Misvaluing Innovation

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ABSTRACT

We demonstrate that a firm's ability to innovate is predictable, persistent, and relatively simple to compute, and yet the stock market ignores the implications of past successes when valuing future innovation. We show that two firms that invest the exact same in research and development (R&D) can have quite divergent, but predictably divergent, future paths. Our approach is based on the simple premise that while future outcomes associated with R&D investment are uncertain, the past track records of firms may give insight into their potential for future success. We show that a long-short portfolio strategy that takes advantage of the information in past track records earns abnormal returns of roughly 11 percent per year. Importantly, these past track records also predict divergent future real outcomes in patents, patent citations, and new product innovations.

Firms engage in a variety of activities. Some of these activities are straightforward, and easy to assess how they will impact firm value (e.g., maintenance capital expenditures). However, some of these activities, while crucially important for the discounted value of a firm's future cash flows, are quite uncertain and difficult to decipher how they will ultimately impact firm value. Although hard to assess, it may still be the case that analysis of publicly available information can give substantive insight into reducing the uncertainty surrounding these actions.

The activity at the heart of our investigation is investment in research and development (R&D). Given that R&D stimulates innovation and technological change, which can in turn lead to improvements in productivity, living standards, and economic output, the proper allocation of R&D investment in the economy is a critical task of the market. And yet, this task is made difficult by the fact that R&D investment is such a highly uncertain activity. Perhaps as a result of this uncertainty, R&D investment has increasingly become a market-driven activity. Although the share of R&D as a percentage of GDP has remained roughly constant (between 2-3%) since the 1960s, the composition of R&D investment in the economy has shifted dramatically, away from federal spending and toward private sector spending.[1] Since the late 1980s, for example, virtually all of the increases in total R&D spending have come from the private sector. The market's role in allocating R&D investment has become more important than ever.

In this paper we demonstrate that the stock market is unable to distinguish between "good" and "bad" R&D investment, despite the fact that successful innovation is in fact predictable. We show that two firms that invest the same amount in R&D can have quite divergent, but predictably divergent, future paths. Our approach is based on the simple premise that while future outcomes associated with R&D investment are uncertain, past information about firms' success at R&D gives us insight into their potential for future success.

Our empirical strategy proceeds from the notion that past track records represent one simple way to gauge the future prospects of firms. Some firms are skilled at certain activities, and some are not, and this skill may be persistent over time. Using this idea

[1] See Congressional Budget Office's 2005 report entitled "R&D and Productivity Growth."

as the starting point for our analysis, we examine the predictability of firm-level R&D investment track records for future returns and future real outcomes. We find that although R&D success is predictable, persistent, and relatively simple to compute, the market largely ignores the information embedded in past track records.

Our identification of past R&D success is based on a simple framework of using a firm's past ability in translating R&D into something the firm values. We then take this "ability" of a firm at R&D and interact it with the amount of research the firm is actually undertaking. For instance, we examine the outcomes of those firms that have been quite good at R&D and are investing heavily in R&D with firms investing identical amounts in R&D, but that have poor past track records. If the market correctly takes into account the prior track records' implications for future success, then whether firms are optimally choosing levels of R&D or not, the market should impound relevant information regarding innovation into prices. In fact, the market could even be completely incorrect in impounding the impact of *every* firm's R&D expenditures (as they do have uncertain effects on future firm value), but this would still have no implication for predictability based on past information, as the market will sometimes overvalue and sometimes undervalue this innovation.

We find that the market consistently misvalues innovation in an ex-ante, predictable way. Specifically, the market does not take into account the information in firms' past R&D abilities. Firms that have been successful in the past and that invest heavily in R&D as a percentage of sales ("GoodR&D" firms) earn substantially higher future stock returns than firms that invest identical amounts in R&D, but that have poor past track records ("BadR&D" firms). A portfolio of GoodR&D firms earns equal- and value-weighted excess returns of 135 basis points per month (t=2.76) and 122 basis points per month (t=2.61), and 4-factor alphas of 90 basis points per month (t=3.11) and 78 basis points per month (t=2.27), respectively. In contrast, the portfolio of firms with poor past track records but that invests the same amount of R&D (BadR&D) earns -15 basis points per month in 4-factor value-weighted alpha (t=0.56). The spread portfolio that takes identical high R&D-level portfolios, but exploits differences in past track records, has a 4-factor alpha of 93 basis points per month (t=2.30) or over 11% per year. Returns to the "GoodR&D" (and spread) portfolios are large and significant in the first year, and then returns remain slightly positive but basically plateau in the second and third years, with no reversal. This suggests that we are not capturing a form of overreaction, but instead that the embedded information regarding innovation that the market is misvaluing is important for fundamental firm value.

