R&D Information Quality and Stock Returns

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Abstract

Ambiguity-averse investors demand a higher risk premium from a firm whose future performance in R&D is difficult to evaluate. We construct a R&D information quality (IQ) measure by linking a firm's historical innovation input (R&D expenditures) and innovation outcome (sales), and find statistically and economically significant evidence that expected excess returns decrease with R&D IQ. The high-minus-low IQ hedge portfolio earns excess return of about −39 (−48) basis points per month in value-weighted (equal-weighted) returns. The IQ-return relationship becomes stronger in firms with greater uncertainty business environment. Finally, we form a R&D IQ factor-mimicking portfolio, which is found to be weakly correlated with commonly used factors and is shown to have incremental pricing effects.

Keywords: Research and Development; Ambiguity Aversion; Information Quality; Return Predictability; Factor Models.

JEL Classification: G12, G14, O32

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I. Introduction

As an essential component of innovation, research and development (R&D) plays a critical role in developing new competitive advantages of firms. However, evaluating R&D information has been posing a challenge to investors because R&D is usually featured with future-oriented, long-term activities in science and technology, whose information is hard to process and whose outcomes are difficult to predict. Moreover, the lack of accounting disclosure suggests that investors may not be fully informed about all information related to firms' R&D activities, resulting in the asymmetric information problem (Aboody and Lev, 2000). All these facts make expected returns on R&D investments subject to a high degree of uncertainty. Even though there are a large number of works that devote to investigating whether stock prices fully impound information contained in firms' R&D, very little attention has been paid to relationship between R&D information uncertainty and stock returns. It is thus an important issue to understand how investors resolve uncertainties inherent in the long road of R&D from conceptualization to commercialization when making investment decisions based on publicly available information. Do they demand a higher risk premium from a firm whose future performance in R&D is hard to evaluate, and does such a behavior affect the firm's future stock return?

There are abundant theoretical works that link information uncertainty to asset prices. As early as in 1921, Knight argues for importance to distinguish uncertainty from risk (Knight, 1921). Chen and Epstein (2002) show in a theoretical model that excess return should be composed of a risk premium and a premium for Knightian uncertainty (ambiguity). Epstein and Schneider (2008) make a further refinement and present a model in which expected excess return decreases with information quality and ambiguity-averse investors require compensation for holding an asset with low quality information. However, Veronesi (2000) considers a pure exchange economy with power utility preferences, and shows that the equity risk premium increases with information quality. In this paper, we focus on this contentious issue using information contained in a firm's R&D activities and empirically investigate the relationship between R&D information quality and future stock returns.

Similar to Cohen, Diether, and Malloy (2013), we argue that a firm's innovative ability is persistent and predictable, and that even though we don't know its future R&D information quality, past information on its success in R&D provides us a useful measure to evaluate its future R&D activities. We therefore propose a measure of R&D information quality by looking at how well a firm's R&D expenditures are translated to its future sales. Specifically, a firm's R&D information quality (IQ) is measured by the R-square from regressing its sales growth on the realized R&D capital. When constructing our measure of R&D information quality, we take into account the facts that different firms may have different R&D lifespans and each year's R&D expenditures may have different impact on future sales growth. Using all firms listed on NYSE, AMEX, and NASDAQ with valid accounting and returns data, we find that the mean (median) value of the resulted R&D IQ measure varies across industries from 0.41 (0.37) for automobiles to 0.67 (0.69) for utilities. R&D IQ is in general not correlated with other firm-specific variables such as size, book-to-market, cash holdings, return of assets, return of equity, and some innovation-related variables. For example, among all variables we consider in this paper, the correlation coefficient ranges from -0.05 to 0.07, indicating that IQ is distinct from the well-known firm characteristics and contains different information.

We hypothesize that when past track record of a firm indicates a high R-square from the regression of its sales growth on the R&D capital, investors become less uncertain and are more willing to make investments in its future R&D activities; otherwise, investors would require higher premium for making such investments. To test our hypothesis, we implement portfolio analysis in ways similar to Fama and French (1996). At the end of June of each year, we sort all firms into three R&D IQ portfolios (low, middle, and high) based on the 30th and 70th percentiles of R&D IQ in the previous year and construct a hedge portfolio that longs the high IQ portfolio and shorts the low IQ portfolio. We hold these portfolios over the next 12 months and compute their value/equal-weighted monthly returns. We find that the average excess portfolio returns decrease with R&D

IQ. For example, the low IQ portfolio earns 127 basis points ($t = 4.23$) per month in value-weighted returns and 126 basis points ($t = 4.14$) per month in equal-weighted returns, whereas the high IQ portfolio earns only 78 basis points ($t = 2.56$) per month in value-weighted excess returns and 88 basis points ($t = 2.99$) per month in equal-weighted excess returns. Furthermore, the monthly return on the hedge portfolio is economically substantial and statistically significant: it is -48 basis points ($t = -4.69$) in value-weighted excess returns and -39 basis points ($t = -4.16$) in equal-weighted excess returns. The same pattern also holds in characteristic- and industry-adjusted returns.

Alphas from the factor models also decrease with R&D IQ. Specifically, in the Fama-French three-factor model (Fama and French, 1993), the monthly alphas for the low, middle, and high R&D IQ portfolios are 16, 14, and -24 basis points, respectively, in value-weighted excess returns, and are 20, 14, and -32 basis points, respectively, in equal-weighted excess returns. The alpha for the high-minus-low IQ hedge portfolio is -40 basis points ($t = -4.04$) per month in value-weighted excess returns and is -52 basis points ($t = -4.73$) per month in equal-weighted excess returns. The pattern for the estimated alphas for the low, middle, and high IQ portfolios, as well as the hedge portfolio is the same in the Carhart four-factor model (Carhart, 1997). The above results indicate that investors are strongly uncertain about low IQ firms' future R&D activities and require higher premium for making such investments.

We further perform the Fama-MacBeth cross-sectional regressions that allow us for controlling for a large number of variables, including size, book-to-market, momentum, leverage, idiosyncratic volatility, illiquidity, innovation-related variables, and so on. In spite of such extensive controls, the coefficient on R&D IQ is alway negative and statistically significant. This finding further supports our hypothesis that expected excess returns decreases with R&D IQ.

If our IQ measure really captures information quality/uncertainty in firms' R&D, it should have little effects on fundamentals. We take return on assets (ROA), cash flows (CF), sales, and performance (PM) as proxies for fundamentals, and examine the relationship between R&D IQ and subsequent operating performance by implementing

Fama-MacBeth regressions. After controlling the standard variables in the regressions such as size, book-to-market, leverage, idiosyncratic volatility, and illiquidity, as well as some innovation-related variables, we find that for all the four proxies of fundamentals, the coefficient on IQ is insignificant, whereas the coefficients on lagged fundamentals and changes of fundamentals are significant. These findings indicate that our IQ measure is nothing related to undervaluation or overvaluation.

We observe that there exists the IQ-return relationship and investors require higher premium for investing in low IQ firms' R&D. We conjecture that this relationship should become stronger among firms with smaller market capitalization, with younger age, with greater financial constraint, and with higher fundamental volatility. These firms may have more uncertain business environments and investors are more ambiguous about their future prospects. To test this hypothesis, we perform independent double sorts on IQ and size, age, the KZ index, and the cash-flow uncertainty. We find that among firms with small size, the monthly value-weighted excess returns on low, middle, and high IQ portfolios are 139 (t = 4.34), 91 (t = 2.57), and 44 (t = 1.05) basis points, respectively, whereas they are 128 (t = 4.39), 122 (t = 4.75), and 100 (t = 3.78) basis points, respectively, among firms with large size. The high-minus-low IQ hedge portfolio earns -76 ($t = -2.91$) basis points per month among firms with small size, whereas it earns only -28 ($t = -2.34$) basis points per month among firms with large size. The alphas from the Fama-French three-factor model and the Carhart four-factor model for the hedge portfolio are -99 ($t = -3.02$) and -110 ($t = -3.23$) basis points per month, respectively, among small firms, whereas they become small and marginally significant, -24 ($t = -1.94$) and -25 ($t = -1.96$) basis points per month, among large firms. Our tests on age, the KZ index, and the cash-flow uncertainty deliver the same implications and provide further evidence on our hypothesis.

To further explore the relationship between R&D IQ and future stock returns and examine whether the IQ effect reflects commonality in returns that is not captured by the existing factors, we construct a factor-mimicking portfolio for R&D information quality following the similar methodology used in Fama and French (1993). At the end of June of each year, we first sort firms into two size groups (small "S" and big "B") and then sort each size group into three IQ subgroups (low "L", middle "M", and high "H"). We thus have six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H). The IQ factor (IQF) is constructed as (S/L + B/L)/2 - (S/H + B/H)/2. We find that the IQF is not highly correlated with the commonly used factors such as the market factor (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (MOM). For example, the monthly correlation between IQF and MKT is only about 3%; its monthly correlations with SMB, HML, and MOM are 22%, -13%, and 19%, respectively. We also find that IQF captures a different pricing factor that is distinct from the existing factors through constructions of tangency portfolios. For example, adding IQF to the Fama-French three factors improves the ex post Sharpe ratio of the tangency portfolio by 14% with the weight on IQF being 42%, larger than weights on MKT (26%), SMB (25%), and HML (7%).

Our study relates with and contributes to two strands of literature. On the one hand, there are many works investigating whether asset prices fully impound information contained in the innovation process. On the innovation input side, Chan, Lakonishok, and Sougiannis (2001) find that R&D intensity measured as R&D expenditures relative to the market value of equity has ability to predict future returns. However, its predictability power disappears when the ratio of R&D expenditures to sales is used. Eberhart, Maxwell, and Siddique (2004) empirically report significant positive long-term abnormal stock returns following unexpected and economically significant increases in R&D and argue that R&D increases are beneficial investments, but the market underreacts to this benefit. Li (2011) argues that the positive relationship between R&D intensity and stock returns exists only in financially constrained firms, and this relationship is robust to measures of R&D intensity. Cohen, Diether, and Malloy (2013) demonstrate that firm-level innovation is persistent and predictable, but the market appears to ignore the publicly available information in R&D when valuing future innovation. On the innovation output side, Gu (2005) finds that changes in patent citations relative to total assets are positively related with firm's future earnings and stock returns. Pandit, Wasley, and Zach

(2011) show that firm's patent citations positively associate with its future operating performance. Hirsleifer, Hsu, and Li (2013, 2015) construct an innovative efficiency (IE) measure and an innovative originality (IO) measure, respectively, using the number of patents and patent citations of a firm and find that both IE and IO positively predict the future stock returns. They mainly attribute this positive IE/IO-return relationship to limited investor attention. However, different from the above works, our paper focuses on information quality/uncertainty related to the innovation process by connecting innovation input (R&D) and innovation outcome (sales).

