LIQ) factor, the citations-based innovative Efficient-Minus-Inefficient (EMI1) factor, the patents-based EMI (EMI2) factor, the Robust-Minus-Weak (RMW) factor and the Conservative-Minus-Aggressive (CMA) factor, or the Undervalued-Minus-Overvalued (UMO) factor, respectively.[24] We also report alphas from the q-factor model of Hou, Xue, and Zhang (HXZ 2015) and the mispricing factor model of Stambaugh and Yuan (2017). Controlling for these additional factors helps ensure that the InnOrig effect is

[24] 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.

not driven by the investment-specific technology risk, the liquidity effect, the innovative efficiency effect, the profitability effect, the investment effect, or existing mispricing factors.

As mentioned in the introduction, the excess returns, industry- and characteristic-adjusted returns, and alphas from different factor models generally increase monotonically with InnOrig from low to high, implying a positive InnOrig-return relation. Furthermore, the InnOrig effect is economically and statistically significant. The monthly alphas of the hedge portfolio range from 0.20% to 0.35% and are generally significant. Consistent with the idea that firms with no R&D investment are the least innovative firms, the alphas of the "No" group are negative and slightly larger in magnitude than those of the low InnOrig group.

To further examine whether the undervaluation of high InnOrig firms is driven by investors not recognizing the implication of high InnOrig on firms' fundamentals, we find that future abnormal returns mostly come from future earnings announcement windows. Specifically, the three-day cumulative abnormal return (CAR relative to the Carhart model) around future earnings announcement is 0.18% for the high InnOrig portfolio, which is 25.33% of its quarterly Carhart alpha.

Although InnOrig is associated with high profitability over the next five years, we find no significant return predictability beyond the first post-sorting year (see Figure 1 for the alphas of the InnOrig spread portfolio over the five post-sorting years from different factor models). For brevity, we only plot the alphas from the Carhart model, the Carhart plus RMW and CMA model, the q-factor model, and the mispricing four-factor model in Figure 1. Therefore, the data seem to suggest that the market fully corrects the undervaluation in the first year after portfolio formation. This is consistent with the argument of Chambers, Jennings, and Thompson (2002) that mispricing-based return predictability should be corrected in a short period while risk-based return predictability should persist for a long period.

Overall, these results suggest that high InnOrig firms are undervalued relative to low InnOrig firms, and the InnOrig effect is incremental to industry effects, well-known characteristics, standard and recently developed risk and mispricing 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 2. 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.

High InnOrig firms on average are larger. Other things equal, we expect large firms to receive greater investor attention, which tends to reduce misvaluation. However, as mentioned earlier, large firms are also generally more complex, making them harder to value (e.g., Cohen and Lou 2012). It is not clear whether this additional attention outweighs complexity to result in more accurate valuation of the innovative originality of large firms. In fact, the return predictive power of InnOrig exists in both small and big firms and does not vary much across size subsamples (untabulated).

We also examine how the returns of the hedge portfolio vary over time. Figure 2 plots the returns on a per annum basis from July of 1982 to June of 2008. The hedge portfolio's returns are negative only in eight out of the 27 years. This portfolio has a monthly market beta (from CAPM) of –0.13 (estimated from CAPM), and the correlation between the hedge portfolio's returns and the market excess returns is –0.53 (–0.25) on an annual (monthly) basis. As discussed earlier, the returns of the high-minus-low InnOrig (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 citations- and patents-based IE factors, the momentum factor, the CMA factor, the IMC factor, and the LIQ factor are small, ranging from –0.10 to 0.25. 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 that of the value (HML) factor (0.37%), and the RMW factor (0.34%). Furthermore, the high-minus-low InnOrig portfolio offers an ex post annual Sharpe ratio of 0.50, which is higher than that of SMB (0.08), HML (0.34), CMA (0.33), IMC (–0.13), the market factor (0.47), the size factor in the mispricing factor model (0.39), and is comparable to that of the investment factor in the q-factor model (0.57), RMW (0.57), and LIQ (0.58). 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 InnOrig portfolio is also puzzling from this perspective.

3.1.2 Double sorts

We next test the implications on the interaction of the InnOrig effect with proxies of valuation uncertainty (VU), investor attention, and the sensitivity of future profitability to InnOrig via independent double sorts.

For VU, we use two proxies.[25] One is an index that combines age and opacity. Age is a popular measure of valuation uncertainty (see, e.g., Kumar 2009).[26] However, age alone may not be

[25] In Table 10, we also report the InnOrig-return relation within R&D intensity subsamples. Since R&D is hard to value by its uncertain nature, R&D intensity is another alternative proxy of VU. The results reported later provide further support for this conditional prediction.
[26] Kumar (2009) also uses turnover and idiosyncratic volatility (IVOL) as additional proxies for valuation uncertainty.

sufficient in fully capturing VU. For example, a young firm with very transparent financial reports may not necessarily involve more valuation uncertainty than an old and established firm with very opaque reports. Opacity is a popular measure of transparency of a firm's financial reports (see, e.g., Hutton, Marcus, and Tehranian 2009). Therefore, we combine both age and opacity to fully capture VU. Specifically, 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 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. The second proxy of VU is analyst forecast dispersion (scaled by the absolute value of mean forecast).

We measure investor attention (ATT) by the inverse of transient institutional investors' ownership. Following Bushee (1998, 2001), we categorize all institutional investors (including hedge funds and mutual funds) into three groups: transient, dedicated, and quasi-indexer. Transient institutional investors trade stocks based on momentum and short-term strategies. As argued in Bushee (1998), they do not pay much attention to firms' fundamentals.[27] Thus we use the fraction of transient institutional investors as a proxy for the fraction of inattentive investors (f^u in our model).

Lastly, we measure the sensitivity (Sen) of future profitability to InnOrig by an industry-level

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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 and is often interpreted as a proxy of short-sale constraints.

[27] On the other hand, dedicated institutional investors take a long-term perspective and are thus more active in corporate governance and value creation.

sensitivity of past ROE to lagged InnOrig.[28] Specifically, we measure Sen by the slope on InnOrig from annual industry-level Fama-MacBeth regression of firms' past ROE on lagged InnOrig and a set of control variables (ROE, change in ROE, market-to-book assets, advertising expenses scaled by book equity, capital expenditure scaled by book equity, R&D scaled by book equity, and citations-based IE). This sensitivity measure is observable to investors before portfolio formation since it is estimated based on prior information.

To ensure that these proxies serve their purpose of capturing different aspects of the three distinct conditional predictions from the model, we examine the correlations among these proxies first. In untabulated results, we find that the correlations among these proxies are very low, ranging from –0.02 to 0.04. In addition, their correlations with size are also very low, ranging from –0.15 to 0.06.

To perform these conditional tests, at the end of June of year t, we conduct 3 by 3 double sorts on InnOrig and each of those conditioning variables listed. As the number of analyst forecast is sparse before 1983, the portfolio sorts for VU based on analyst dispersion start in June of 1984. The three InnOrig portfolios are formed as in the single sort. The conditioning variables are measured in year $t - 1$. To compare the InnOrig effect across the subgroups, we also form a high-minus-low InnOrig (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 5, we calculate the average monthly excess returns, industry- and characteristic-adjusted returns, and alphas estimated from different factor models.

The results in Table 6 support the predictions. For brevity, we only tabulate the alphas from the Carhart model, the Carhart plus RMW and CMA model, the q-factor model, and the mispricing

[28] To reduce estimation error, measuring Sen at the firm level would require a long time-series of each sample firm, which would severely limit sample size. We therefore estimate Sen at the industry level.

four-factor model. The hedge portfolio's returns and alphas are substantial and significant in the high VU group (firms with VU in the top tercile), but small and often insignificant in the low VU group (firms with VU in the bottom tercile). For example, in Panel A1 of Table 6, among high VU index firms, the monthly average excess returns as well as 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 0.82% (the q-factor model) to 1.08% (controlling for the Carhart four factors plus LIQ) and are significant at the 1% level. In contrast, among low VU index firms, these returns and alphas are small and insignificant, ranging from 0.07% to 0.19%. Similarly, in Panel A2, the alphas of the InnOrig hedge portfolio range from 0.47% (the Carhart four factors plus RMW and CMA factors) to 0.69% (the Carhart four factors) and are generally significant at the 5% level among high VU firms (based on high analyst forecast dispersion), but these alphas are smaller and generally insignificant among low VU firms.[29]

Similarly, the InnOrig effect is also much stronger among firms with lower investor attention or higher sensitivity of future profitability to InnOrig (see Panels B and C). Specifically, the monthly alphas from different factor models for the hedge portfolio range from 0.42% (controlling for the Carhart four factors plus EMI1) to 0.58% (controlling for the Carhart four factors) and are significant at the 1% level among low attention firms. These alphas range from 0.51% (the q-factor model) to 0.81% (controlling for the Carhart four factors plus LIQ) and are significant at the 1% level among high sensitivity firms. But they are small and insignificant among firms with high attention or low sensitivity.

[29] The results are even stronger when we restrict the sample to firms with at least five analyst forecasts. The alphas of the hedge portfolio among the high dispersion group range from 0.50% to 0.76%, all significant at the 5% or 1% level.

We also verify that these contrasts are not due to the difference in the InnOrig measure spreads. The spread in InnOrig does not vary much across these subsamples and is very similar to that in the single sort as shown in Table 2. Furthermore, similar to the unconditional return predictive power of InnOrig, the significant InnOrig 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 InnOrig portfolios range from $316 to $895 million in the high VU index group, $782 million to $2.31 billion in the high analyst forecast dispersion group, $1.11 to $3.12 billion in the low attention group, and $759 million to $4.44 billion in the high sensitivity group (untabulated).

The high VU, low attention, and high sensitivity firms also constitute a significant portion of the CRSP universe. When we measure VU by combining age with opacity, the high VU subsample weighs 5.3% of total CRSP universe. The high VU subsample based on analyst forecast dispersion weighs 8.1% of the CRSP universe.[30] The low ATT (high sensitivity) subsample constitutes 28.3% (21.7%) of total CRSP universe. Therefore, the subsamples with the strongest InnOrig-return relation account for a significant fraction of the overall market, especially the low-ATT and high-Sen subsamples.

Overall, independent double sorts provide fairly strong evidence supporting the model predictions on the conditional return predictive power of InnOrig.

3.2 Fama-MacBeth regressions

3.2.1 Full-sample Fama-MacBeth regressions

We next examine the ability of InnOrig to predict the cross section of returns using monthly Fama-MacBeth regressions. This analysis allows us to control more extensively for other characteristics

[30] The high VU subsample based on R&D intensity (see Table 10) weighs 11.1% of the CRSP universe.

that can predict returns, to verify whether the positive InnOrig-return relation as measured in portfolio sorts is driven by other known return predictors.