Our findings add to a growing literature highlighting the market's inability to properly value investments in R&D. On one hand, some researchers argue that investors may overestimate the benefits from R&D or simply ignore the fact that many R&D investments are not profitable (Jensen (1993)), leading to the overpricing of R&D-intensive firms. For example, Lakonishok, Shleifer, and Vishny (1994) find that growth stocks earn low future returns, while Daniel and Titman (2006) show that this growth stock underperformance is concentrated in stocks with significant "intangible" information, consistent with market overreaction to intangible information that is difficult to interpret.[2] However, the recent evidence on firm-level R&D activity suggests that, if anything, the market appears to *underreact* to the information contained in R&D investments. For example, Chan, Lakonishok, and Sougiannis (2001) and Lev and Sougiannis (1996) demonstrate that firms with high ratios of R&D relative to market equity earn high subsequent returns; Eberhart et al. (2004) find that large increases in R&D expenditures predict positive future abnormal returns; and Hirshleifer et al. (2010) show that firm-level innovative "efficiency" (measured as patents scaled by R&D) forecasts future returns.[3] We show that our results are unaffected by the inclusion of these measures in our tests, and are roughly 3 times larger in magnitude than the findings in, for example, Eberhart et al. (2004) and Hirshleifer et al. (2010), suggesting that our approach is picking up a new and previously undetected pattern in the cross-section of stock returns associated with the market's misvaluation of high R&D ability firms.

To combat the concern that our results are due to data mining, we run a series of out-of-sample tests on our findings. We find that our classification of high ability R&D firms is also predictive of future returns in an international sample (including the UK, Japan, and Germany) and in the period immediately preceding our sample period (1974-

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[2] See also Daniel, Hirshleifer, and Subrahmanyam (1998, DHS)'s distinction between public and private information. DHS theorize that investors are overconfident about the precision of their private signals, and therefore overreact to intangible private information and underreact to tangible public information.

[3] See also Porter (1992), Hall (1993a), and Hall and Hall (1993), who argue that investors may be myopic and discount the cash flows from R&D capital at a very high rate, leading to underpricing.

1980). For example, when we employ our baseline Fama-MacBeth cross-sectional regression on an international sample that pools together the universe of stocks from the UK, Japan, and Germany (using dollar-returns on all stocks), we find a coefficient on R&D$_{\text{high}}$*ability$_{\text{high}}$ of 0.501 (t=2.24), which is similar in magnitude and significance to our U.S. findings. In addition, while our baseline U.S. portfolio results are driven by a small number of firms (the High Ability-High R&D portfolio described above contains an average of 10 stocks per month), the percentage of market capitalization in the portfolio (0.71% of the stock market's annual value on average) is larger than that of the "small value" portfolio (0.50% of the stock market's annual value on average) that is featured in hundreds of asset pricing papers, and which remains one of the most studied anomalies in the literature.

Lastly, we run a series of tests designed to pinpoint the mechanism behind our results. First, we explore real outcomes associated with our high R&D ability firms. Specifically, we show that the firms that we classify as high ability firms and that invest heavily in R&D also produce tangible results with their research and development efforts. They generate significantly more patents, achieve significantly more patent-citations, and develop significantly more new products than firms that invest the *same* levels of R&D, but have poor track records. In addition, we demonstrate that high ability firms exhibit significant persistence in R&D skill, that this skill may be positively related to the presence of a founder, and that the market's failure to understand the implications of R&D track records is related to heterogeneity in information provision by firms. For example, we show that the predictability in future returns is significantly lower for high ability firms who provide more earnings guidance; under the assumption that firms that provide more earnings guidance are also likely to provide more information to investors more generally (as in Jones (2007)), these findings suggest that cross-sectional variation in information opacity may help explain why the market fails to properly understand the information embedded in firms' past track records.

I. Data and Summary Statistics

We combine a variety of data sources to create the sample we use in this paper. We draw monthly stock returns, shares outstanding, and volume capitalization from

CRSP, and extract a host of firm-specific accounting variables, such as research and development (R&D) expenditures, sales and general administrative expenses (SG&A), book equity, etc., from Compustat. We combine these items with firm-level patent data drawn from the NBER's U.S. Patent Citations Data File,[4] segment-level product data from the Compustat Segment Data File, earnings' guidance data from First Call and CEO founder data from Fahlenbrach's (2009) hand-collected data and the Corporate Data Library. We draw international stock return data from Datastream and accounting data from Worldscope. We filter the datastream stock return data and identify common stocks using the procedures and suggestions outlined in Ince and Porter (2006) and Griffin, Nadari, and Kelly (2010).

Table I presents summary statistics for the sample we use in this paper (Panel B), compared to the entire universe of stocks on CRSP (Panel A), over our July 1980 to December 2009 sample period. Our sample includes all NYSE, AMEX, and Nasdaq common stocks (CRSP share code 10-12) with a valid (i.e., non-missing) R&D estimate in a given year, as well as a valid estimate for the "Ability" measure that features in our analysis.