On the other hand, how information quality/uncertainty affects asset returns has attracted a large amount of attention. Veronesi (2000) considers a pure exchange economy with a power utility preferences, and find that the equity risk premium increases with information quality. Brevik and d'Addona (2010) introduce Epstein-Zin recursive preferences to Veronesi's model and find an opposite result: high information quality decreases the equity premium. Epstein and Schneider (2008) build a theoretical model and show in markets with ambiguous information, expected excess returns decrease with future information quality. Ai (2010) develops a production-based long-run risk model, which indicates that high information quality decreases equity premium. Zhang (2006) implements an empirical investigation on information uncertainty and stock returns. He finds that greater information uncertainty leads to higher expected excess returns following good news but lower returns following bad news. Focusing on R&D-related information, we find robust empirical results that expected excess returns contain an uncertainty/ambiguity premium, and the higher the information quality is, the smaller the future excess return is.

The rest of the paper is organized as follows. Section II introduces the data and provides summary statistics. Section III investigates the return predictability based on R&D information quality using portfolio analysis and Fama-MacBeth cross-sectional analysis. Section IV provides further evidence on the return predictability power of R&D information quality. Section V constructs a R&D information quality factor. Section VI concludes the paper.

II. The Data and Summary Statistics

A. The Data and R&D Information Quality

The sample we use in this paper combines different data sources and spans over the period from July 1980 to July 2012. We obtain firm-specific accounting data, such as R&D expenditures, sales, and book equity from Compustat, and monthly stock returns, shares outstanding, and volume capitalization from Center for Research in Security Prices (CRSP). All common stocks trading on NYSE, AMEX, and NASDAQ with valid accounting and returns data are included in the sample. Firms need to be listed on Compustat for two years before including in our sample. We exclude financial firms, which have four-digit standard industrial classification (SIC) codes between 6000 and 6999 (finance, insurance, and real estate sectors). Similar to Fama and French (1993), we further discard closed-end funds, trusts, American Depository Receipts, Real Estate Investment Trusts, units of beneficial interest, and firms with negative book equity. For some of our tests, we also use the firm-level patent-related data, which are mainly drawn from the updated National Burearu of Economic Research (NBER) patent database originally developed by Hall, Jaffe, and Trajtenberg (2001). However, these data are only available up to December 2006.

We measure R&D information quality by assessing how well a firm's past R&D expenditures are translated to its future sales growth. Similar to Cohen, Diether, and Malloy (2013), we argue that a firm's innovative ability is persistent and predictable and that even though we don't know its future R&D information quality, past information on its success in R&D provides us a useful measure to evaluate its future R&D activities. Specifically, we regress sales growth separately on each of the past five-year's realized R&D capitals, and then take the largest resulted R-square as our measure of information quality. When constructing this measure, we take into account the facts that different firms may have different R&D lifespans and each year's R&D expenditures may have different impact on future sales growth. Therefore, our regression for any firm i at each year t takes the form of

$$\log\left(\frac{sales_{i,t}}{sales_{i,t-1}}\right) = \alpha_{i,j} + \beta_{i,j}\log(1 + RDC^{k}_{i,t-j}) + \epsilon_{i,t}, \tag{1}$$

where

$$RDC^{k}_{i,t-j} = \frac{k}{10}RD_{i,t-j-1} + (\frac{k}{10})^2 RD_{i,t-j-2} + (\frac{k}{10})^3 RD_{i,t-j-3} + (\frac{k}{10})^4 RD_{i,t-j-4}, \tag{2}$$

for $j = 1, 2, ..., 5$, and $k = 1, 2, ..., 9$, where RD is R&D expenditures, and RDC is the realized R&D capital. Equation (1) assumes that R&D capitals from year $t-5$ to $t-1$ are relevant to sales of year t. In fact, we have tried other assumptions on R&D lifespan up to ten years. We find that our results are identically the same. Our definition of R&D capital in Equation (2) is more flexible than that defined in Chan, Lakonishok, and Sougiannis (2001) who assume that the productivity of R&D spending declines linearly by 20 percent each year. The key points in Equations (1) and (2) are that simply assuming the same time-span between R&D input and output and the same R&D productivity decay rate for all firms is too restrictive. Some firms may take longer time to materialize R&D spendings (e.g., pharmacy) than other firms (e.g., utilities); and technologies and services in some industries (e.g., chemicals) can be utilized for a longer time than those in other industries (e.g., machinary). To accommodate these concerns, we regress the sales growth on R&D inputs in two dimensions: time span between R&D input and output (j) and R&D capital decay rate (k).

The regression is run for each firm at each fiscal year t on time series from year $t-7$ to year t. We require that there are at least 6 valid observations on R&D expenditures and at least 4 RDCs are non-zero. As a result, for each firm-year, there are in total 45 regressions. R&D information quality is then defined as

$$IQ_{i,t} = \max\left\{R^2(j,k)\right\}, \tag{3}$$

where $R^2(j,k)$ is the R-square resulted from the regression in Equation (1). The selection of the largest value of R-squares in Equation (3) should not pose any problem to our study, as our hypothesis is that the lower information quality is, the higher excess return we expect. Taking maximum here in fact works against finding any significant results.

The previous studies mainly examine the relationship between stock returns and innovation input (R&D) and/or output (patents) and check whether the market fully impounds information contained in the innovation process. For example, Chan, Lakonishok, and Sougiannis (2001), Eberhart, Maxwell, and Siddique (2004), and Li (2011) directly investigate the effect of firms' R&D on future stock returns. Cohen, Diether, and Malloy (2013) explore the R&D-return relationship by constructing a measure for firms' innovation ability based on similar premise to ours. Gu (2005), Pandit, Wasley, and Zach (2011), and Hirsleifer, Hsu, and Li (2013, 2015) try to use information contained in patents to check the effect of innovation on operating performance and stock returns. Differently, our work focuses on the effect of innovation information quality on stock returns by connecting innovation input (R&D) and innovation outcome (sales).

B. Summary Statistics

Panel A of Table I presents the pooled mean, standard deviation, median, 25th and 75th percentiles of the R&D IQ measure for each industry according to Fama-French 17 industry classifications. It also reports the number of firms in each industry included in our sample, the market share of each industry in our sample, and the market share of each industry in the universal sample.

The mean (median) value of the R&D IQ measure varies across industries from 0.41 (0.37) for Automobiles to 0.67 (0.69) for Utilities. The standard deviation does not vary much across industries: its minimum is 0.20 for Transportation, and its maximum is 0.25 for Retails Stores. However, the number of firms in each industry included in our sample are very different. For example, there are in total 583 firms from Machinery and Business Equipment; 122 firms from Drugs, Soap, Perfumes, and Tobacco; 11 firms from Mining and Minerals; and only 4 firms from Utilities. This fact indicates that it is important to control industry effect when examining the R&D IQ-return relationship.

Having compared market share of each industry in our sample and that in universal sample, we find that for most industries these two shares are quite similar. For example, the market share of Textiles, Apparel & Footware in our sample is 0.9%, and it is 0.8% in the universal sample; the market share of Food in our sample is 4.9% and it is 5.7% in the universal sample. There are a couple of exceptions: Utilities in our sample takes 0.1%, whereas it takes 5.3%; and Machinery takes 28.2% in our sample, but only 13.8% in the universal sample. This fact suggests that overall our sample is economically meaningful and representative, but it also suggests once again that it is important to control industry effect in our study.

In Panel B, we presents average values of some firm-specific variables for the three R&D IQ portfolios constructed according to the 30th and 70th percentiles of the lagged IQ (see Section III for detailed discussions). These variables include (log) market equity (ME), book-to-market ratio (BEME), return on assets (ROA, Income before extraordinary items plus interest expenses divided by lagged total assets), return on equity (ROE, Income before extraordinary items plus interest expenses divided by lagged common equity), leverage (DXA, long-term debt plus debt in current liability divided by total assets), cash holding, industry concentration index (HHI, Hou and Robinson, 2006), and idiosyncratic volatility (IVOL, standard deviation of Fama-French three-factor residuals for the past 12 months). We also construct some innovation-related variables: R&D intensity (RDA, R&D expenditures divided by total assets), innovation ability (InnAb, Cohen, Diether, and Malloy, 2013), and innovative efficiency (IE, Hirsleifer, Hsu, and Li, 2013).

We find that innovation ability increases with R&D information quality. It is 0.29, 0.57, and 0.80 for the low, middle, and high IQ portfolios, respectively, whereas the innovative efficiency of low and high IQ portfolios is quite similar (3.08) and is larger than that of the middle IQ portfolio (2.66). The difference of size among these three portfolio is not big: the high IQ portfolio has a little larger size than the low IQ portfolio. The low IQ portfolio has larger ROA, but smaller ROE than the high IQ portfolio. The book-to-market, R&D intensity, leverage, cash holdings, industry concentration, and idiosyncratic volatility do not vary much across these three portfolios.

Panel C reports the time-series average of cross-sectional correlations between IQ and the above-mentioned firm characteristics. IQ is weakly correlated with these variables. The correlations range from -0.05 (with ROA) to 0.07 (with InnAb). Its correlations with ROE, R&D intensity, and IE are the smallest, ± 0.01. The above findings indicate that our R&D IQ measure is distinct from the well-known firm characteristics and may contain different information.

III. R&D Information Quality and Return Predictability

In this section, we examine the relationship between R&D IQ and future stock returns. Our main hypothesis is that there exists a premium for information uncertainty and expected excess returns should decrease with R&D information quality. We first implement portfolio sorts in Subsection A, then perform Fama-MacBeth cross-sectional regressions in Subsection B, and finally investigates effects of R&D IQ on firms' subsequent operating performance in Subsection C.