As in 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 the natural log of one plus InnOrig of year t – 1, different sets of control variables, and industry fixed effects based on Fama and French 48 industry classifications.

Table 7 shows the time-series average slopes (in percentage) and corresponding Newey-West heteroscedasticity-robust and autocorrelation-adjusted t-statistics (in parentheses) from the monthly cross-sectional regressions for different model specifications. We winsorize all independent variables at the 1% and 99% levels to reduce the impact of outliers, and then standardize all independent variables (except dummies) to zero mean and one standard deviation to facilitate the comparison of economic effects of all variables. We set InnOrig to zero for firms without InnOrig, and include a dummy that equals one for firms with no patent and no R&D over the past five years and the interaction of this dummy with the other control variables in the regressions. For brevity, we omit the slopes on these terms and the industry dummies in the tabulations.

Model 1 is a univariate regression of future returns on InnOrig. The slope on InnOrig is 0.15% (t = 2.91). Model 2 controls for institutional ownership (InstOwn), stock illiquidity (ILLIQ), short-term return reversal (REV), BTM, size, momentum (MOM), and industry dummies based on Fama and French 48 industry classifications. InnOrig 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. The slope on InnOrig is statistically significant: 0.15% (t = 5.34). The slopes on the other variables are consistent with previous studies. Although the slopes on momentum are insignificant, they are positive. Furthermore, in unreported results, we find significantly positive slope on momentum if we only control for size and book-to-market.

In Model 3, we control for additional return predictors related to innovation (CIE or PIE, CTA, and RDME), investment (AG and IA), financing (NS), profitability (ROA), idiosyncratic volatility (IVOL), and total skewness (SKEW) measured in year t – 1.[31] IVOL is included as Pastor and Veronesi (2009) and Garleanu, Panageas, and Yu (2012) propose that new technologies are associated with idiosyncratic risk, and SKEW is included as Kapadia (2006) argues that investors prefer high-tech stocks for their positive skewness. CIE (PIE) is the natural log of one plus the citations-based (patents-based) IE measure following Hirshleifer, Hsu, and Li (2013). Missing CIE and PIE are set to zero. 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 InnOrig slopes remain statistically significant: 0.10% (t = 3.58) controlling for CIE, and 0.12% (t = 4.42) controlling for PIE. The slopes on the control variables are generally consistent with previous studies. The slope on IVOL is significantly positive, which is consistent with Bali, Cakici, and Whitelaw (2011). Moreover, the InnOrig slopes remain similar when we use other

[31] 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 Hou, Xue, and Zhang (2015). 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).

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.[32]

Lastly, we also control for sales diversity measured by two proxies: the first is the number of sales segments (NSD) defined by Fama-French 48 industries over the previous five years (year t – 5 to year t – 1). The second is one minus the Herfindahl index of segment sales (HHISD, based on Fama-French 48 industry classifications) over year t – 5 to year t – 1. We use the segment sales data from Compustat segment files following Cohen and Lou (2012) among others. Since the two proxies are very highly correlated, we only report the results from controlling for NSD. However, the results (unreported) from controlling for HHISD are almost the same. As shown in Model 4, the slopes on InnOrig remain almost the same in magnitude with statistical significance. Therefore, the InnOrig effect is robust to controlling for sales diversity in product markets.

Overall, the results above indicate that the predictive power of InnOrig is distinct from, and robust to the inclusion of, other commonly known return predictors, innovation-related variables, industry effects, and sales diversity. Although the magnitudes of the InnOrig slopes are modest, we mainly rely on Fama-MacBeth regressions to illustrate the statistical significance of the InnOrig effect and portfolio sorts to identify the economic magnitude of abnormal returns following Fama and French (2006).[33]

3.2.2 Subsample Fama-MacBeth regressions

[32] 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 is the slope on the squared market factor returns from the regression for ISKEW. Expected idiosyncratic skewness is measured in the previous month.

[33] As pointed out in Fama and French (2006), "cross-section return regressions can identify variables that help describe average stock returns, but the economic significance of the average slopes is not always easy to judge. Moreover, the average slopes from the return regressions cannot tell us whether the regressions are well-specified."

We also perform Fama-MacBeth regressions in subsamples split by these conditioning variables as in the double sorts. We use the same method and model specifications as in the test of the unconditional InnOrig effect above. For brevity, we only report the slopes estimated from Model 3 in Table 8 since the slope on sales diversity is small and insignificant (see Table 7). For each panel, we report results from controlling for CIE (PIE) on the left (right).

The results show a sharp contrast in the InnOrig effect across the subsamples even after we control for many well-known return predictors and industry effects. Specifically, controlling for citations-based IE and others (Model 3A), the slopes on InnOrig are 0.21%, 0.15%, 0.16%, 0.23% among high VU index, high VU (based on analyst forecast dispersion), low attention, and high sensitivity firms, respectively, and are generally significant at the 1% or 5% level. In contrast, their counterparts are only 0.01%, 0.07%, 0.00%, and 0.05% among low VU index, low dispersion, high attention, and low sensitivity firms, respectively, and are insignificant. These sharp contrasts remain the same if we control for patent-based IE (Model 3B).

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

3.3 Innovative originality versus innovative efficiency

In previous tests, we showed that the InnOrig effect is distinct from the IE effects by controlling for the citations- or patents-based EMI factor in the portfolio sorts and the two types of IE in the Fama-MacBeth regressions. In this subsection, we further examine the incremental return predictive power of InnOrig by conducting Fama-MacBeth regressions within IE subsamples

(Table 9) for both types of IE.

A strong incremental InnOrig effect remains and is significantly stronger among low IE firms for both types of IE measures. On ex ante grounds, it is not clear why the InnOrig effect is stronger among low IE firms. One possibility is that there is a tradeoff between being innovatively efficient (which may require being tough about cancelling projects that are not producing output quickly) and original (which may require high tolerance for failure and providing a lot of slack for highly speculative projects in the hope that they may someday pay off). The low IE category, in combination with high InnOrig, may be especially good at identifying the high originality that the market underweights.

3.4 Innovative originality and R&D intensity

Since R&D is a crucial input for generating innovation and firms that invest heavily in R&D are also harder to value due to the uncertain nature of R&D investment, we hypothesize that the InnOrig-return relation is stronger among higher R&D firms. To test this hypothesis, we use the same method as in Table 8, and obtain supporting evidence in the Fama-MacBeth subsample regressions within subsamples split on R&D expenses scaled by total assets. Specifically, Table 10 shows that the slope on InnOrig among high R&D firms is positive and significant. The magnitude is also much larger than that among low R&D firms. For example, when we control for CIE, the slopes on InnOrig are 0.14% (t = 2.01) and 0.05% (t = 1.07) among high and low R&D firms, respectively.

3.5 Potential alternative explanations

Although overall the evidence above is consistent with limited attention, we do not rule out potential risk-based explanations. To address the possibility that InnOrig captures information asymmetry, we examine whether our InnOrig measure correlates 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 InnOrig effect exists in both small and big firms and does not have a significant interaction with size. Since size is inversely associated with financing constraints (e.g., Gertler and Gilchrist 1994; Campello and Chen 2010), this evidence suggests that constraints risk cannot explain the InnOrig effect. Furthermore, as discussed earlier, the correlation between our InnOrig measure and size is very low.

To address the possibility that the InnOrig 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 InnOrig hedge portfolio's returns on IMC.[34] 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, the loading (untabulated) of the InnOrig hedge portfolio on IMC is –0.10 (t = –0.79) in the Carhart model augmented with the IMC factor. Furthermore, to capture technology-related risk we construct a portfolio that is long on firms in high-tech industries and is short on firms in the other industries. The correlation between this mimicking portfolio's returns and the returns of the InnOrig hedge

[34] Greenwood, Hercowitz, and Krusell (1997) suggest that investment-specific technological changes explain aggregate economic growth; later, Kogan and Papanikolaou (2014) 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.

portfolio is also very low and insignificant. In addition, the correlation between the InnOrig 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 InnOrig firms might be *less* susceptible to obsolescence risk, as high InnOrig 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 InnOrig-return relation rather than the positive one that we find.

As mentioned earlier, ambiguity aversion may also predict undervaluation of InnOrig. However, the ambiguity aversion hypothesis does not require InnOrig to predict future profitability in order to generate mispricing. Even if InnOrig does not predict profitability, ambiguity aversion predicts over-discounting/undervaluing firms with higher InnOrig or more complex innovation.

Lastly, one may wonder why firms would choose high InnOrig 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 InnOrig 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 InnOrig. 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).

4. Conclusion

Based upon the psychology of limited attention in which, under empirically realistic conditions, firms with greater innovative originality (measured by the average range of knowledge drawn upon by a firm's patents) will be undervalued by the market if InnOrig is a favorable indicator of future fundamentals that is neglected by some investors. More original innovations allow a firm to charge customers a price premium and provide a sustainable competitive advantage. In addition, the greater complexity associated with higher InnOrig makes it harder to cognitively process this signal, and research in psychology suggests that lower processing fluency results in more skeptical appraisal. We further hypothesize that the effect of InnOrig upon misvaluation will be stronger among firms with greater valuation uncertainty, lower investor attention, and stronger InnOrig predictive ability for fundamentals.

Our tests support these hypotheses. Firms with higher InnOrig have more persistent, and less volatile future profitability as well as gross margin. These findings are consistent with the intuition that InnOrig creates sustainable competitive advantages as it reflects the capability of a firm's managers and scientists in effectively combining technologies from various knowledge domains to innovate in ways that are hard for its competitors to match.

We further find that high InnOrig 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 InnOrig. These findings are robust to industry adjustment, characteristics adjustment, risk-adjustment methods, recently developed mispricing factors, and 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 InnOrig. The high Sharpe ratio of the high-minus-low InnOrig portfolio also suggests that this relation is not entirely explained by rational pricing. Moreover, the stronger InnOrig predictive ability among firms with greater sensitivity of future profitability to InnOrig 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. Affymetrix and its competitors

In this appendix, we discuss an exemplar of recombining distant knowledge components to make important technological breakthrough – DNA microarray – which greatly facilitates scientists' investigation of mutations in genes.