A. Portfolio Analysis

We first examine R&D information quality and return predictability using portfolio sorts. At the end of June of each year from 1981 to 2012, similar to Fama and French (1996), we sorts all firms into three R&D IQ portfolios (low, middle, and high). The low IQ portfolio contains all stocks below the 30th percentile in R&D IQ, and the high IQ portfolio contains all stocks above the 70th percentile in R&D IQ. The rest of stocks between the 30th and 70th percentiles belongs to the middle IQ portfolio. We further form a hedge portfolio that longs the high IQ portfolio and shorts the low IQ portfolio. We hold these portfolios over the next twelve months and compute their value/equal-weighted monthly returns.

Panel A of Table II presents both value- and equal-weighted average monthly returns in excess of one-month Treasury bill rate for these portfolios. The characteristicand industry-adjusted returns are also reported in order to make sure that the results are robust for firm characteristics and industry effects. The characteristic-adjusted returns are computed following Daniel et al. (1997) as the difference between individual firms' returns and 125 size/book-to-market/momentum benchmark portfolios, and the industry-adjusted returns are calculated as the difference between individual firms' returns and the returns of firms in the same industry according to Fama-French 17 industry classifications.

We clearly see that portfolio returns decrease with R&D IQ. This result holds for both value- and equal-weighted excess returns, characteristic-adjusted returns, and industry-adjusted returns. For example, the low IQ portfolio earns 127 basis points ($t = 4.23$) per month in value-weighted excess returns and 126 basis points ($t = 4.14$) per month in equal-weighted excess returns; it earns 18 basis points ($t = 2.25$) per month in value-weighted characteristic-adjusted returns and 16 basis points ($t = 1.98$) per month in equal-weighted characteristic-adjusted returns; and it earns 30 basis points ($t = 2.46$) per month in value-weighted industry-adjusted returns and 14 basis points ($t = 0.91$) per month in equal-weighted industry-adjusted returns. However, the high IQ portfolio only earns 88 basis points ($t = 2.99$) per month in value-weighted excess returns and 78 basis points ($t = 2.56$) in equal-weighted excess returns; and its returns become even smaller after control of firm characteristics and industry effects. Furthermore, the monthly returns of the high-minus-low hedge portfolio are economically substantial and statistically significant. The hedge portfolio earns -39 basis points ($t = -4.16$), -42 basis points ($t = -4.23$), and -45 basis points ($t = -4.80$) per month, respectively, in value-weighted excess returns, characteristic- and industry-adjusted returns and -48 basis points ($t = -4.69$), -50 basis points ($t = -4.46$), and -50 basis points ($t = -4.90$) per month, respectively, in equal-weighted excess returns, characteristic- and industry-adjusted returns.

Panel B and Panel C of Table II present alphas and factor loadings from the Fama-French three-factor model (Fama and French, 1993) and the Carhart four-factor model (Carhart, 1997). The estimates of alphas deliver the same implication. In both models, the alpha is positive for the low IQ portfolio, whereas it is negative for the high IQ portfolio, in both value- and equal-weighted returns. For example, in the Carhart four-factor model, it is 25 basis points ($t = 2.70$) per month in the value-weighted returns and 29 basis points ($t = 3.08$) per month in equal-weighted returns for the low IQ returns; however, it is -13 basis points ($t = -1.29$) per month in the value-weighted returns and -20 basis points ($t = -2.01$) per month in equal-weighted returns for the high IQ portfolio. The hedge portfolio's alpha is negative, economically substantial, and highly statistically significant in both models. For example, the alpha from the Carhart four-factor model is -38 basis points ($t = -3.71$) per month in value-weighted returns and -49 basis points ($t = -4.40$) per month in equal-weighted returns. These findings indicate that investors are quite uncertain about low IQ firms' future R&D activities and usually require high compensation for making investments in their future R&D.

All three IQ portfolios load positively and significantly on the market, size, and value factors, but negatively and significantly on momentum, and the factor loadings are quite similar across these three portfolios. Furthermore, the factor loadings for the hedge portfolio are small and hardly significant, indicating that returns on this portfolio do not covary with any of these well-known factors. This result suggests that there may be important factor(s) missed apart from these well-known factors.

Our results above provide an empirical support to some theoretical implications. Brevik and d'Addona (2010) introduce Epstein-Zin recursive preferences to Veronesi's (2001) pure exchange economy model and find high information quality decreases the equity premium. Ai (2010) develops a production-based long-run risk model, which indicates that high information quality decreases equity premium. Epstein and Schneider (2008) build a theoretical model and show in markets with ambiguous information, expected excess returns decrease with future information quality. They further show that ambiguity-averse investors require compensation for holding an asset with low quality information. Furthermore, as R&D spending is usually regarded as a good signal of firms' future prospect, our results are also consistent with those in Zhang (2006) who implements an empirical investigation on information uncertainty and stock returns and finds that greater information uncertainty leads to higher expected excess returns following good news but lower returns following bad news.

Figure 1 presents the time series of annual equal-weighted (upper panel) and value-weighted (lower panel) excess returns on short position of the hedge portfolio over the period from July 1981 to July 2012. We can see that the annual returns to this strategy are relatively stable over time. The volatility is about 7.9% for the value-weighted returns and is about 8.5% for the equal-weighted returns, whereas it is about 17.3% for the excess market returns over the same period. The annual correlation of returns on this strategy with the excess market returns is low: it is about 28.3% for the value-weighted returns and about 30.3% for the equal-weighted returns.

We further test our hypothesis by looking at the long-term cumulative portfolio returns. As before, at the end of June of each year, we construct three R&D IQ portfolios and a hedge portfolio and hold them over the next 12, 24, and 36 months. Table III reports the value-weighted excess returns and three- and four-factor alphas for these portfolios. Even though the low, middle, and high IQ portfolios have similar cumulative returns and the hedge portfolio's cumulative return is not significant for the past 12 months, the low IQ portfolio earns much higher cumulative return, 13.38% ($t = 4.77$), than the high IQ portfolio, 9.70% ($t = 2.99$) and the hedge portfolio cumulative return is statistically significant, -3.68% ($t = -2.80$) for the future 12 months. The same results can been seen in three- and four-factor alphas. All returns and alphas for three IQ portfolios and hedge portfolio keep increasing and statistically significant in the future 24 and 36 months, and we have not seen any reversals, indicating that our IQ measure does capture a premium for information quality instead of any form of overreaction.

B. Fama-MacBeth Cross-Sectional Analysis

We further test the return predictive power of R&D IQ by employing monthly Fama and MacBeth (1973) cross-sectional regressions. This analysis can allow us for extensive controls of industry effects and those variables that have been found to have predictive power to stock returns. To be specific, we control for size (Banz, 1981), book-to-market ratio

(Fama and French, 1992), and momentum (Carhart, 1997). Additionally, we further include in our regressions leverage (Miller and Modigliani, 1958; Ozdagli, 2012), illiquidity (Amihud, 2002), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006; Bali, Cakici, and Whitelaw, 2011), one-month lagged returns, turnover, capital expenditures (CapEX), and industry concentration (HHI). In our regressions, an industry dummy is also introduced to control for any industry-related effects that may drive our results. The definitions of these variables have been given previously in Section II.

For each month from July of year t to June of year $t+1$, we regress monthly excess returns of individual stocks on our R&D IQ measure and the above control variables of year $t-1$. Table IV presents the regression results that further confirms our hypothesis: the lower R&D information quality is, the higher excess returns we expect, as the coefficient on IQ in each of regressions we consider is negative and statistically significant. Model 1 in the table considers a simple regression in which we exclude all control variables and take R&D IQ as the only predictor. The coefficient on R&D IQ is -0.81 and highly statistically significant ($t = -4.36$), and the adjusted R^2 is about 1.3%, but highly statistically significant ($t = 6.46$). When we introduce the effects of size, book-to-market, momentum, leverage, lagged returns, and turnover in Model 2, the slope estimate on IQ becomes slightly small, -0.69, but still highly significant ($t = -3.67$). The coefficients on the other variables are not statistically significant. The adjusted R^2 increases to 5.4% ($t = 13.0$). We further introduce idiosyncratic volatility and illiquidity in Model 3 and find that the coefficient of our interest, IQ, is -0.53 ($t = -2.94$) and the adjusted R^2 is further increased to 7.2% ($t = 15.2$). The coefficient on turnover is negative and significant, -0.59 ($t = -2.91$), and the coefficient on IVOL is positive and marginally significant, 0.04 ($t = 1.91$), which is consistent with Bali, Cakici, and Whitelaw (2011). Model 4, which introduces capital expenditures to Model 2, and Model 5, which introduces industry concentration to Model 2, deliver the similar implication that the coefficient on IQ is still negative and significant. We note that in both Model 4 and Model 5, the coefficient on turnover is negative and significant and that in Model 4, the coefficient on CapEx is negative and highly significant. The adjusted R^2s from these two models are 5.6% ($t = 13.5$) and 5.5% ($t = 13.2$), respectively.

Recently, several works find that there exists a positive R&D-return relationship (Chan, Lakonishok, and Sougiannis, 2001; Eberhart, Maxwell, and Siddique, 2004; and Li, 2011). Cohen, Diether, and Malloy (2013) construct an innovation ability measure and argue that firms that exhibit high ability in the past and that continue to spend a large amount of R&D outperform in the future. We therefore introduce variables of R&D intensity: RDS (R&D expenditures scaled by sales) and RDA (R&D expenditures relative to total assets), and innovation ability in our regressions. The estimates in Model 6 show that after controlling for R&D intensity, RDA, and the variables used in Model 2, our estimate on IQ is still negative and significant, -0.64 ($t = -3.46$), and the coefficient on RDA is not significant. We find that in this model, the coefficient on turnover is negative and significant. Furthermore, the estimates in Model 7 show that even after controlling for both R&D intensity, RDS, and innovation ability, we obtain the similar result as before: the estimate on IQ is negative and significant, -0.56 ($t = -3.04$). The coefficient on RDS is insignificant and the coefficient on InnAb is negative and significant, -0.28 ($t = -2.53$). The adjusted R^2s from Model 6 and Model 7 are 6.0% ($t = 13.7$) and 6.2% (14.1), respectively.

Hirsleifer, Hsu, and Li (2013) show that firms' patents and patent citations contain rich information on future stock returns. We therefore construct their innovative efficiency measure (IE) and include it in our test. As patent database from NBER is only updated to December 2006. Our sample here is from July 1980 to July 2006. Model 8 shows that when even introducing IE in the Fama-MacBeth regression, the coefficient on IQ is still negative and statistically significant, -0.69 ($t = -2.78$), whereas the coefficient on IE is insignificant. The adjusted R^2 is about 5.7% ($t = 11.2$).

C. R&D IQ and Subsequent Operating Performance

In this part, we take one step further to show that our R&D IQ measure should not capture undervaluation or overvaluation. If IQ constructed in Equation (3) really captures information quality in firms' R&D, it should have little effects on fundamentals.

We take return on assets (ROA), cash flows (CF), sales, and performance (PM, operating income before depreciation scaled by the lagged sales) as proxies for fundamentals and examine the relationship between IQ and subsequent operating performance by implementing Fama-MacBeth regressions. As before, we control for size, book-to-market, leverage, idiosyncratic volatility, illiquidity, and some innovation-related variables such as R&D intensity and innovation ability. We also introduce the lagged values and the changes of fundamental variables in the regressions.

Table V reports the Fama-MacBeth regression results. We find that for all the four proxies of fundamentals, the coefficients on IQ are insignificant. For example, the coefficient on IQ is -0.01 ($t = -1.36$) in the ROA regression, -26.3 ($t = -1.02$) in the Sales regression, 0.02 ($t = 1.53$) in the PM regression, and -0.01 ($t = -1.47$) in the CF regression. For these four regressions, the coefficients on the lagged fundamentals and changes of fundamentals are highly statistically significant except for the changes of performance. We also find that the coefficient on size is highly statistically significant in all cases, indicating that the larger the firm size is, the better its subsequent performance is. These findings suggest that our IQ measure is nothing related to undervaluation or overvaluation.

IV. Further Empirical Evidence

In this section, we provide further evidence on the relationship between R&D IQ and future stock returns. If our IQ measure really captures information quality in firms' R&D, and there really exists a premium for R&D IQ in excess returns, we conjecture that the relationship should become stronger and the premium should be larger in firms with smaller size, younger age, greater financial constraints, and higher return and fundamental volatility, as in general these firms have more uncertain business environments and investors are more ambiguous to their future prospects.

We perform independent double sorts on R&D IQ and firm size, firm age, financial constraint, return volatility, and fundamental volatility. At the end of June of each year, we first sort all firms into three portfolios based on each of the above conditioning variables, and then sort each of these three portfolios into three subgroups based on R&D IQ and form a high-minus-low IQ hedge portfolio in each of these three portfolios. In his study, Zhang (2006) uses firm size, firm age, stock return volatility, and cash flow volatility (as well as analyst coverage) to measure information uncertainty. In what follows, we only report the results based on value-weighted portfolio returns. The results in equal-weighted returns are quite similar and available in an unreported appendix, where we also implement monthly Fama-MacBeth cross-sectional regressions across subsamples split by the above conditioning variables, respectively, and find that the same results as presented below hold.

A. Firm Size

We measure firm size by its market capitalization. Small firms usually have more expensive access to outside financial fundings; are more likely to be growing firms in rapidly developing and intrinsically volatile industries; are less diversified; and have more serious asymmetric information problem. Banz (1981) regards firm size a proxy for risk; Amihud and Mendelson (1986) and Liu (2006) find that the size effect is linked to liquidity risk; Zhang (2006) takes firm size as a proxy for information uncertainty.

Table VI presents the double-sorting results in the value-weighted returns, and they strongly confirm our conjecture. From Panel A, we find that the hedge portfolio's returns and alphas are economically substantial and statistically significant in small size firms, whereas they become smaller in big size firms. For example, its monthly excess returns, characteristic- and industry-adjusted returns are -96 basis points ($t = -2.91$), -100 basis points ($t = -3.02$), and -104 basis points ($t = -3.03$), respectively, in small size firms, whereas they are only -28 basis points ($t = -2.34$), -32 basis points ($t = -2.57$), and -30 basis points ($t = -2.58$), respectively, in big size firms. The Fama-French three-factor alpha is -99 basis points ($t = -3.02$) per month and the Carhart four-factor alpha is -110 basis points ($t = -3.23$) per month in small size firms; however, these two alphas become only -24 basis points per month and -25 basis points per month, respectively, and are only marginally significant in big size firms.

B. Firm Age

Young firms may face liability of newness (Stinchcombe, 1965). They are vulnerable to unexpected shocks and their growth paths are hardly predictable. This makes their future prospects more ambiguous to investors. On the contrary, old firms may have smoother growth paths with fewer bumps and surprises and usually have more easy-to-access information available to investors (Barry and Brown, 1985). Investors should become more concerned when they observe low quality information in young firms' R&D.

Panel B reports portfolio results based on firm age and R&D IQ. Firm age is defined as the number of years listed on Compustat with non-missing price data. Consistent to our conjecture, we find that for young firms, the low IQ portfolio always earns higher returns per month, which are always statistically significant, than the high IQ portfolio, whose returns are hardly significant. For example, for young firms, the excess return, the characteristic- and industry-adjusted returns are 150 basis points ($t = 4.13$), 41 basis points ($t = 2.46$), 55 basis points ($t = 2.94$) per month, respectively, and the three-factor and four-factor alphas are 42 basis points ($t = 2.27$) and 43 basis points ($t = 2.22$), respectively, for the low IQ portfolio, whereas all three returns and two alphas become smaller for the high IQ portfolio. However, the pattern that holds for young firms is hardly seen for old firms.

Furthermore, the high-minus-low IQ hedge portfolio earns much more substantial and significant returns and alphas per month in young firms than in old firms. The hedge portfolio earns -120 basis points of excess return per month, -112 basis points of characteristic-adjusted return per month, and -123 basis points of industry-adjusted return per month, all of which are statistically significant at 1% level, and its three- and four-factor alphas are -110 basis points ($t = -3.98$) and -91 basis points ($t = -3.22$) per month, respectively. However, for older firms, the hedge portfolio's returns and alphas are very small and completely insignificant.

C. *Firm's Financial Constraints*

Firms with financial constraints have limited ability to fund their desired investments. Lamont, Polk, and Saá-Requejo (2001) show that financial constraints affect firm value and the severity of constraints varies over, but constrained firms surprisingly earn lower returns than unconstrained firms. However, Whited and Wu (2006) find that more constrained firms earn higher average returns than less constrained firms, but the difference is not significant. Livdan, Sapriza, and Zhang (2009) revisit the relationship between financial constraints and stock returns and find that more financially constrained firms are riskier and earn higher expected stock returns than less financially constrained firms. Campello and Chen (2010) find evidence suggesting that financially constrained firms have higher systematic risk and that the constraint risk is priced in the financial markets. Li (2011) finds that the positive R&D-return relationship only exists in financially constrained firms.

Financial constraint is alway related to firm size and firm age. Small firms and young firms are usually considered to be more financial constrained than larger firms and old firms. Li (2011) takes firm size and firm age as two proxies for financial constraint. We have seen above that for small firms and young firms, the relationship between R&D IQ and future stock returns are much stronger than that for large and old firms, indirectly indicating that investors require higher premium for ambiguous R&D information quality. Here we further investigate this implication by using a more formal measure of financial constraint, the KZ index (Kaplan and Zingales, 1997).

Panel C compares R&D IQ effect between financially constrained (high KZ index) firms and financially unconstrained (low KZ index) firms. We find that the IQ effect becomes much stronger in firms with high KZ index. The returns and alphas of the hedge portfolio are large and statistically significant in financially constrained firms, whereas they become small and alway insignificant in financially unconstrained firms. For example, the monthly excess return, characteristic- and industry-adjusted return of the hedge portfolio are -42 basis points ($t = -3.18$), -41 basis points ($t = -3.02$), and -51 basis points ($t = -3.83$), respectively, in high KZ index firms, whereas they are only -23 basis ponts, -37 basis points, and -41 basis points, respectively, and are not statistically significant. The estimates of Fama-French three-factor alpha and Carhart four-factor alpha exhibit the same pattern.

D. Firm's Fundamental and Return Volatility

Zhang (2006) takes both fundamental volatility and return volatility as two proxies for information uncertainty. In a theoretical model, Epstein and Schneider (2008) show that investors require more compensation for poor information quality when fundamentals are more volatile, whereas when fundamentals do not move much, investors do not care much whether information quality is good or not. We investigate this issue here by using our R&D IQ measure.

Fundamental volatility is measured by the cash flow uncertainty, which is defined as the standard deviation of return on asset (ROA) for the past three years. In Panel D, we do find that returns and alphas of the high-minus-low hedge portfolio are much more economically substantial and statistically significant in high fundamental volatility firms than in low fundamental volatility firms. For example, the monthly excess return, characteristic- and industry-adjusted returns of the hedge portfolio are -103 basis points ($t = -3.91$), -103 basis points ($t = -3.58$), and -110 basis points ($t = -4.43$), respectively, and its Fama-French and Carhart alphas are -98 basis points ($t = -3.54$) and -104 basis points ($t = -3.42$) per month, respectively, in high fundamental volatility firms. However, both returns and alphas of the hedge portfolio become much small and insignificant in low fundamental volatility firms.

We further examine the R&D IQ effect in high return volatility firms and low return volatility firms, where return volatility is calculated as the standard deviation of the Fama-French three-factor residuals for the past 12 months. We find exactly the same pattern as above (not reported).

V. A R&D Information Quality Factor

We have seen in Table II that the commonly used factor models, such as the Fama-French three-factor model and the Carhart four-factor model, can not fully explain return dynamics. To further examine whether R&D IQ effect on future stock returns reflects commonality in returns that is not captured by the existing factors, we construct a factor-mimicking portfolio for R&D information quality following the same methodology as in Fama and French (1993). Given that the firm size increases with R&D IQ as reported in Table I, we control for size in constructing the R&D IQ factor. At the end of June of year t from 1981 to 2012, we firstly sort firms into two size portfolios (small "S" and big "B") based on NYSE median size breakpoint at the end of June of year t, and then sort each size portfolio into three R&D IQ portfolios (low "L", middle "M", and high "H") based on the 30th and 70th percentiles of R&D IQ in year $t-1$. As a result, there are in total six size-IQ portfolios, namely, S/L, S/M, S/H, B/L, B/M, and B/H.