Mutations denote permanent alterations in the DNA sequence that makes up a gene. Human genome contains more than 30,000 genes, and at any given moment, some genes are expressed (turned on), and others are silenced (turned off). Analyzing the mutations of such a large number of genes to detect mutations was a time-consuming work before the introduction of DNA microarray. In 1991, Dr. Stephen Fodor, a biochemist, and his colleagues applied the photolithography technology used in the semiconductor industry for manufacturing computer microchips to build the first DNA microarray, i.e., a chip that is designed and manufactured to examine whether the DNA contains mutations in genes.[1] The surface of each DNA microarray contains a large number of orderly arranged spots, each contains a DNA strand for a particular gene expression. By placing both the DNA strands from the subject and the control sample in each spot within one chip, investigators are able to identify the corresponding gene mutation by the binding of these DNA strands in the spot. This breakthrough technology in gene expression analysis was covered by *Science*.[2]

Dr. Fodor founded Affymetrix in 1992, which had been a leading company in DNA microarray since then. A large portion of Affymetrix's patents are based on semiconductor- or electronics-related technologies, which indicates that Affymetrix drew knowledge from widely different areas to innovate in a novel way. Figures A1 and A2 plot the InnOrig measure and the number of granted

[1] See http://www.the-scientist.com/?articles.view/articleNo/16657/title/The-DNA-Microarray/

[2] S.P. Fodor et al., "Light-directed, spatially addressable parallel chemical synthesis," Science, 251:767–73, 1991.

patents each year for Affymetrix and its two direct competitors: Incyte and Lynx Therapeutics.[3] Affymetrix' InnOrig increased from 8 in 1996 (its IPO year) to 21 in 2006, and it is persistently ranked in the top tercile ("High InnOrig" group). In contrast, the two competitors' InnOrig only ranges between 3 and 5, and they are persistently ranked in the bottom tercile ("Low InnOrig" group). These patterns reflect the change in Affymetrix's innovative strategy by combining more diverse technologies in its innovation. In addition, the higher InnOrig of Affymetrix cannot be simply attributed to the size of its patent portfolios because Incyte's annual number of granted patents is quite close to Affymetrix's until 2002 (see Figure A2).

Consistent with a positive economic link between InnOrig and firms' operating performance, Figures A3 and A4 show that the market capitalization and profitability (ROA) of Incyte started to underperform Affymetrix since 1998/1999, roughly the same time when Affymetrix's InnOrig started to surge. These results exemplify the intuition that innovative originality offers a firm with sustainable competitive advantage ("moat") that allows it to charge a price premium and obtain significantly higher profitability and higher stock returns than its competitors.

We then further examine how Affymetrix's patents differ from its competitors' in four respects. First, we examine the number of unique technology classes (both primary and secondary) of all patents cited by the patents granted to these three firms in the *whole* sample period. Affymetrix cited a total of 213 unique classes, while its competitors, Incyte and Lynx Therapeutics, only cited a total of 119 and 30 classes, respectively. Figures A5-A7 illustrate the distribution of these cited patents across different technology classes. They present a much more diverse distribution for Affymetrix.

[3] These two competitors are identified from Affymetrix's 10-K. Other competitors that are subsidiaries of conglomerates or operate in foreign countries are not considered.

Second, we check whether these three companies have drawn knowledge from semiconductor devices in particular by focusing on the four technology classes listed in Appendix 1 of Hall et al. (2001): 257, 326, 438, and 505. Affymetrix cited three of these, Incyte cited two, while Lynx only cited one.[4] These observations, again, support Affymetrix's leading position in embedding semiconductor knowledge in creating biomedical products in a novel way.

Third, we investigate the patents contributing to the major product line of Affymetrix, GeneChip®, since its IPO. US Patent 6307042, one of the key patents protecting GeneChip®, cites patents from 12 unique technology classes. More importantly, two of these have never been cited by Incyte or Lynx Therapeutics: Class 125—Stone working, and Class 451—Abrading.

Lastly, we report the number of patents in electronics and optics (Classes 335-361) cited by these three firms in the whole sample period. Table A1 shows that Affymetrix cited more patents from these classes than its competitors.

Affymetrix was acquired by Thermo Fisher Scientific Inc. (NYSE:TMO) for approximately $1.3 billion in March 2016.

[4] Class 505—Superconductor technology: apparatus, material, process—has been cited by Affymetrix. Class 257—Active solid-state devices (e.g., transistors, solid-state diodes) —has been cited by Affymetrix and Incyte, and Class 438—Semiconductor device manufacturing: process—has been cited by Affymetrix and Incyte.

Figure A1. InnOrig

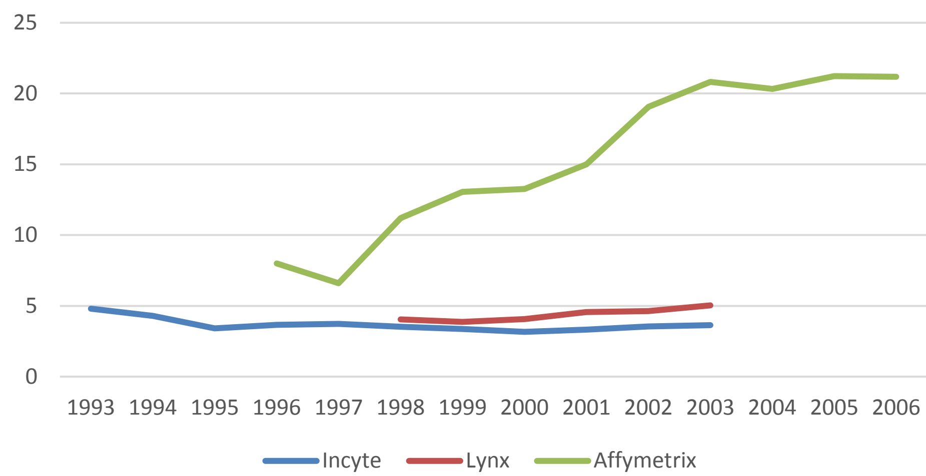
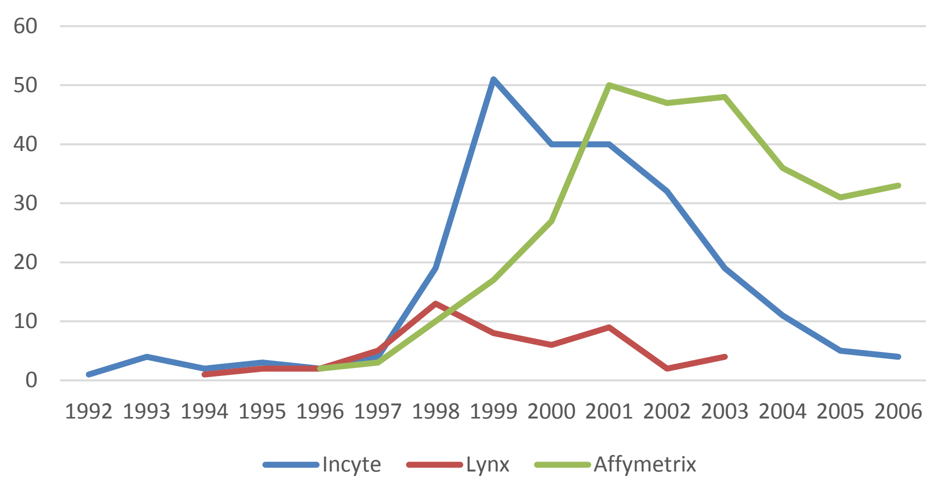


Figure A2. Number of granted patents



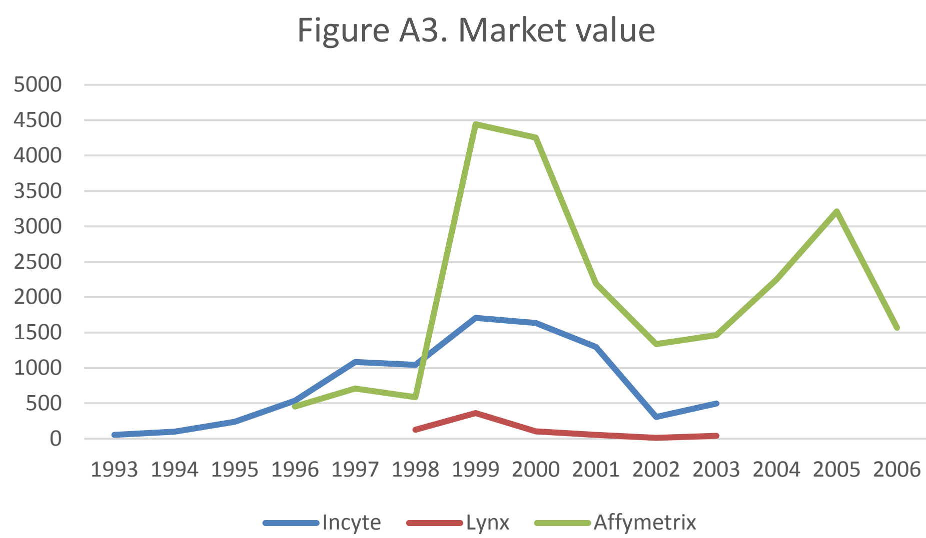


Figure A3. Market value
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006
Incyte
Lynx
Affymetrix

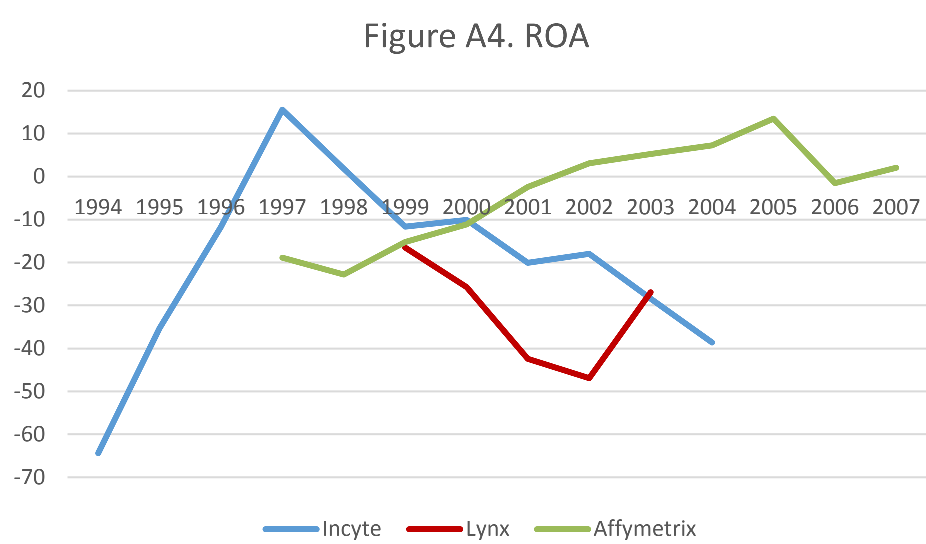


Figure A4. ROA
20
10
0
-10
-20
-30
-40
-50
-60
-70
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007
Incyte
Lynx
Affymetrix

Figure A5. Affymetrix

Figure A6. Incyte

Figure A7. Lynx

Table A1. The Distribution of Patents Cited across Technology Classes 335 to 361

In this table, we presents the number of patents from technology classes 335 to 361 cited by the patents of Affymetrix, Incyte, and Lynx Therapeutics in the whole sample period, 1976-2006.