We hold these six portfolios over the next 12 months and compute their monthly value-weighted returns. The factor-mimicking portfolio for R&D IQ (IQF) is constructed as follows: (S/L + B/L)/2 - (S/H + B/H)/2. The IQF factor is thus size-adjusted and reflects the return comovement associated with R&D information quality. The IQF factor constructed from equal-weighted returns is quite similar and available upon request. Panel A of Table VII reports the means, standard deviations, and ex post Sharpe ratios of IQF and the commonly used factors, i.e., the market factor (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (MOM). In order to have a comparison with other innovation-related measures, we construct the following innovation factors: RDF (the factor based on R&D intensity), RDGF (the factor based on significant R&D growth), IEF (the factor based on Hirsleifer, Hsu, and Li (2013)'s innovative efficiency), and NPF (the factor based on the number of patents scaled by market equity).

The average return of IQF is 30 basis points per month, which is smaller than that of MKT (60 basis points), HML (36 basis points), and MOM (60 basis points), but larger than average returns of SMB (10 basis points) and all innovation-related factors. The standard deviation of IQF is 2.83%, which is smaller than nearly all the factors considered except NPF (2.67%). Furthermore, when we take a look at the ex post Sharpe ratios of these factors, we see that IQF offers a Sharpe ratio of 0.11, which is a little bit lower than those of MKT (0.13), HML (0.12), and MOM (0.13), but larger than those of SMB (0.04) and all innovation-related factors.

Panel B of Table VII presents the monthly correlations of all these factors. We find that IQF is weakly correlated with and distinct from these factors. Its correlation with MKT is the smallest, 0.03, and its correlation with RDF is the strongest, 0.27. The average of the absolute correlations between IQF and other factors is about 0.17, which is smaller than all other factors except MOM (0.13) and RDGF (0.15).

Figure 2 plots annual returns on the IQ factor (IQF) and the market factor (MKT) from 1981 to 2012. The market factor is more volatile than the IQ factor. It can be as large as about 30% and as small as nearly -40%, and its standard deviation is about 17.32%. However, the IQ factor ranges from about -15% to about 20% and has a standard deviation of 8.45%. In the figure, we also highlight the NBER recessions using the gray-shadowed areas. We can see for four recessions in 1982, 1991, 2001, and 2008, the IQ factor performs better than the market factor in 1982, 2001, and 2008, and its outperformance is particularly striking during the internet bubble burst in 2001 and the recent global financial crisis in 2008. In 2001, the market factor has a return of -15.2%, whereas the IQ factor earns a positive return of 8.27%. In 2008, there is a severe market downturn: the return on the market factor reaches its historical low, -38.34%; however, the return on the IQ factor is still positive, 3.36%. The annual correlation between MKT and IQF is about 34.2%.

These above findings indicate that IQF captures a different factor and it may be beneficial to add IQF to the existing factor models. For this purpose, similar to Hirshleifer, Hsu, and Li (2013), we construct different tangency portfolios using the above risk factors. Panel C presents optimal portfolio weights and Sharpe ratios for these tangency portfolios. We can see that when we only use the market factor (MKT), the monthly optimal Sharpe ratio is 0.13. Whenever we introduce SMB together with MKT, the optimal weight on SMB is only 3%, whereas it is 97% on MKT. The optimal Sharpe ratio remains the same as above (0.13). When we use the Fama-French three factors (MKT, SMB, and HML) to construct the tangency portfolio, the optimal Sharpe ratio increases to 22% with mean 0.40 and standard deviation 1.79, and the largest weigh is on HML (52%), followed by MKT (33%) and SMB (15%).

Now we put our R&D IQ factor (IQF) and the Fama-French three factors together. We find that the optimal Sharpe ratio further increases to 0.25 with mean 0.39 and standard deviation 1.54. The largest portfolio weight is now on IQF (42%) and the smallest weight is on HML (7%). When the momentum factor (MOM) is also available, the optimal Sharpe ratio reaches 0.31 with mean 0.44 and standard deviation 1.44. For this tangency portfolio, the largest weight is still on IQF (37%), followed by SMB (24%), MKT (15%), MOM (19%), and HML (5%).

From row 6 to 9, we introduce one-by-one the innovation-related factors, that is, RDF, RDGF, IEF, and NPF, to the tangency portfolio, together with IQF and the Fama-French three factors. We find that the Sharpe ratios of these tangency portfolios are nearly the same as that only using IQF and the Fama-French three factors, and the weights on these innovation-related factors are quite small, ranging from 2% (in row 6) to 5% (in row 7). When we put all factors together in row 10, the Sharpe ratio is 0.31, the same as that of the tangency portfolio in row 5, and the weights on these innovation-related factors are still very small (ranging from -3% for RDF to 5% for NPF). The largest weight for these tangency portfolio is again on IQF, ranging from 35% to 42%.

The significant weight on IQF in these tangency portfolios and its role in improving the ex post Sharpe ratio are consistent to what we have see in Panel A and Panel B, where IQF has relatively high mean and small standard deviation, and its correlation with other factors are very small. The above findings suggest that IQF does capture a pricing factor that is distinct from the other existing well-known factors.

VI. Conclusion

R&D investments are surrounded by a high degree of uncertainty due to the nature of R&D activity and the lack of accounting disclosure. We hypothesize that there exists a premium for ambiguous R&D information. Even though we do not know future information quality of a firm's R&D activities, past information on its success in R&D provides us a useful measure to evaluate its future R&D activities. We construct a R&D information quality (IQ) measure by connecting innovation input (R&D expenditures) and innovation outcome (sales). Specifically, R&D information quality is captured by the R-square from the regression of sales growth on the realized R&D capital.

We find strong evidence that expected excess returns decrease with R&D information quality. The high-minus-low IQ hedge portfolio earns excess return of about -39 basis point per month, characteristic-adjusted return of about -42 basis points per month, and industry-adjusted return of about -45 basis points per month in value-weighted returns. The risk-adjusted monthly alpha of the hedge portfolio is about -40 basis points in the Fama-French three-factor model and about -38 basis points in the Carhart four-factor model in value-weighted returns. All of them are highly statistically significant. The same pattern is also found in equal-weighted returns. The Fama-MacBeth cross-sectional analysis shows that these results are robust to controlling for firm-specific variables that have been shown to have return predictability power and for some innovation-related variables.

The IQ-return relationship becomes even stronger in firms with smaller size, younger age, greater financial constraints, and higher fundamental and return volatility, as these firms usually have more uncertain business environments and investors are more ambiguous to their future prospects. Based on R&D IQ, we form a factor-mimicking portfolio (IQF), which is found to be weakly correlated with commonly used factors such as the market, size, value and momentum factors, and those innovation-related factors proposed in literature. The constructions of tangency portfolio show that adding IQF to the Fama-French three factors improves the ex post Sharpe ratio by 14% and that the weight on IQF dominates the other factors, indicating that IQF has incremental pricing effects relative to the well-known pricing factors.

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Table I: **Summary Statistics**

Panel A reports the pooled mean, standard deviation, 25th percentile, median, and 75th percentile of the R&D information quality (IQ) measure across industries according to the Fama-French 17 industry classifications from 1980 to 2012. The number of firms in each industry included in the sample (NFirm), the market share of each industry in the sample (SShare), and the market share of each industry in Compustat (MShare) are also reported. Panel B reports the average values of some of firm-specific variables, including (log) market equity (ME), book-to-market ratio (BEME), return on assets (ROA, Income before extraordinary items plus interest expenses divided by lagged total assets), return on equity (ROE, Income before extraordinary items plus interest expenses divided by lagged common equity), leverage (DXA, long-term debt plus debt in current liability divided by total assets), cash holding, industry concentration index (HHI, Hou and Robinson, 2006), idiosyncratic volatility (IVOL, standard deviation of Fama-French three-factor residuals for the past 12 months), R&D intensity (RDA, R&D expenditures divided by total assets), innovation ability (InnAb, Cohen, Diether, and Malloy, 2013), and innovative efficiency (IE, Hirsleifer, Hsu, and Li, 2013) for the three R&D IQ portfolios constructed according to the 30th and 70th percentiles of the lagged IQ. Panel C reports the time-series correlations between R&D IQ and the above-mentioned firm characteristics.

Panel A: R&D Information Quality across Industries

	Mean	STD	Q25	Median	Q75	NFirms	SShare	MShare
Cars	0.41	0.21	0.24	0.37	0.56	43	1.5	2.0
Chems	0.43	0.23	0.23	0.38	0.62	74	3.2	2.4
Clths	0.47	0.22	0.28	0.46	0.62	45	0.9	0.8
Cnstr	0.46	0.22	0.29	0.42	0.61	83	2.8	2.6
Cnsum	0.47	0.23	0.26	0.44	0.67	122	19.2	12.5
Durbl	0.46	0.23	0.25	0.42	0.65	94	2.0	1.0
FabPr	0.47	0.23	0.27	0.45	0.62	28	0.6	0.3
Food	0.44	0.24	0.24	0.40	0.61	63	4.9	5.7
Machn	0.45	0.23	0.26	0.42	0.61	583	28.2	13.8
Mines	0.45	0.21	0.29	0.43	0.57	11	0.6	0.8
Oil	0.55	0.23	0.34	0.59	0.73	29	4.9	9.1
Other	0.49	0.23	0.29	0.47	0.67	693	27.6	30.5
Rtail	0.54	0.25	0.34	0.51	0.77	22	0.2	7.9
Steel	0.47	0.23	0.26	0.46	0.63	42	1.2	0.8
Trans	0.49	0.20	0.33	0.47	0.67	52	2.0	4.4
Utils	0.67	0.22	0.54	0.69	0.85	4	0.1	5.3

Panel B: Summary Statistics across IQ Portfolios

	ME	BEME	ROA	ROE	DXA	Cash	HHI	Ivol	RDA	IE	InnAb
Low IQ	205	0.68	0.03	-0.04	0.18	0.43	0.18	10.5	0.06	3.08	0.29
Mid IQ	248	0.73	0.02	-0.09	0.19	0.43	0.19	10.8	0.05	2.66	0.57
High IQ	278	0.71	0.01	0.09	0.20	0.52	0.19	11.3	0.06	3.08	0.80

Panel C: Correlation Matrix

	IQ	ME	BEME	ROA	ROE	DXA	Cash	HHI	Ivol	RDA	IE	InnAb
IQ	1.00											
ME	0.03	1.00										
BEME	0.02	-0.12	1.00									
ROA	-0.05	0.12	-0.14	1.00								
ROE	0.01	0.01	0.00	0.07	1.00							
DXA	0.05	-0.01	0.06	-0.11	0.01	1.00						
Cash	0.02	-0.02	-0.05	-0.19	-0.02	-0.13	1.00					
HHI	-0.02	-0.04	0.10	0.10	0.02	0.12	-0.10	1.00				
Ivol	0.06	-0.11	0.09	-0.38	-0.01	-0.01	0.09	-0.14	1.00			
RDA	-0.01	-0.06	-0.16	-0.45	-0.05	-0.17	0.26	-0.24	0.29	1.00		
IE	-0.01	0.32	-0.05	0.06	0.01	-0.01	-0.02	0.01	-0.05	-0.04	1.00	
InnAb	0.07	-0.04	0.04	-0.03	-0.01	0.05	-0.00	0.04	0.06	-0.06	-0.04	1.00

Table II: **R&D Information Quality and Return Predictability**

This table presents average monthly portfolio returns (in %) based on single sort using R&D IQ. Each month stocks with non-missing lagged IQ are sorted into three groups based on the 30%/40%/30% breakpoints of IQ. When forming portfolios, we impose the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). We hold these portfolios over the next 12 months and compute both their equal-weighted and value-weighted returns. In Panel A, we report excess returns, characteristic-adjusted returns, and industry-adjusted returns. Excess return is the difference between portfolio returns and the one-month Treasury bill rate. Characteristic-adjusted returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (Daniel et al., 1997), and industry-adjusted returns are computed by adjusting returns using 17 industry portfolios (Fama and French, 1997). In Panel B and C, we report the alphas and factor loadings from regressing portfolio excess returns on the Fama-French three factors (Fama and French, 1993) and Carhart four factors (Carhart, 1997). The sample period is from July 1981 to June 2012.

	Value-Weighted Returns				Equal-Weighted Returns			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Panel A: Portfolio Returns								
Excess Returns	1.27	1.23	0.88	-0.39	1.26	1.22	0.78	-0.48
	(4.23)	(4.32)	(2.99)	(-4.16)	(4.14)	(4.14)	(2.56)	(-4.69)
Char-Adj Returns	0.18	0.14	-0.24	-0.42	0.16	0.11	-0.33	-0.50
	(2.25)	(1.84)	(-2.70)	(-4.23)	(1.98)	(1.45)	(-3.36)	(-4.46)
Ind-Adj Returns	0.30	0.23	-0.15	-0.45	0.14	0.07	-0.36	-0.50
	(2.46)	(1.96)	(-1.37)	(-4.80)	(0.91)	(0.47)	(-2.08)	(-4.90)
Panel B: Alphas and Loadings from the Fama-French Three-Factor Model								
Alpha	0.16	0.14	-0.24	-0.40	0.20	0.14	-0.32	-0.52
	(1.59)	(1.58)	(-2.32)	(-4.04)	(2.02)	(1.52)	(-2.94)	(-4.73)
MKT	1.06	1.04	1.06	-0.01	1.02	1.02	1.03	0.01
	(44.9)	(40.7)	(42.3)	(-0.29)	(47.6)	(36.7)	(41.4)	(0.43)
SMB	0.45	0.44	0.41	-0.04	0.58	0.55	0.51	-0.07
	(6.33)	(6.06)	(6.07)	(-1.28)	(9.90)	(7.72)	(7.78)	(-1.82)
HML	0.15	0.14	0.21	0.06	0.07	0.12	0.16	0.09
	(2.97)	(2.81)	(3.68)	(1.58)	(1.51)	(2.48)	(2.81)	(2.14)
Panel C: Alphas and Loadings from the Carhart Four-Factor Model								
Alpha	0.25	0.22	-0.13	-0.38	0.29	0.20	-0.20	-0.49
	(2.70)	(2.30)	(-1.29)	(-3.71)	(3.08)	(2.02)	(-2.01)	(-4.40)
MKT	1.04	1.02	1.02	-0.01	0.99	1.00	1.00	0.00
	(44.2)	(42.3)	(35.7)	(-0.46)	(45.7)	(38.6)	(36.3)	(0.16)
SMB	0.46	0.45	0.42	-0.04	0.59	0.56	0.52	-0.07
	(7.68)	(7.09)	(7.89)	(-1.23)	(12.3)	(8.74)	(10.2)	(-1.80)
HML	0.12	0.11	0.17	0.05	0.03	0.10	0.12	0.09
	(2.44)	(2.55)	(3.53)	(1.46)	(0.83)	(2.25)	(2.63)	(2.04)
MOM	-0.11	-0.09	-0.13	-0.02	-0.11	-0.07	-0.14	-0.03
	(-3.71)	(-2.75)	(-3.58)	(-0.90)	(-4.25)	(-2.06)	(-3.92)	(-0.98)

Table III: **R&D Information Quality and Long-Term Future Returns**

This table presents long-term portfolio cumulative returns (in %) based on single sort using R&D IQ. At the end of June of each year, stocks with non-missing lagged IQ are sorted into three groups based on the 30%/40%/30% breakpoints of IQ. We then hold these portfolios over the next 12/24/36 months and compute value-weighted returns of these IQ portfolios. We report excess returns, and the three-factor (Fama and French, 1993) and four-factor (Carhart, 1997) alphas. When forming portfolios, we also impose the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). We also report the past 12-month portfolio returns. The sample period is from July 1981 to June 2012.

	Past 12-Month Returns				Future 12-Month Returns			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	25.66	27.82	24.68	-0.98	13.38	13.49	9.73	-3.64
	(7.55)	(7.23)	(6.71)	(-0.36)	(4.77)	(5.44)	(2.99)	(-2.80)
FF3F Alphas	23.13	24.30	21.93	-1.20	16.70	15.78	12.54	-4.16
	(7.11)	(5.87)	(4.94)	(-0.38)	(3.72)	(3.83)	(2.51)	(-2.48)
Carhart4F Alphas	24.26	25.25	24.10	-0.16	14.13	13.33	10.92	-3.21
	(5.10)	(4.97)	(4.09)	(-0.05)	(3.68)	(3.48)	(2.49)	(-1.80)
	Future 24-Month Returns				**Future 36-Month Returns**			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	24.46	26.42	18.62	-5.84	37.83	39.62	29.24	-8.60
	(5.15)	(5.48)	(3.53)	(-2.66)	(4.82)	(5.38)	(4.43)	(-2.89)
FF3F Alphas	28.70	29.97	22.44	-6.27	43.26	44.36	31.96	-11.30
	(4.59)	(4.98)	(3.44)	(-2.64)	(4.67)	(5.84)	(4.26)	(-3.82)
Carhart4F Alphas	28.40	30.62	23.32	-5.09	39.53	42.09	31.13	-8.40
	(4.59)	(4.58)	(3.47)	(-1.75)	(4.57)	(5.41)	(4.13)	(-2.31)

Table IV: **Fama-MacBeth Cross-Sectional Regressions**

This table presents monthly Fama-MacBeth (1973) regressions of returns on R&D IQ. IQ is computed as described in Eq. 3. Control variables include: size (Banz, 1981), book-to-market ratio (Fama and French, 1992), momentum (Carhart, 1997), leverage (Miller and Modigliani, 1958; Ozdagli, 2012), illiquidity (Amihud, 2002), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006; Bali, Cakici, and Whitelaw, 2011), one-month lagged returns, turnover, capital expenditures (CapEX), and industry concentration (HHI). Some innovation-related variables are also taken into consideration: R&D expenditures scaled by sales, R&D expenditures scales by total assets, innovation ability (Cohen, Diether, and Malloy, 2013), and innovative efficiency (Hirsleifer, Hsu, and Li, 2013). All regressions includes industry dummies (using Fama and French (1997) 17-industry classification scheme). The regressions only include stocks with lagged price greater than $5. The sample period is from July 1981 to June 2012. t-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IQ	-0.81	-0.69	-0.53	-0.68	-0.66	-0.64	-0.56	-0.69
	(-4.36)	(-3.67)	(-2.94)	(-3.61)	(-3.46)	(-3.46)	(-3.04)	(-2.78)
log(ME)		0.04	0.08	0.05	0.04	0.04	-0.02	0.02
		(0.85)	(2.05)	(1.01)	(0.82)	(0.88)	(-0.35)	(0.25)
BEME		0.04	0.08	-0.02	0.03	0.03	-0.02	0.26
		(0.22)	(0.50)	(-0.08)	(0.17)	(0.17)	(-0.11)	(1.23)
MOM		0.08	0.10	0.09	0.08	0.06	0.10	0.12
		(0.53)	(0.71)	(0.59)	(0.51)	(0.41)	(0.68)	(0.71)
DXA		-0.13	-0.27	-0.21	-0.08	-0.10	-0.31	-0.13
		(-0.38)	(-0.78)	(-0.61)	(-0.22)	(-0.29)	(-0.90)	(-0.29)
R_{-1}		-0.00	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00
		(-0.49)	(-1.26)	(-0.45)	(-0.48)	(-0.53)	(-0.40)	(-0.20)
turnover		-0.38	-0.59	-0.42	-0.39	-0.44	-0.29	-0.28
		(-1.92)	(-2.91)	(-2.12)	(-1.98)	(-2.26)	(-1.46)	(-1.08)
IVOL			0.04					
			(1.91)					
ILLIQ			-0.00					
			(-0.91)					
CapEx				-3.69				
				(-2.93)				
HHI					-0.34			
					(-1.13)			
RDS							-0.54	
							(-0.61)	
RDA						1.24		
						(1.03)		
InnAb							-0.28	
							(-2.53)	
IE								-0.01
								(-0.89)
Intercept	1.40	0.95	0.01	1.06	0.99	0.94	1.71	1.16
	(4.29)	(1.25)	(0.02)	(1.39)	(1.31)	(1.32)	(2.22)	(1.18)
Adj R^2	1.3	5.4	7.2	5.6	5.5	6.0	6.2	5.7
	(6.46)	(13.0)	(15.2)	(13.5)	(13.2)	(13.7)	(14.1)	(11.2)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table V: **R&D Information Quality and Subsequent Operating Performance**

This table reports the average slopes (in percent) and their time series t-statistics in parentheses from annual Fama-MacBeth (1973) cross-sectional regressions of individual stocks' operating performance measures in year t+1 on IQ and other control variables in year t. We measure operating performance by return on assets (ROA), cash flows (CF), sales, and performance (PM, operating income before depreciation scaled by the lagged sales). We control for size, book-to-market, leverage, idiosyncratic volatility, illiquidity, and some innovation-related variables such as R&D intensity and innovation ability. We also introduce the lagged values and the changes of fundamental variables in the regressions. Industry dummies are also introduced based on the Fama and French (1997) 17 industry classification. The reported adjusted R^2 is the time series average of the adjusted R2 of each annual cross-sectional regression.