Class	Class description	Affymetrix	Incyte	Lynx Therapeutics
335	Electricity: magnetically operated switches, magnets, and electromagnets	1		
336	Inductor devices	1		
338	Electrical resistors	1		
340	Communications: electrical	1		
341	Coded data generation or conversion	1		
345	Computer graphics processing and selective visual display systems	1		
346	Recorders	1	2	
347	Incremental printing of symbolic information	1	1	
348	Television	1	1	1
349	Liquid crystal cells, elements and systems	1		
351	Optics: eye examining, vision testing and correcting	1	2	
353	Optics: image projectors	1		
355	Photocopying	4		
356	Optics: measuring and testing	7	2	1
358	Facsimile and static presentation processing	1	1	
359	Optical: systems and elements	1	1	
360	Dynamic magnetic information storage or retrieval	1		
361	Electricity: electrical systems and devices	1		

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Table 1
Innovative originality of selected industries

This table reports the pooled mean, median, standard deviation (Stdev), coefficient of variation (CV), 1st percentile (P1), 5th percentile (P5), 30th percentile (P30), 70th percentile (P70), 95th percentile (P95), and 99th percentile (P99) of the innovative originality (InnOrig) measure for firms in selected industries based on Fama-French 48 industry classifications. We also report CV across industries at the bottom. The sample is from 1981 to 2006 and excludes financial and utility firms. To compute a firm's InnOrig, 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 InnOrig in year *t* by the average of citation diversity across all patents granted to the firm over the past five years (year *t* – 4 to *t*).

Industry	Mean	Median	Stdev	CV	P1	P5	P30	P70	P95	P99
Medical equipment	7.38	6.04	4.91	0.67	1	2.38	4.47	8.35	17.40	25.67
Pharmaceutical products	6.59	5.50	4.41	0.67	1	2.00	4.33	7.00	14.50	23.27
Chemicals	6.53	5.80	3.83	0.59	1	2.59	4.61	7.25	13.40	23.00
Machinery	5.95	5.12	3.38	0.57	1	2.00	4.00	6.93	13.00	16.67
Electrical equipment	5.78	5.00	3.92	0.68	1	2.00	3.71	6.50	12.00	19.25
Automobiles and trucks	5.10	4.92	2.45	0.48	1	2.00	3.83	5.75	10.00	13.26
Business services	7.88	6.60	5.43	0.69	1	2.00	5.00	8.83	17.50	27.00
Computers	6.26	5.50	3.75	0.60	1	2.00	4.08	7.25	13.00	20.00
Electronic equipment	5.92	5.00	3.82	0.65	1	2.00	4.00	6.50	13.00	21.00
Measuring and control equipment	6.25	5.33	3.82	0.61	1	2.00	4.00	7.26	13.50	20.33
Coefficient of variation (CV)	0.13	0.10								

Table 2
Summary statistics and correlations

At the end of June of year t from 1982 to 2007, we sort firms with non-missing innovative originality (InnOrig) measure into three groups (Low, Middle, High) based on the 30th and 70th percentiles of the InnOrig measure in year t – 1. In addition, we assign firms with missing InnOrig (i.e., no patents) but positive R&D over any of the last five years into the "Low" group and firms with neither R&D investment nor patents into the "No" group. InnOrig is defined in Table 1. Panel A reports the time-series mean of cross-sectional average characteristics (both raw value and percentile ranks) of firms in each InnOrig group. The number of firms is the number of firms in each group averaged over 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). 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. Citations-based innovative efficiency measure (CIE) in year t – 1 is adjusted patent citations received in year t – 1 by patents granted to a firm in years t – 2 to t – 6 scaled by the sum of R&D expenses in years t – 4 to t – 8. The adjusted citations in year t to patent k are citations to patent k in year t divided by the mean citations to patents of the same subcategory and grant year group in year t. Patents-based innovative efficiency measure (PIE) in year t – 1 is patents granted to a firm in year t – 1 scaled by research and development (R&D) capital in year t – 3. R&D capital is computed as the five-year cumulative R&D expenses with a 20% annual depreciation. 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 the prior month. Stock illiquidity (ILLIQ) is defined as absolute stock return in June of year t divided by dollar trading volume in June of year t (the raw value is multiplied by 1,000,000). Number of segments (NSD) is the number of different sales segments defined by Fama-French 48 industries over the previous five years (year t – 5 to year t – 1). HHI-based sales diversity (HHISD) is one minus the Herfindahl index of sales across the number of segments. We winsorize all variables at the 1% and 99% levels except the number of firms, InnOrig, NSD, and HHISD. Panel B reports the times-series average of cross-sectional correlations between InnOrig and the other characteristics.

Panel A. Summary statistics

	Raw value					Percentile ranks			
	No	Low	Middle	High	All	No	Low	Middle	High
Number of firms	2426	1283	550	409	4671				
Innovative originality (InnOrig)		3.02	5.37	9.78	5.97		15	50	85
Size ($mn)	718	702	4334	2033	1311	46	45	66	59
Book-to-market (BTM)	0.90	0.68	0.70	0.64	0.78	55	45	46	44
Momentum (MOM)	0.11	0.13	0.15	0.15	0.12	49	48	53	52
Idiosyncratic volatility (IVOL)	0.04	0.04	0.03	0.03	0.04	49	56	38	45
Skewness (SKEW)	0.61	0.64	0.39	0.47	0.58	50	52	44	47
R&D/Market equity (RDME)	0.10%	6.76%	6.03%	5.90%	3.60%	27	69	67	66
Patents/Assets (CTA)	0.00%	0.84%	2.84%	3.45%	0.98%	38	48	75	72
Citations-based innovative efficiency (CIE)	0.00	0.18	0.68	0.81	0.42	26	36	67	66
Patents-based innovative efficiency (PIE)	0.00	0.07	0.25	0.28	0.15	28	37	67	65
Return on assets (ROA)	4.66%	-2.84%	3.05%	0.29%	1.54%	52	45	52	49
Return on equity (ROE)	7.95%	-4.17%	5.56%	1.10%	2.96%	54	43	52	47
Asset growth (AG)	0.18	0.18	0.14	0.16	0.17	51	48	49	49
Capex/Assets (IA)	0.10	0.07	0.07	0.07	0.08	53	45	49	49
Net stock issuance (NS)	0.06	0.07	0.04	0.05	0.06	48	52	48	51
Institutional ownership (InstOwn)	0.31	0.29	0.45	0.40	0.33	47	45	63	57
Short-term return reversal (REV)	0.57%	0.53%	0.65%	0.67%	0.56%	50	49	50	50
Illiquidity (ILLIQ)	0.68	0.49	0.15	0.18	0.53	52	53	36	42
Number of sales segments (NSD)	1.34	1.34	1.69	1.47	1.39	48	48	56	51
HHI Sales diversity (HHISD)	0.08	0.08	0.16	0.12	0.09	48	48	57	51

Panel B. Correlations		
	Pearson corrlations	Spearman rank correlations
	Innovative Originality	Innovative Originality
Size ($mn)	-0.01	0.05
Book-to-market (BTM)	-0.07	-0.08
Momentum (MOM)	0.00	0.01
Idiosyncratic volatility (IVOL)	0.04	-0.01
Skewness (SKEW)	0.01	-0.01
R&D/Market equity (RDME)	0.01	0.05
Patents/Assets (CTA)	0.09	0.11
Citations-based innovative efficiency (CIE)	0.13	0.15
Patents-based innovative efficiency (PIE)	0.06	0.09
Return on assets (ROA)	-0.06	-0.02
Return on equity (ROE)	-0.06	-0.03
Asset growth (AG)	0.03	0.02
Capex/Assets (IA)	0.04	0.05
Net stock issuance (NS)	0.04	0.04
Institutional ownership (InstOwn)	-0.03	0.03
Short-term return reversal (REV)	0.00	0.00
Illiquidity (ILLIQ)	-0.01	-0.05
Number of sales segments (NSD)	-0.03	0.00
HHI Sales diversity (HHISD)	-0.03	0.00

Table 3
Innovative originality and future profitability

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. In Panel A, we regress future change in profitability on *InnOrig* and other control variables. In Panel B, we regress standard deviation of profitability in year $t + 1$ to $t + 5$ on *InnOrig* and other controls. Profitability is measured by return on equity (*ROE*) in Panels A1 and B1, and by return on assets (ROA) in Panels A2 and B2. ΔROE_t (ΔROA_t) is the change in *ROE* (*ROA*) between year *t* and year $t - 1$. *R&D* is R&D expenditure divided by assets. *Capex* is capital expenditure divided by assets. *MTB* is market-to-book assets. *Adv* is advertising expense divided by assets. All the other control variables are defined as in Table 2. We also control for industry dummies based on the Fama and French (1997) 48 industries. We set missing values for InnOrig, IE, advertising expenses, and R&D expenses to zero. In addition, we control for a dummy, which equals one for firms with no R&D investment over the past five years and 0 otherwise, and its interactions with all the other control variables. We omit the slopes on the 48 industry dummies, the slopes on the missing dummy, and its interactions with other control variables for brevity. We winsorize all variables at the 1% and 99% levels and standardize all independent variables (except the dummies) to zero mean and one standard deviation. Financial and utility firms are excluded. R-square (Firms) is the time-series average of the R-squares (number of firms) from the annual cross-sectional regressions. The sample is from 1981 to 2006.