	ROA_{t+1}	$Sales_{t+1}$	PM_{t+1}	CF_{t+1}
IQ	-0.01	-26.3	0.02	-0.01
	(-1.36)	(-1.02)	(1.53)	(-1.47)
ROA	0.61			
	(13.67)			
ΔROA	-0.13			
	(-3.64)			
Sales		1.05		
		(89.9)		
ΔSales		36.4		
		(2.50)		
PM			0.59	
			(4.96)	
ΔPM			0.06	
			(1.08)	
CF				0.58
				(15.2)
ΔCF				-0.22
				(-9.66)
log(ME)	0.00	48.1	0.02	0.01
	(4.46)	(9.97)	(3.37)	(6.06)
BEME	-0.02	13.3	-0.01	-0.00
	(-3.44)	(1.78)	(-1.08)	(-0.63)
DXA	-0.02	33.3	0.04	0.08
	(-1.95)	(1.02)	(1.23)	(6.22)
IVOL	-0.00	0.41	-0.00	-0.00
	(-6.24)	(0.44)	(-0.36)	(-3.18)
ILLIQ	0.00	0.05	-0.00	-0.00
	(1.39)	(1.38)	(-0.09)	(-2.56)
RDS	-0.02	-5.24	-0.04	-0.05
	(-2.38)	(-0.47)	(-0.27)	(-2.94)
InnAb	-0.00	1.70	-0.00	-0.00
	(-0.85)	(2.26)	(-0.46)	(-0.96)
Intercept	0.03	-473.4	-0.11	0.01
	(2.26)	(-6.30)	(-1.92)	(0.23)
Adj R^2	43.6	97.4	55.6	39.4

Table VI: **Firm Characteristics and Return Predictability Power of IQ**

This table presents monthly portfolio returns (in %) based on double sorts on firm characteristics and R&D IQ. At each month stocks with non-missing lagged firm characteristics and R&D IQ are firstly sorted into three portfolios at 30%/40%/30% breakpoints based on each firm's characteristics (firm size in Panel A, firm age in Panel B, firm's financial constraints in Panel C, and fundamental volatility in Panel D) and each of these portfolios is then sorted into three sub-groups at 30%/40%/30% breakpoints based on R&D IQ. Excess return is the difference between portfolio returns and the one-month Treasury bill rate. Characteristic-adjusted returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (Daniel et al., 1997), and industry-adjusted returns are computed by adjusting returns using 17 industry portfolios (Fama and French, 1997). When forming portfolios, we impose the restriction that lagged price must be greater than $5. The three-factor (Fama and French, 1993) and four-factor (Carhart, 1997) alphas are also reported. The sample period is from July 1981 to June 2012.

Panel A: Firm's Size

	Small Size				Big Size			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	1.39	0.91	0.44	-0.76	1.28	1.22	1.00	-0.28
	(4.34)	(2.57)	(1.05)	(-2.91)	(4.39)	(4.75)	(3.78)	(-2.34)
Char-Adj Returns	0.11	-0.34	-0.89	-1.00	0.21	0.19	-0.11	-0.32
	(0.56)	(-1.55)	(-2.84)	(-3.02)	(2.15)	(2.21)	(-1.11)	(-2.57)
Ind-Adj Returns	0.47	-0.11	-0.58	-1.04	0.25	0.26	-0.06	-0.30
	(1.65)	(-0.49)	(-1.72)	(-3.03)	(2.11)	(2.28)	(-0.51)	(-2.58)
FF3F Alphas	0.50	-0.12	-0.51	-0.99	0.13	0.15	-0.10	-0.24
	(2.24)	(-0.57)	(-1.57)	(-3.02)	(1.13)	(1.31)	(-0.80)	(-1.94)
Carhart4F Alphas	0.54	-0.13	-0.56	-1.10	0.23	0.30	-0.02	-0.25
	(2.27)	(-0.59)	(-1.71)	(-3.23)	(2.03)	(2.49)	(-0.18)	(-1.96)

Panel B: Firm's Age

	Young Age				Old Age			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	1.50	1.16	0.30	-1.20	1.07	1.14	1.09	0.01
	(4.13)	(3.60)	(0.84)	(-4.47)	(3.82)	(4.37)	(3.49)	(0.08)
Char-Adj Returns	0.41	0.12	-0.71	-1.12	0.14	0.14	0.06	-0.08
	(2.46)	(0.91)	(-3.63)	(-4.30)	(1.11)	(1.37)	(0.36)	(-0.44)
Ind-Adj Returns	0.55	0.16	-0.68	-1.23	0.15	0.23	0.02	-0.13
	(2.94)	(1.03)	(-3.36)	(-4.90)	(1.03)	(1.58)	(0.12)	(-0.74)
FF3F Alphas	0.42	0.11	-0.68	-1.10	-0.00	0.08	-0.00	0.00
	(2.27)	(0.79)	(-3.29)	(-3.98)	(-0.03)	(0.68)	(-0.02)	(0.01)
Carhart4F Alphas	0.43	0.24	-0.48	-0.91	0.07	0.16	0.04	-0.02
	(2.22)	(1.62)	(-2.32)	(-3.22)	(0.47)	(1.29)	(0.23)	(-0.13)

Panel C: Firm's Financial Constraint

	Low KZ Index				High KZ Index			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	1.16	1.17	0.93	-0.23	1.28	1.32	0.86	-0.42
	(2.94)	(3.32)	(2.92)	(-0.87)	(4.65)	(4.88)	(2.95)	(-3.18)
Char-Adj Returns	0.10	0.04	-0.26	-0.37	0.17	0.25	-0.24	-0.41
	(0.52)	(0.18)	(-1.38)	(-1.47)	(1.93)	(2.74)	(-2.13)	(-3.02)
Ind-Adj Returns	0.35	0.22	-0.06	-0.41	0.29	0.31	-0.22	-0.51
	(1.38)	(0.96)	(-0.29)	(-1.53)	(2.22)	(2.33)	(-1.78)	(-3.83)
FF3F Alphas	-0.12	0.01	-0.28	-0.16	0.23	0.28	-0.19	-0.43
	(-0.53)	(0.03)	(-1.30)	(-0.61)	(2.14)	(2.58)	(-1.56)	(-3.07)
Carhart4F Alphas	-0.05	0.08	-0.15	-0.10	0.33	0.38	-0.13	-0.46
	(-0.21)	(0.39)	(-0.75)	(-0.34)	(3.43)	(3.34)	(-1.04)	(-3.27)

Panel D: Firm's Fundamental Volatility

	Low Volatility				High Volatility			
	IQ_L	IQ_M	IQ_H	H-L	IQ_L	IQ_M	IQ_H	H-L
Excess Returns	1.33	1.29	1.05	-0.27	1.20	0.96	0.17	-1.03
	(4.99)	(5.31)	(3.69)	(-1.82)	(3.25)	(2.95)	(0.47)	(-3.91)
Char-Adj Returns	0.21	0.20	-0.01	-0.22	0.09	-0.04	-0.94	-1.03
	(1.96)	(2.08)	(-0.06)	(-1.48)	(0.50)	(-0.23)	(-4.60)	(-3.58)
Ind-Adj Returns	0.35	0.24	-0.02	-0.37	0.24	-0.037	-0.86	-1.10
	(2.19)	(1.83)	(-0.17)	(-2.41)	(1.18)	(-0.38)	(-4.76)	(-4.43)
FF3F Alphas	0.23	0.24	-0.02	-0.25	0.06	-0.13	-0.92	-0.98
	(1.72)	(2.11)	(-0.12)	(-1.64)	(0.32)	(-0.84)	(-4.55)	(-3.54)
Carhart4F Alphas	0.31	0.31	0.11	-0.20	0.18	-0.02	-0.85	-1.04
	(2.50)	(2.82)	(0.67)	(-1.27)	(0.84)	(-0.09)	(-3.95)	(-3.42)

Table VII: **The Factor-Mimicking Portfolios**

At the end of June of year t from 1981 to 2012, we firstly sort firms into two size portfolios (small "S" and big "B") based on NYSE median size breakpoint at the end of June of year t, and then sort each size portfolio into three R&D IQ portfolios (low "L", middle "M", and high "H") based on the 30th and 70th percentiles of R&D IQ in year $t-1$. As a result, there are in total six size-IQ portfolios, namely, S/L, S/M, S/H, B/L, B/M, and B/H. We hold these six portfolios over the next 12 months and compute their monthly value-weighted returns. The factor-mimicking portfolio for R&D IQ (IQF) is constructed as follows: (S/L + B/L)/2 - (S/H + B/H)/2. Size is the market equity at the end of June of year t. We also construct four innovation-related factors based on R&D intensity (R&d expenditures scaled by sales), significant R&D growth (RDG), innovative efficiency (IE), and the number of patents scaled by market equity, respectively. MKT is the return on the value-weighted NYSE, Amex, and Nasdaq portfolio minus the one-month Treasury bill rate. SMB and HML are the returns on two factor-mimicking portfolios associated with the size effect and the book-to-market effect, respectively. MOM denotes the momentum factor. Panel A reports the mean, standard deviation, and ex post Sharpe ratio (SR) for these factors. Panel B reports the Pearson correlation coefficients among these factors. Panel C report the portfolio weights and monthly Sharpe ratios of ex post tangency portfolios based on investing in subsets of these factor-mimicking portfolios. All returns and standard deviations are in percentage.