Panel A1. InnOrig and mean reversion of future ROE

Dependent	$InnOrig_t$	ΔROE_t	$InnOrig_t*\Delta ROE_t$	$CIE_t*\Delta ROE_t$	ROE	ADV_t	$R\&D_t$	$Capex_t$	CIE_t	MTB_t	Intercept	R^2	Firms
ΔROE_{t+1}	2.18	-13.57	1.97	-0.92	-19.43	0.72	-7.04	0.75	0.13	0.77	-2.79	0.19	3047
	(7.43)	(-13.81)	(3.49)	(-1.69)	(-5.66)	(2.42)	(-4.86)	(1.49)	(0.47)	(0.97)	(-2.67)		

Dependent	$InnOrig_t$	ΔROE_t	$InnOrig_t*\Delta ROE_t$	$PIE_t*\Delta ROE_t$	ROE	ADV_t	$R\&D_t$	$Capex_t$	PIE_t	MTB_t	Intercept	R^2	Firms
ΔROE_{t+1}	2.27	-13.69	1.34	1.62	-19.32	0.69	-7.04	0.75	-0.20	0.83	-2.83	0.19	3047
	(7.63)	(-13.63)	(2.08)	(2.49)	(-5.61)	(2.37)	(-4.84)	(1.49)	(-0.71)	(1.04)	(-2.67)		

Panel A2. InnOrig and mean reversion of future ROA

Dependent	$InnOrig_t$	ΔROA_t	$InnOrig_t*\Delta ROA_t$	$CIE_t*\Delta ROA_t$	ROA	ADV_t	$R\&D_t$	$Capex_t$	CIE_t	MTB_t	Intercept	R^2	Firms
ΔROA_{t+1}	0.49	-3.04	0.22	-0.17	-4.92	0.28	-1.40	0.11	0.05	0.48	-0.05	0.21	3049
	(7.11)	(-7.63)	(2.10)	(-1.75)	(-6.26)	(2.85)	(-3.88)	(0.68)	(1.05)	(2.33)	(-0.16)		

Dependent	$InnOrig_t$	ΔROA_t	$InnOrig_t*\Delta ROA_t$	$PIE_t*\Delta ROA_t$	ROA	ADV_t	$R\&D_t$	$Capex_t$	PIE_t	MTB_t	Intercept	R^2	Firms
ΔROA_{t+1}	0.53	-3.06	0.16	-0.04	-4.91	0.27	-1.41	0.12	-0.11	0.49	-0.06	0.21	3049
	(7.33)	(-7.63)	(1.72)	(-0.71)	(-6.26)	(2.67)	(-3.88)	(0.71)	(-1.47)	(2.32)	(-0.18)		

Panel B1. InnOrig and volatility of future ROE

Dependent	$InnOrig_t$	CIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	$ROE\_VOL_{t-4,t}$	Intercept	R^2	Firms
$ROE\_VOL_{t+1,t+5}$	-2.79	0.65	0.39	15.12	-0.99	-0.29	12.56	25.11	0.12	1745
	(-4.62)	(1.22)	(1.06)	(6.31)	(-1.30)	(-0.34)	(11.16)	(10.70)		

Dependent	$InnOrig_t$	PIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	$ROE\_VOL_{t-4,t}$	Intercept	R^2	Firms
$ROE\_VOL_{t+1,t+5}$	-2.79	0.87	0.38	15.11	-0.99	-0.31	12.58	25.11	0.12	1745
	(-4.52)	(1.44)	(1.01)	(6.31)	(-1.33)	(-0.36)	(11.15)	(10.86)		

Panel B2. InnOrig and volatility of future ROA

Dependent	$InnOrig_t$	CIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	$ROA\_VOL_{t-4,t}$	Intercept	R^2	Firms
$ROA\_VOL_{t+1,t+5}$	-0.68	0.12	-0.08	2.76	-0.32	0.08	3.09	6.07	0.32	1745
	(-7.19)	(1.96)	(-1.34)	(5.93)	(-2.57)	(0.52)	(12.03)	(15.35)		

Dependent	$InnOrig_t$	PIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	$ROA\_VOL_{t-4,t}$	Intercept	R^2	Firms
$ROA\_VOL_{t+1,t+5}$	-0.68	0.17	-0.08	2.76	-0.33	0.08	3.09	6.06	0.32	1745
	(-6.80)	(2.34)	(-1.34)	(5.92)	(-2.63)	(0.52)	(12.07)	(15.31)		

Table 4
Innovative originality and future gross margin

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. In Panel A, we regress future gross margin (GM) on *InnOrig* and other control variables. Slopes on four lagged GMs and interaction of InnOrig with the four lagged GMs are omitted for brevity. In Panel B, we regress standard deviation of GM in year $t + 1$ to $t + 5$ on *InnOrig* and other controls. GM is measured by (Sales-Cost of goods sold)/Sales. If GM exceeds 1, it is set to 1. If GM is lower than – 1, it is set to – 1. *R&D* is R&D expenditure divided by assets. *Capex* is capital expenditure divided by assets. *MTB* is market-to-book assets. *Adv* is advertising expense divided by assets. All the other control variables are defined as in Table 2. We also control for industry dummies based on the Fama and French (1997) 48 industries. We set missing values for InnOrig, IE, advertising expenses, and R&D expenses to zero. In addition, we control for a dummy, which equals one for firms with no R&D investment over the past five years and 0 otherwise, and its interactions with all the other control variables. We omit the slopes on the 48 industry dummies, the slopes on the missing dummy, and its interactions with other control variables for brevity. We winsorize all control variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Financial and utility firms are excluded. R-square (Firms) is the time-series average of the R-squares (number of firms) from the annual cross-sectional regressions. The sample is from 1981 to 2006.

Panel A. InnOrig and persistence of gross margin (GM)

Dependent	$InnOrig_t$	GM_t	$InnOrig_t*GM_t$	CIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	Intercept	R^2	Firms
GM_{t+1}	-0.16	23.90	0.71	0.06	0.46	-0.29	0.06	0.81	29.19	0.70	2374
	(-1.37)	(16.41)	(1.97)	(2.78)	(10.39)	(-1.44)	(0.43)	(3.34)	(51.85)		
Dependent	**$InnOrig_t$**	**GM_t**	**$InnOrig_t*GM_t$**	**PIE_t**	**ADV_t**	**$R\&D_t$**	**$Capex_t$**	**MTB_t**	**Intercept**	**R^2**	**Firms**
GM_{t+1}	-0.11	23.91	0.72	-0.01	0.46	-0.29	0.06	0.82	29.22	0.70	2374
	(-0.98)	(16.40)	(1.99)	(-0.16)	(10.12)	(-1.41)	(0.47)	(3.33)	(51.76)		

Panel B. InnOrig and volatility of future gross margin (GM)

Dependent	$InnOrig_t$	CIE_t	ADV_t	$R\&D_t$	$Capex_t$	MTB_t	$GM\_VOL_{t-4,t}$	Intercept	R^2	Firms
$GM\_VOL_{t+1,t+5}$	-0.28	0.14	-0.28	1.85	-0.17	0.23	3.14	3.63	0.29	1735
	(-3.42)	(2.12)	(-7.17)	(4.56)	(-1.81)	(1.87)	(8.98)	(17.88)		
Dependent	**$InnOrig_t$**	**PIE_t**	**ADV_t**	**$R\&D_t$**	**$Capex_t$**	**MTB_t**	**$GM\_VOL_{t-4,t}$**	**Intercept**	**R^2**	**Firms**
$GM\_VOL_{t+1,t+5}$	-0.27	0.17	-0.29	1.85	-0.18	0.23	3.14	3.62	0.29	1735
	(-3.46)	(4.56)	(-7.37)	(4.56)	(-1.89)	(1.84)	(8.87)	(18.03)		

Table 5
Return predictive power of innovative originality – Single-sorted portfolio analysis

At the end of June of year *t* from 1982 to 2007, we form portfolios based on innovative originality (InnOrig) in year *t* – 1 as in Table 2. We also construct a high-minus-low (High–Low) portfolio by holding a long (short) position in the high (low) InnOrig portfolio. We then hold these portfolios over the next twelve months (July of year *t* to June of year *t* + 1). In Panel A, we report their average monthly returns in excess of one-month Treasury bill rate (Exret) as well as their average monthly 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 Panels B and C, we report the alphas and R^2 from the regression of the time-series of portfolio excess returns on various factor models: the Fama-French three factors (the market factor–MKT, the size factor–SMB, and the value factor–HML) plus the momentum (UMD) factor (4F) model, 4F plus the investment-minus-consumption (IMC) factor (Papanikolaou 2011), the liquidity (LIQ) factor (Pastor and Stambaugh 2003), the citations- or patents-based innovative efficient-minus-inefficient (EMI1 or EMI2) factor as in Hirshleifer, Hsu, and Li (2013), the robust-minus-weak (RMW) factor and the conservative-minus-aggressive (CMA) factor as in Fama and French (2015), or the undervalued-minus-overvalued (UMO) factor of Hirshleifer and Jiang (2010). We also report the alpha from the investment-based factor model (q-factor model) of Hou, Xue, and Zhang (HXZ 2015) and the mispricing factor model of Stambaugh and Yuan (2017). All returns and alphas are value-weighted and expressed in percentage. The *t*-statistics are reported in parentheses. R-square is adjusted.

A. Excess and adjusted returns				B. Alphas from different factor models									C. R^2 of different factor models								
					4F plus									4F plus							
InnOrig	Exret	Ind-adjret	Char-adjret	4F	IMC	LIQ	EMI1	EMI2	RMW + CMA	UMO	HXZ	Mis-pricing	4F	IMC	LIQ	EMI1	EMI2	RMW + CMA	UMO	HXZ	Mis-pricing
No	0.61	-0.02	-0.03	-0.13	-0.13	-0.15	-0.06	-0.04	-0.13	-0.12	-0.13	-0.05	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.92	0.92
	(2.54)	(-0.47)	(-0.15)	(-1.86)	(-1.79)	(-2.09)	(-0.94)	(-0.52)	(-1.79)	(-1.66)	(-1.67)	(-0.55)									
Low	0.51	-0.14	-0.09	-0.11	-0.11	-0.12	-0.05	-0.03	-0.04	-0.07	-0.06	-0.12	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.93
	(1.74)	(-1.97)	(-0.36)	(-1.44)	(-1.33)	(-1.51)	(-0.59)	(-0.39)	(-0.56)	(-0.96)	(-0.68)	(-1.34)									
Middle	0.73	0.03	0.07	0.16	0.17	0.17	0.09	0.07	0.17	0.15	0.15	0.09	0.94	0.94	0.94	0.95	0.95	0.95	0.94	0.95	0.94
	(2.83)	(0.76)	(0.31)	(2.49)	(2.48)	(2.55)	(1.45)	(1.08)	(2.68)	(2.33)	(2.41)	(1.23)									
High	0.80	0.09	0.19	0.24	0.24	0.23	0.20	0.19	0.20	0.23	0.14	0.19	0.91	0.91	0.91	0.91	0.91	0.91	0.90	0.90	0.91
	(3.09)	(1.86)	(0.76)	(2.74)	(2.71)	(2.54)	(2.23)	(2.12)	(2.19)	(2.57)	(1.59)	(2.07)									
High-Low	0.29	0.23	0.28	0.35	0.35	0.35	0.25	0.22	0.24	0.30	0.20	0.30	0.21	0.22	0.21	0.27	0.27	0.25	0.21	0.23	0.20
	(2.29)	(2.51)	(2.36)	(3.00)	(2.87)	(2.90)	(2.12)	(1.79)	(1.99)	(2.53)	(1.67)	(2.32)									

Table 6
Return predictive power of innovative originality – Double-sorted portfolio analysis

At the end of June of each year *t*, we conduct independent double sorts on innovative originality (InnOrig) and proxies of valuation uncertainty (VU), investor attention (ATT), or the sensitivity of future profitability to InnOrig. In Panel A1, we proxy VU by a composite index of firm age and opacity of financial reports (standardized opacity minus standardized age). In Panel A2, we proxy VU by the analyst forecast dispersion. In Panel B, we proxy attention (ATT) by the inverse of the ownership percentage of transient institutional investors. In Panel C, we proxy the sensitivity (Sen) by an industry-level sensitivity of past ROE to lagged InnOrig. The InnOrig portfolios are formed as in Table 5. The VU, attention, and sensitivity portfolios are based on tercile breakpoints. We also construct a high-minus-low InnOrig portfolio in each VU (ATT, and Sen) group and hold these portfolios for the next 12 months. For each portfolio, we report average monthly value-weighted excess return (Exret), industry-adjusted returns (Ind-adjret), characteristic-adjusted returns (Char-adjret), and alphas and R^2 from different factor models. The alphas are estimated from the regression of the time-series of portfolio excess returns on various factor models including the Fama-French three factors (the market factor–MKT, the size factor–SMB, and the value factor–HML) plus the momentum (UMD) factor (4F) and 4F plus the robust-minus-weak (RMW) factor and the conservative-minus-aggressive (CMA) factor as in Fama and French (2015). We also report alphas from the investment-based factor model of Hou, Xue, and Zhang (HXZ 2015) and the mispricing factor model of Stambaugh and Yuan (2017). All returns and alphas are in percentage. The *t*-statistics are reported in parentheses. The sample period for returns is from July 1982 to June 2008 except for analyst forecast dispersion subsamples, which start from July 1984 due to sparsity of analyst forecast data before 1983. R-square is adjusted.

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

Panel A1. VU based on age and opacity

					Alphas from factor models				R^2 of different models			
VU	InnOrig	Exret	Ind-adjret	Char-adjret	4F	4F + RMW + CMA	HXZ	Mis-pricing	4F	4F + RMW + CMA	HXZ	Mis-pricing
Low	Low (L)	0.66	-0.04	0.03	-0.07	-0.19	-0.22	-0.20	0.83	0.85	0.85	0.83
		(2.68)	(-0.67)	(0.13)	(-0.61)	(-1.72)	(-1.95)	(-1.67)				
	Middle	0.74	0.03	0.06	0.13	0.08	0.05	0.03	0.92	0.93	0.93	0.92
		(3.06)	(0.50)	(0.29)	(1.66)	(1.07)	(0.63)	(0.39)				
	High (H)	0.73	0.05	0.12	0.12	-0.08	-0.13	-0.07	0.77	0.80	0.80	0.77
		(3.17)	(0.79)	(0.56)	(0.98)	(-0.69)	(-1.13)	(-0.62)				
	H-L	0.07	0.09	0.09	0.18	0.11	0.09	0.13	0.04	0.05	0.05	0.04
		(0.51)	(1.02)	(0.67)	(1.23)	(0.74)	(0.64)	(0.84)				
High	Low (L)	0.23	-0.45	-0.43	-0.23	0.15	0.08	0.10	0.86	0.88	0.86	0.83
		(0.47)	(-2.15)	(-0.99)	(-0.96)	(0.61)	(0.30)	(0.36)				
	Middle	0.89	0.10	0.22	0.40	0.67	0.49	0.78	0.74	0.75	0.74	0.76
		(1.95)	(0.44)	(0.51)	(1.43)	(2.28)	(1.71)	(2.60)				
	High (H)	1.32	0.54	0.74	0.84	1.00	0.90	1.08	0.72	0.71	0.69	0.72
		(2.60)	(2.02)	(1.52)	(2.77)	(3.08)	(2.68)	(3.16)				
	H-L	1.10	0.99	1.17	1.07	0.85	0.82	0.98	0.04	0.08	0.05	0.04
		(3.88)	(3.66)	(3.84)	(3.07)	(2.38)	(2.38)	(2.51)				

Panel A2. VU based on analyst forecast dispersion

					Alphas from factor models				R^2 of different models			
VU	InnOrig	Exret	Ind-adjret	Char-adjret	4F	4F + RMW + CMA	HXZ	Mis-pricing	4F	4F + RMW + CMA	HXZ	Mis-pricing
Low	Low (L)	0.55	-0.17	-0.03	-0.04	-0.23	-0.23	-0.25	0.74	0.76	0.75	0.75
		(2.04)	(-1.66)	(-0.10)	(-0.31)	(-1.59)	(-1.50)	(-1.64)				
	Middle	0.67	-0.02	0.05	0.15	0.05	0.10	-0.03	0.86	0.86	0.84	0.86
		(2.57)	(-0.19)	(0.19)	(1.64)	(0.57)	(1.03)	(-0.28)				
	High (H)	0.84	0.14	0.15	0.30	0.13	0.16	0.06	0.71	0.73	0.71	0.73
		(3.30)	(1.50)	(0.59)	(2.06)	(0.90)	(1.10)	(0.43)				
	H-L	0.29	0.30	0.18	0.35	0.36	0.39	0.30	0.02	0.02	0.02	0.01
		(1.52)	(2.48)	(0.93)	(1.74)	(1.71)	(1.85)	(1.45)				
High	Low (L)	0.48	-0.05	-0.20	-0.24	0.02	0.02	-0.20	0.77	0.79	0.80	0.76
		(1.25)	(-0.28)	(-0.59)	(-1.29)	(0.09)	(0.09)	(-1.08)				
	Middle	0.90	0.23	0.14	0.15	0.31	0.23	0.23	0.76	0.77	0.78	0.77
		(2.32)	(1.78)	(0.42)	(0.79)	(1.57)	(1.26)	(1.15)				
	High (H)	1.15	0.38	0.53	0.45	0.49	0.50	0.42	0.66	0.68	0.68	0.67
		(2.86)	(1.89)	(1.47)	(1.80)	(1.87)	(1.92)	(1.51)				
	H-L	0.67	0.43	0.73	0.69	0.47	0.48	0.62	0.06	0.11	0.07	0.06
		(2.59)	(1.97)	(2.96)	(2.74)	(1.78)	(1.64)	(2.43)				

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

					Alphas from factor models				R^2 of different models			
ATT	InnOrig	Exret	Ind-adjret	Char-adjret	4F	4F + RMW + CMA	HXZ	Mis-pricing	4F	4F + RMW + CMA	HXZ	Mis-pricing
Low	Low (L)	0.53	-0.13	-0.13	-0.07	0.09	0.09	0.06	0.89	0.89	0.88	0.88
		(1.51)	(-1.22)	(-0.42)	(-0.58)	(0.69)	(0.59)	(0.41)				
	Middle	0.82	0.11	0.07	0.25	0.37	0.35	0.42	0.87	0.88	0.88	0.88
		(2.48)	(1.33)	(0.25)	(1.96)	(3.17)	(2.73)	(2.95)				
	High (H)	1.04	0.29	0.32	0.50	0.55	0.54	0.55	0.86	0.86	0.86	0.87
		(3.21)	(3.12)	(1.01)	(3.75)	(3.87)	(3.74)	(3.66)				
	H-L	0.51	0.43	0.45	0.58	0.46	0.45	0.49	0.08	0.13	0.09	0.06
		(3.40)	(3.43)	(3.05)	(3.49)	(2.83)	(2.45)	(2.54)				
High	Low (L)	0.43	-0.26	-0.11	-0.14	0.17	0.30	0.04	0.85	0.86	0.85	0.77
		(1.12)	(-1.12)	(-0.28)	(-0.90)	(1.14)	(1.86)	(0.21)				
	Middle	0.75	-0.09	-0.06	-0.03	0.14	0.14	-0.20	0.65	0.68	0.66	0.57
		(1.99)	(-0.34)	(-0.15)	(-0.10)	(0.55)	(0.48)	(-0.70)				
	High (H)	0.81	0.00	0.29	0.20	0.40	0.29	0.01	0.71	0.72	0.69	0.64
		(2.17)	(0.02)	(0.79)	(0.83)	(1.70)	(1.03)	(0.04)				
	H-L	0.39	0.26	0.40	0.33	0.23	-0.01	-0.03	0.04	0.05	0.10	0.09
		(1.83)	(1.42)	(1.83)	(1.39)	(0.93)	(-0.05)	(-0.13)				

Panel C. Return predictive power of InnOrig and industry-level profitability sensitivity (Sen)

					Alphas from factor models				R^2 of different models			
Sen	InnOrig	Exret	Ind-adjret	Char-adjret	4F	4F + RMW + CMA	HXZ	Mis-pricing	4F	4F + RMW + CMA	HXZ	Mis-pricing
Low	Low (L)	0.81	-0.09	0.16	0.15	0.32	0.27	0.37	0.80	0.81	0.81	0.81
		(2.46)	(-0.80)	(0.54)	(1.03)	(2.10)	(1.69)	(2.58)				
	Middle	1.03	0.05	0.30	0.39	0.43	0.48	0.45	0.78	0.78	0.79	0.79
		(3.55)	(0.87)	(1.16)	(2.53)	(2.63)	(2.87)	(2.66)				
	High (H)	0.65	0.00	0.03	0.03	0.00	-0.22	0.02	0.69	0.70	0.71	0.70
		(2.30)	(0.01)	(0.10)	(0.19)	(-0.02)	(-1.32)	(0.11)				
	H-L	-0.16	0.10	-0.13	-0.12	-0.32	-0.49	-0.36	0.16	0.19	0.21	0.17
		(-0.74)	(0.65)	(-0.63)	(-0.60)	(-1.59)	(-2.33)	(-1.75)				
High	Low (L)	0.29	-0.21	-0.36	-0.21	-0.21	-0.17	-0.12	0.81	0.80	0.80	0.80
		(0.97)	(-2.21)	(-1.31)	(-1.49)	(-1.48)	(-1.10)	(-0.76)				
	Middle	0.61	0.12	0.03	0.24	0.23	0.24	0.22	0.84	0.84	0.83	0.81
		(2.03)	(2.02)	(0.12)	(1.68)	(1.72)	(1.51)	(1.20)				
	High (H)	0.89	0.22	0.30	0.54	0.43	0.34	0.58	0.73	0.73	0.69	0.70
		(2.93)	(2.02)	(1.11)	(3.07)	(2.39)	(1.56)	(2.71)				
	H-L	0.59	0.43	0.65	0.75	0.64	0.51	0.70	0.08	0.08	0.07	0.05
		(2.92)	(2.81)	(3.23)	(3.31)	(2.75)	(2.13)	(2.78)				

Table 7
Return predictive power of innovative originality – Fama-MacBeth regressions (full sample)

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted 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 the natural log of one plus InnOrig of year *t* – 1, different sets of control variables, and industry fixed effects except Model 1, which is a simple regression. We set missing values for InnOrig, PIE, CIE and R&D expenses to zero, and control for a dummy variable (missing), which equals 1 for firms with no R&D investment and patent for the past five years and 0 otherwise, and its interactions with all the control variables in the multiple regressions. We omit the intercept, the slopes on the 48 industry dummies, and the slopes on the missing dummy and its interactions with all other control variables for brevity. All variables are defined as in Table 2. Size is the log of market capitalization at the end of June of year *t*. Book-to-market is also in the natural log form. Intuitional ownership and BTM are measured in year *t* – 1. ILLIQ and REV are the previous month's stock illiquidity and stock return, respectively. In Model 3, we control for additional return predictors related to innovation (CIE for Model 3A or PIE for Model 3B, 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. CIE (PIE) is the natural log of one plus the citations- (patents-) 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 4, we further control for sales diversity measured by the number of segments (NSD) as defined in Table 2. All independent variables are normalized to zero mean and one standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1982 to June of 2008. R-square (number of firms) is the time-series average of the R-squares (number of firms) from the monthly cross-sectional regressions.