Panel A: Summary Statistics

	IQF	MKT	SMB	HML	MOM	RDF	RDGF	IEF	NPF
Mean	0.30	0.60	0.10	0.36	0.60	0.06	0.12	0.06	0.03
Stdev	2.83	4.54	3.09	3.04	4.57	3.68	3.18	3.10	2.67
SR	0.11	0.13	0.03	0.12	0.13	0.02	0.04	0.02	0.01

Panel B: Correlation Matrix

	IQF	MKT	SMB	HML	MOM	RDF	RDGF	IEF	NPF
IQF	1.00								
MKT	0.03	1.00							
SMB	0.22	0.23	1.00						
HML	-0.13	-0.33	-0.34	1.00					
MOM	0.19	-0.18	0.05	-0.13	1.00				
RDF	0.27	0.28	0.38	-0.44	0.11	1.00			
RDGF	0.16	0.14	0.06	-0.19	0.12	0.38	1.00		
IEF	0.23	0.15	0.26	-0.29	-0.09	0.40	0.08	1.00	
NPF	0.09	0.14	0.16	-0.22	-0.14	0.34	-0.07	0.84	1.00

Panel C: Constructions of Tangency Portfolio

	Portfolio Weights									Sharpe Ratio		
	MKT	SMB	HML	IQF	MOM	RDF	RDGF	IEF	NPF	Mean	Stdev	SR
1.	1.00									0.60	4.54	0.13
2.	0.97	0.03								0.58	4.42	0.13
3.	0.33	0.15	0.52							0.40	1.79	0.22
4.	0.26	0.25	0.07	0.42						0.39	1.54	0.25
5.	0.15	0.24	0.05	0.37	0.19					0.44	1.44	0.31
6.	0.25	0.25	0.06	0.42		0.02				0.38	1.52	0.25
7.	0.24	0.24	0.07	0.40			0.05			0.37	1.47	0.25
8.	0.25	0.24	0.06	0.41				0.04		0.38	1.50	0.25
9.	0.25	0.24	0.06	0.41					0.03	0.38	1.50	0.25
10.	0.12	0.22	0.04	0.35	0.18	-0.03	0.03	0.04	0.05	0.41	1.31	0.31

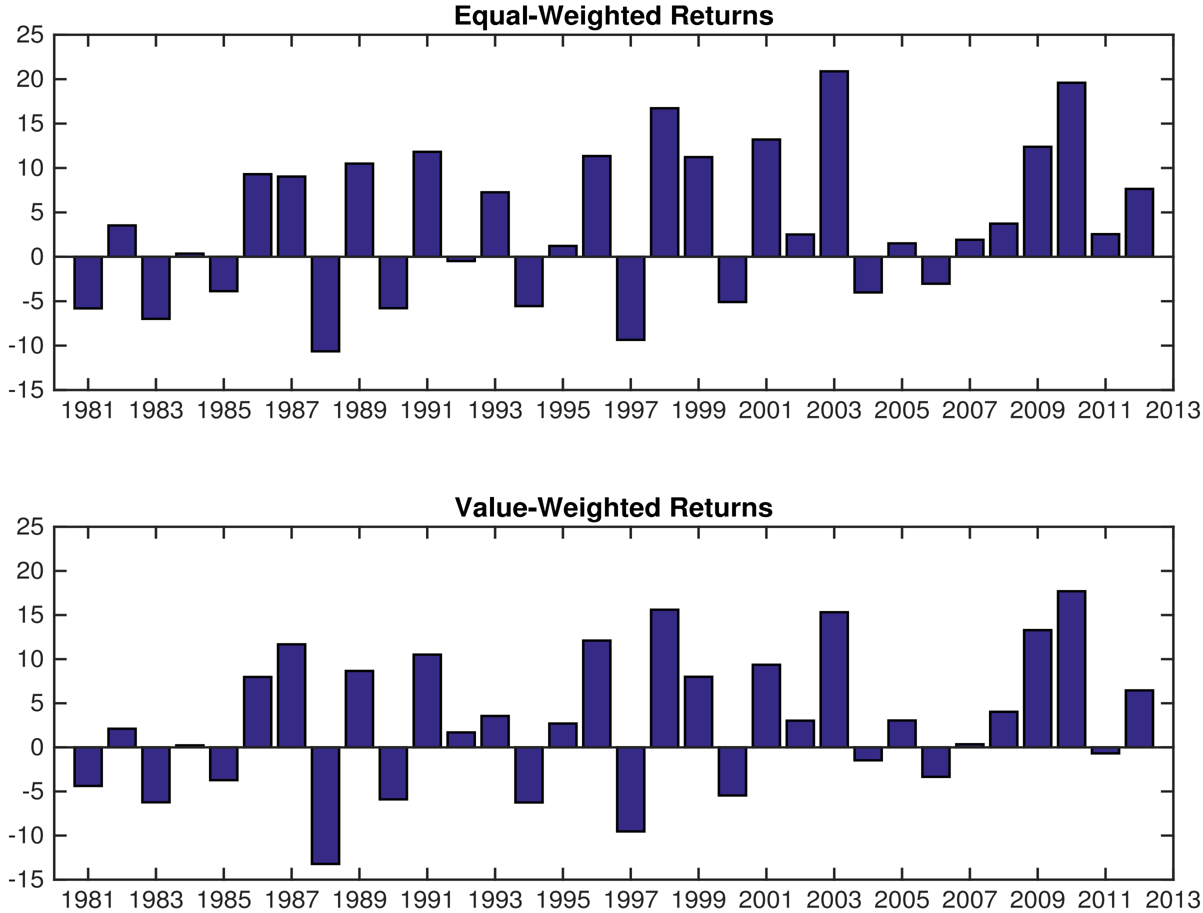

Figure 1: **Annual Returns on IQ Spread Portfolios**

This figure presents the time series of annual equal-weighted (upper panel) and value-weighted (lower panel) excess returns on short position of the high-minus-low hedge portfolio over the period from July 1981 to July 2012. Each month stocks with non-missing lagged IQ are sorted into three groups based on the 30%/40%/30% breakpoints of R&D IQ. We hold these portfolios over the next 12 months and compute both equal-weighted and value-weighted returns of these IQ portfolios.

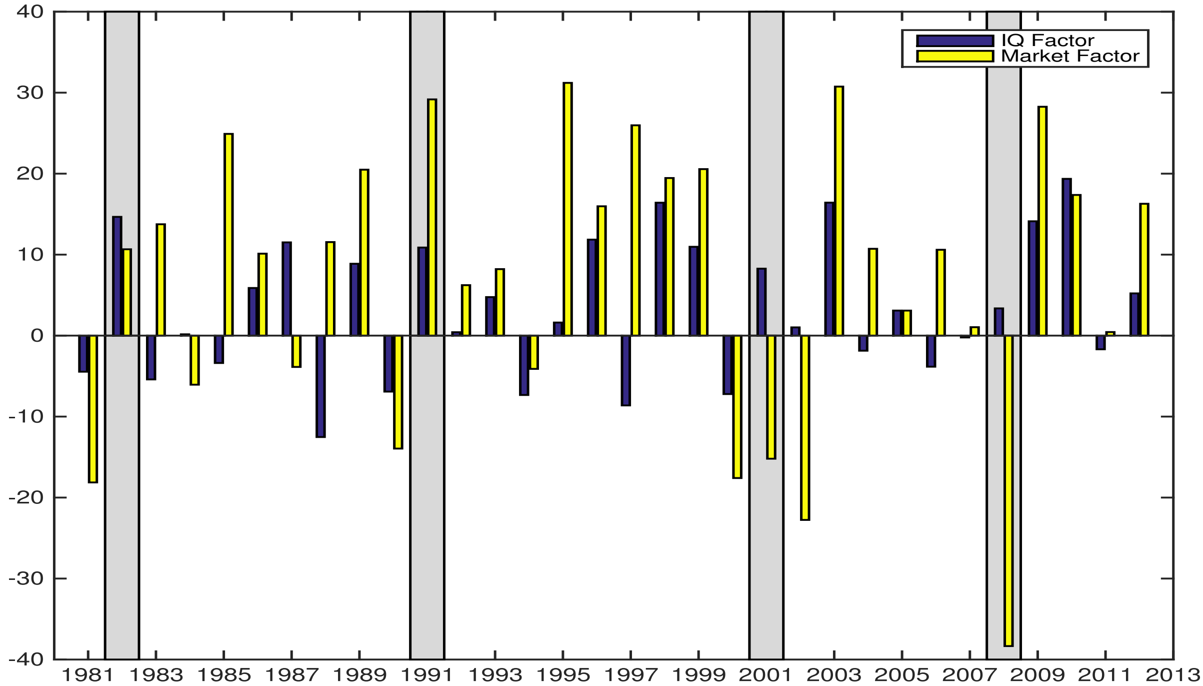

Figure 2: **Annual Returns on the IQ Factor and the Market Factor**

This figure plots the return (on a per annum basis) for the IQF factor and the market factor from 1981 to 2012. MKT is the return on the value-weighted NYSE, Amex, and Nasdaq portfolio minus the one-month Treasury bill rate. At the end of June of year t from 1981 to 2012, we firstly sort firms into two size portfolios (small "S" and big "B") based on NYSE median size breakpoint at the end of June of year t, and then sort each size portfolio into three R&D IQ portfolios (low "L", middle "M", and high "H") based on the 30th and 70th percentiles of R&D IQ in year $t-1$. As a result, there are in total six size-IQ portfolios, namely, S/L, S/M, S/H, B/L, B/M, and B/H. We hold these six portfolios over the next 12 months and compute their monthly value-weighted returns in excess of the one-month Treasury bill rates. The factor-mimicking portfolio for R&D IQ (IQF) is constructed as follows: (S/L + B/L)/2 - (S/H + B/H)/2. The gray-shadowed areas represent NBER recessions.