	Model 1		Model 2		Model 3A		Model 3B		Model 4A		Model 4B	
Innovative originality (InnOrig)	0.15	(2.91)	0.15	(5.34)	0.10	(3.58)	0.12	(4.42)	0.09	(3.53)	0.12	(4.34)
Size			-0.24	(-1.88)	-0.13	(-1.50)	-0.12	(-1.45)	-0.11	(-1.24)	-0.11	(-1.21)
Book-to-market (BTM)			0.43	(5.41)	0.20	(2.75)	0.20	(2.75)	0.21	(2.96)	0.21	(2.94)
Momentum (MOM)			0.09	(1.00)	0.01	(0.09)	0.01	(0.09)	0.00	(0.05)	0.00	(0.05)
Institutional ownership (InstOwn)			0.09	(1.55)	0.09	(2.05)	0.09	(2.12)	0.08	(1.90)	0.09	(1.98)
Illiquidity (ILLIQ)			0.49	(6.47)	0.37	(3.74)	0.37	(3.74)	0.37	(3.71)	0.37	(3.71)
Short-term return reversal (REV)			-1.03	(-9.77)	-1.12	(-10.71)	-1.12	(-10.71)	-1.11	(-10.50)	-1.11	(-10.50)
Asset growth (AG)					-0.22	(-4.60)	-0.22	(-4.50)	-0.22	(-4.68)	-0.22	(-4.58)
Capex/Assets (IA)					-0.05	(-1.15)	-0.06	(-1.15)	-0.05	(-1.05)	-0.05	(-1.05)
Patents/Assets (CTA)					0.01	(0.28)	0.03	(0.75)	0.01	(0.23)	0.03	(0.68)
R&D/Market equity (RDME)					0.21	(2.98)	0.21	(2.99)	0.21	(3.06)	0.21	(3.08)
Net stock issuance (NS)					-0.09	(-2.00)	-0.09	(-2.00)	-0.09	(-1.98)	-0.09	(-1.99)
Return on assets (ROA)					0.10	(1.71)	0.10	(1.73)	0.08	(1.37)	0.08	(1.39)
Idiosyncratic volatility (IVOL)					0.31	(2.04)	0.31	(2.02)	0.31	(2.00)	0.31	(1.99)
Skewness (SKEW)					-0.10	(-2.72)	-0.10	(-2.69)	-0.10	(-2.78)	-0.10	(-2.75)
Citations-based IE (CIE)					0.06	(3.41)			0.06	(3.49)		
Patents-based IE (PIE)							-0.01	(-0.55)			-0.01	(-0.46)
Number of sales segments (NSD)									-0.03	(-1.18)	-0.03	(-1.07)
R^2	0.00		0.07		0.10		0.10		0.10		0.10	
Number of firms	4693		3789		3093		3093		3073		3073	

Table 8
Return predictive power of innovative originality – Fama-MacBeth regressions (subsamples)

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions as in Model 3 of Table 7 within subsamples split by valuation uncertainty (VU), investor attention (ATT), and the sensitivity of future profitability to innovative originality (InnOrig) in Panels A, B, and C, respectively. The proxies of VU, ATT, and sensitivity are defined as in Table 6. The Low (High) subsample refers to the bottom (top) 30%. All variables are defined as in Tables 2 and 7.

Panel A. Valuation uncertainty (VU) subsamples																
	A1. VU based on age and opacity								A2. VU based on analyst forecast dispersion							
	Model 3A				Model 3B				Model 3A				Model 3B			
	Low VU		High VU		Low VU		High VU		Low VU		High VU		Low VU		High VU	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
Innovative originality	0.01	(0.25)	0.21	(2.74)	0.04	(0.78)	0.24	(3.24)	0.07	(1.34)	0.15	(1.95)	0.08	(1.49)	0.16	(2.06)
Size	-0.12	(-1.05)	-0.41	(-2.53)	-0.11	(-0.95)	-0.41	(-2.52)	-0.04	(-0.38)	-0.07	(-0.57)	-0.03	(-0.34)	-0.08	(-0.64)
Book-to-market	0.10	(1.20)	0.19	(1.62)	0.09	(1.06)	0.20	(1.74)	0.18	(1.81)	0.08	(0.77)	0.18	(1.87)	0.07	(0.69)
Momentum	0.08	(0.59)	-0.01	(-0.05)	0.08	(0.61)	-0.02	(-0.12)	0.15	(1.32)	0.06	(0.49)	0.15	(1.28)	0.06	(0.47)
Institutional ownership	-0.03	(-0.45)	0.22	(1.89)	-0.03	(-0.39)	0.22	(1.93)	0.10	(1.56)	0.04	(0.45)	0.09	(1.49)	0.03	(0.40)
Illiquidity	-0.08	(-0.83)	0.35	(1.76)	-0.08	(-0.84)	0.35	(1.76)	-0.42	(-0.77)	0.14	(0.52)	-0.46	(-0.82)	0.14	(0.55)
Short-term return reversal	-0.54	(-7.03)	-1.15	(-6.53)	-0.54	(-6.96)	-1.16	(-6.51)	-0.80	(-7.19)	-0.82	(-7.68)	-0.80	(-7.14)	-0.83	(-7.67)
Asset growth	-0.12	(-1.92)	-0.31	(-3.37)	-0.12	(-1.83)	-0.30	(-3.26)	-0.07	(-0.93)	-0.06	(-0.65)	-0.07	(-0.93)	-0.05	(-0.55)
Capex/Assets	-0.08	(-1.16)	0.20	(2.78)	-0.08	(-1.13)	0.21	(2.79)	-0.09	(-1.12)	0.02	(0.26)	-0.10	(-1.18)	0.04	(0.44)
Patents/Assets	-0.01	(-0.12)	0.13	(1.53)	0.01	(0.19)	0.16	(1.60)	0.07	(1.00)	0.09	(1.30)	0.11	(1.49)	0.11	(1.39)
R&D/Market equity	0.06	(1.50)	0.28	(1.99)	0.07	(1.71)	0.28	(2.01)	0.28	(2.14)	0.37	(3.62)	0.27	(2.12)	0.37	(3.67)
Net stock issuance	-0.07	(-1.28)	-0.05	(-0.38)	-0.07	(-1.26)	-0.06	(-0.49)	-0.12	(-1.49)	0.00	(0.01)	-0.11	(-1.43)	0.00	(-0.01)
Return on assets	0.03	(0.47)	0.26	(2.52)	0.02	(0.34)	0.26	(2.48)	0.30	(3.07)	0.10	(1.31)	0.30	(3.11)	0.10	(1.31)
Idiosyncratic volatility	0.18	(1.41)	0.35	(1.80)	0.18	(1.40)	0.34	(1.77)	0.10	(0.50)	0.01	(0.04)	0.10	(0.51)	-0.01	(-0.05)
Skewness	-0.10	(-1.64)	-0.19	(-2.32)	-0.10	(-1.68)	-0.19	(-2.28)	-0.12	(-2.09)	-0.15	(-2.09)	-0.11	(-1.95)	-0.15	(-2.11)
Citations-based IE	0.10	(1.97)	0.06	(1.02)					0.02	(0.48)	0.00	(0.01)				
Patents-based IE					0.02	(0.65)	-0.04	(-0.46)					-0.03	(-0.89)	-0.06	(-0.85)
R^2	0.20		0.16		0.20		0.16		0.25		0.26		0.25		0.26	
Number of firms	770		736		770		736		517		497		517		497	

	Panel B. Investor attention (ATT) subsamples								Panel C. Profitability sensitivity (Sen) subsamples							
	Model 3A				Model 3B				Model 3A				Model 3B			
	High ATT		Low ATT		High ATT		Low ATT		Low Sen		High Sen		Low Sen		High Sen	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
Innovative originality	0.00	(-0.06)	0.16	(2.91)	0.03	(0.58)	0.17	(3.15)	0.05	(0.69)	0.23	(3.22)	0.05	(0.61)	0.24	(3.41)
Size	-0.26	(-3.24)	-0.12	(-1.34)	-0.26	(-3.28)	-0.13	(-1.35)	0.01	(0.10)	-0.16	(-1.24)	-0.01	(-0.08)	-0.15	(-1.15)
Book-to-market	0.33	(4.19)	-0.04	(-0.51)	0.32	(4.13)	-0.05	(-0.67)	0.15	(1.43)	0.04	(0.36)	0.15	(1.44)	0.04	(0.35)
Momentum	0.07	(0.75)	0.31	(2.95)	0.07	(0.73)	0.31	(2.93)	0.14	(0.85)	0.51	(3.50)	0.14	(0.86)	0.51	(3.54)
Institutional ownership	0.05	(1.02)	-0.08	(-1.55)	0.05	(1.15)	-0.08	(-1.54)	0.03	(0.51)	0.03	(0.33)	0.04	(0.72)	0.02	(0.21)
Illiquidity	0.14	(1.45)	-0.10	(-0.98)	0.14	(1.43)	-0.10	(-0.98)	-0.03	(-0.06)	0.23	(0.45)	-0.05	(-0.09)	0.25	(0.48)
Short-term return reversal	-1.04	(-8.98)	-0.58	(-7.38)	-1.03	(-8.89)	-0.58	(-7.40)	-0.81	(-7.55)	-0.60	(-5.45)	-0.82	(-7.58)	-0.61	(-5.43)
Asset growth	-0.12	(-1.79)	-0.10	(-1.50)	-0.13	(-1.87)	-0.09	(-1.43)	-0.27	(-2.05)	-0.15	(-1.25)	-0.25	(-1.89)	-0.15	(-1.20)
Capex/Assets	-0.09	(-1.14)	-0.05	(-0.64)	-0.09	(-1.06)	-0.06	(-0.77)	0.16	(1.51)	0.02	(0.17)	0.15	(1.45)	0.01	(0.11)
Patents/Assets	0.10	(1.43)	0.09	(1.14)	0.13	(1.53)	0.08	(0.92)	0.14	(0.66)	-0.25	(-1.36)	0.14	(0.56)	-0.28	(-1.39)
R&D/Market equity	0.35	(2.57)	0.16	(2.22)	0.35	(2.60)	0.16	(2.21)	0.08	(0.57)	0.17	(1.30)	0.07	(0.47)	0.18	(1.38)
Net stock issuance	-0.22	(-3.26)	-0.15	(-3.23)	-0.22	(-3.16)	-0.15	(-3.36)	-0.19	(-1.95)	-0.26	(-2.74)	-0.19	(-1.89)	-0.25	(-2.64)
Return on assets	0.22	(3.23)	-0.02	(-0.28)	0.23	(3.29)	-0.02	(-0.25)	0.30	(1.68)	0.20	(1.07)	0.29	(1.61)	0.19	(1.01)
Idiosyncratic volatility	-0.01	(-0.06)	-0.13	(-0.94)	-0.01	(-0.08)	-0.14	(-0.96)	0.29	(1.02)	-0.17	(-0.60)	0.26	(0.92)	-0.18	(-0.64)
Skewness	0.00	(0.02)	-0.13	(-2.90)	0.00	(0.02)	-0.12	(-2.85)	-0.04	(-0.51)	-0.12	(-1.37)	-0.04	(-0.54)	-0.12	(-1.40)
Citations-based IE	0.12	(1.93)	0.01	(0.30)					-0.08	(-1.54)	0.00	(-0.02)				
Patents-based IE					0.02	(0.27)	0.01	(0.17)					-0.09	(-0.96)	0.01	(0.11)
R^2	0.26		0.30		0.26		0.30		0.30		0.28		0.30		0.28	
Number of firms	902		914		902		914		814		972		814		972	

Table 9
Return predictive power of innovative originality versus innovative efficiency – Fama-MacBeth regressions (subsamples)

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions as in Model 3 of Table 7 within subsamples split by citations-based (patents-based) innovative efficiency measure. The Low (High) IE subsample refers to the bottom (top) 30%. All variables are defined as in Tables 2 and 7.

	Citations-based IE				Patents-based IE			
	Low IE		High IE		Low IE		High IE	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
Innovative originality	0.10	(2.72)	-0.02	(-0.44)	0.17	(4.14)	-0.01	(-0.13)
Size	-0.28	(-2.33)	-0.11	(-0.90)	-0.26	(-2.65)	-0.08	(-0.80)
Book-to-market	0.30	(3.81)	0.18	(2.19)	0.27	(3.53)	0.15	(1.80)
Momentum	-0.07	(-0.59)	0.07	(0.73)	-0.06	(-0.63)	0.03	(0.41)
Institutional ownership	0.22	(3.44)	0.05	(0.79)	0.17	(2.97)	0.06	(1.07)
Illiquidity	0.28	(3.27)	0.13	(1.28)	0.33	(3.78)	-0.11	(-1.39)
Short-term return reversal	-1.16	(-10.17)	-0.79	(-9.70)	-1.14	(-10.18)	-0.90	(-10.22)
Asset growth	-0.27	(-3.36)	-0.11	(-1.66)	-0.29	(-4.08)	-0.09	(-1.29)
Capex/Assets	0.02	(0.36)	-0.06	(-0.97)	-0.04	(-0.74)	-0.01	(-0.17)
Patents/Assets	-0.03	(-0.64)	0.05	(0.66)	0.00	(0.00)	0.07	(0.83)
R&D/Market equity	0.14	(1.58)	0.23	(2.49)	0.14	(1.86)	0.25	(2.49)
Net stock issuance	-0.03	(-0.45)	-0.12	(-1.83)	-0.08	(-1.26)	-0.16	(-2.53)
Return on assets	0.06	(0.66)	0.22	(2.69)	0.10	(1.24)	0.09	(1.06)
Idiosyncratic volatility	0.34	(2.10)	0.29	(1.96)	0.36	(2.38)	0.22	(1.59)
Skewness	-0.12	(-2.26)	-0.03	(-0.57)	-0.12	(-2.22)	-0.10	(-2.49)
R^2	0.17		0.21		0.15		0.20	
Number of firms	586		381		725		415	

Table 10
Return predictive power of innovative originality and R&D intensity – Fama-MacBeth regressions (subsamples)

This table reports the average slopes (in %) and their Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions as in Model 3 of Table 7 within subsamples split by R&D intensity. R&D intensity is defined as R&D expenses scaled by total assets. The Low (High) R&D subsample refers to the bottom (top) 30%. All variables are defined as in Tables 2 and 7.

	Model 3A				Model 3B			
	Low R&D		High R&D		Low R&D		High R&D	
	Slope	*t* -stat	Slope	*t* -stat	Slope	*t* -stat	Slope	*t* -stat
Innovative originality	0.05	(1.07)	0.14	(2.01)	0.13	(1.64)	0.18	(2.66)
Size	0.07	(0.80)	-0.34	(-2.65)	0.08	(0.90)	-0.34	(-2.65)
Book-to-market	0.29	(4.70)	0.19	(1.73)	0.29	(4.76)	0.18	(1.72)
Momentum	0.20	(2.52)	-0.10	(-0.76)	0.20	(2.51)	-0.10	(-0.76)
Institutional ownership	0.01	(0.20)	0.18	(1.87)	0.01	(0.21)	0.20	(2.04)
Illiquidity	0.27	(3.41)	0.53	(4.14)	0.27	(3.38)	0.53	(4.13)
Short-term return reversal	-0.82	(-10.30)	-1.33	(-10.43)	-0.83	(-10.33)	-1.33	(-10.44)
Asset growth	-0.27	(-4.33)	-0.25	(-2.85)	-0.27	(-4.26)	-0.24	(-2.72)
Capex/Assets	0.00	(0.01)	0.02	(0.27)	0.00	(0.00)	0.02	(0.24)
Patents/Assets	0.02	(0.42)	0.02	(0.25)	0.12	(1.81)	0.06	(0.59)
Net stock issuance	-0.08	(-1.84)	-0.02	(-0.17)	-0.08	(-1.82)	-0.01	(-0.16)
Return on assets	0.15	(2.29)	0.26	(2.57)	0.14	(2.19)	0.26	(2.56)
Idiosyncratic volatility	0.17	(1.43)	0.07	(0.50)	0.17	(1.39)	0.07	(0.48)
Skewness	-0.07	(-1.90)	-0.07	(-0.90)	-0.07	(-1.89)	-0.07	(-1.03)
Citations-based IE	0.10	(2.08)	0.12	(1.72)				
Patents-based IE					-0.13	(-2.36)	-0.02	(-0.24)
R^2	0.16		0.15		0.16		0.15	
Number of firms	717		438		717		438	

Figure 1. Monthly Average Alphas of InnOrig Spread Portfolio over the Five Post-Sorting Years

Figure 1 plots the value-weighted monthly average alphas for the high-minus-low innovative originality portfolio (as formed in Table 5) over the five post-sorting years. All the factor models used are described in Table 5.

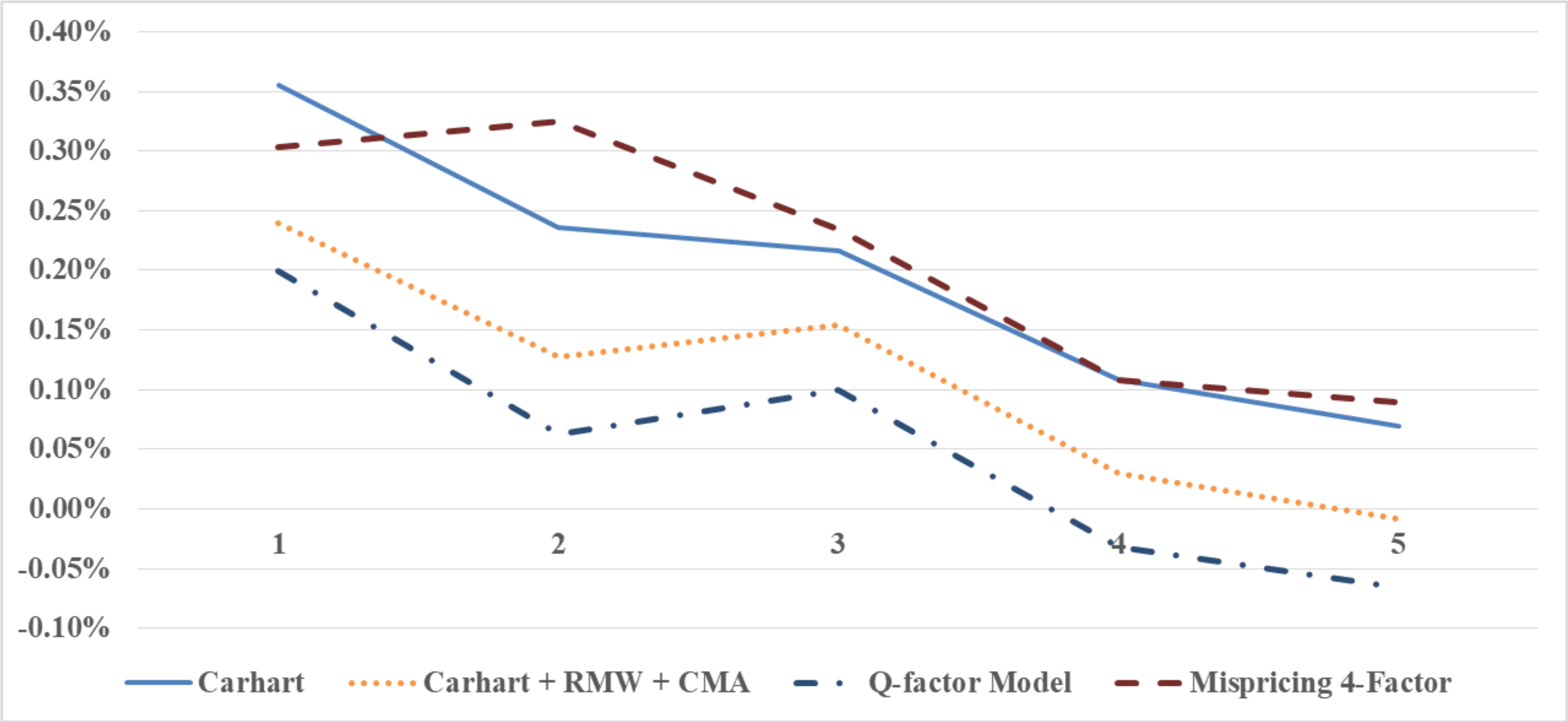

Figure 2. High-minus-Low Innovative Originality Portfolio Returns

Figure 2 plots the value-weighted return on the high-minus-low innovative originality portfolio (as formed in Table 5) on a per annum basis from July of 1982 to June of 2008. There are only six months in 1982 and 2008.