The notion of "Ability" is meant to capture simply how good a firm is at turning R&D expenditures into something the firm values. We have run our tests using a number of measures of what the firm "values" and our results are robust to the various measures we have tried. The measure we show in the paper is how R&D translates into actual future sales revenue of the firm.[5] One additional concern may be the horizon we use to identify the translated effect of R&D on future outcomes. As we describe below, we try to be flexible on this dimension and use up to a five-year lag in measuring the impact of past R&D expenditures on future firm outcomes.

Thus, for sales (reported in the paper), we compute firm "Ability" by running rolling firm-by-firm regressions of firm-level sales growth (defined as $\log(Sales_t/Sales_{t-1})$) on lagged R&D ($R\&D_{t-j}/Sales_{t-j}$; where j=1,2,3,4,5). We run separate regressions for 5

[4] The patent data is collected, maintained, and provided by the National Bureau of Economic Research Patent Data Project. All data files we use, along with documentation, can be obtained from the project's website at https://sites.google.com/site/patentdataproject/Home.

[5] As mentioned, we have used various measures of profitability, such as return-on-assets (ROA), instead of sales growth. The results are very similar in magnitude and significance. For instance, the analog of the Spread portfolios from Table III using ROA have monthly 3- and 4-factor alphas of 51 and 59 basis points (t=2.10 and 2.39), respectively.

different lags of R&D (i.e., R&D from years *t-1, t-2, t-3, t-4,* and *t-5*); we then take the average of these five R&D regression coefficients as our measure of ability (regression specification shown in Table II). Again, the idea behind this measure is to isolate the extent to which a given firm successfully converts its R&D investments into future sales. We have analyzed a variety of different specifications here, and our results are robust to these permutations; for example, running a single regression for each firm of sales growth on the average of the past 5 years of R&D, and using this single coefficient as our measure of ability yields similar, and often stronger, results (we show these results in Appendix Table A5).

In estimating a firm's ability, for every firm in each year we use 8 years of past data for each firm-level regression, and we then run these regressions on a rolling basis each year using the prior 8 years of data. For each regression, we require a minimum of 6 (75%) non-missing R&D observations and that at least half the R&D observations are non-zero; otherwise, we set the slope coefficients to missing values.[6] Panel B of Table I indicates that our final sample is quite similar to the overall sample of CRSP stocks. Comparing characteristic-by-characteristic, our sample does contain slightly larger stocks, with a modest growth tilt relative to the overall sample of CRSP stocks. While the stocks in our sample are slightly less levered, the price momentum, turnover, and stock volatility are nearly identical to the entire universe. Overall, the differences between the two samples appear small.

Panel A of Table II presents the full-sample sample averages of the rolling firm-by-firm regression coefficients that form the basis of our ability measure. The average ability estimate is 3.33, with an average sales growth of roughly 7%, while average R&D expenditures equate to roughly 17% of sales.

We then turn to some diagnostics of our Ability measure. If we are truly capturing a meaningful measure of a firm's ability at Research and Development, we

[6] We have analyzed back-windows of 6-10 years of past data as well, with the trade-off coming between fewer data points required (so more observations estimated) per firm, but less reliable estimates, compared with, say requiring 10 years of data, which allows fewer observations to be estimated (and more auto-correlated estimates as only 1 observation changes per estimation period), but more precise estimates. We choose the mid-point of using 8 years of past data. The results look very similar across these estimation windows, in magnitude and significance. In fact, in magnitude the results for both 6- and 10-year windows are a bit larger (for instance the value-weighted Spread portfolio using a 10-year back window has 4-factor alpha abnormal returns of 101 basis points per month (t=2.49) as opposed to the 93 basis points reported in Table III).

might expect to see some level of persistence in this measure (i.e., it would be odd to see firms simply jump from being classified as "good" at R&D to "poor" at R&D, and back, year after year). Panel B of Table II examines this issue by showing the annual persistence in a firm's ability quintile assignment, for yearly lags out to 5 years. We find that firms in the highest quintile of ability remain in this same top quintile in the following year 70% of the time.[7] Overall, Panel B demonstrates that there is substantial persistence in firm-level R&D ability, but that firms do transition out (on average) of the high ability category within several years.[8]

II. Results

A. Portfolio Returns

In this section we examine average returns on portfolios formed using information about both a firm's ability *and* its level of R&D. We scale R&D by sales, and use three-way sorts using the same methodology of Fama and French (1996), namely: $R\&D_{low}$ contains all stocks below the 30th percentile in R&D (but who have R&D greater than zero), and $R\&D_{high}$ contains all stocks above the 70th percentile in R&D. We compute firm-year ability as described earlier, using the annual average of the rolling regression coefficients of sales growth on 5 lags of R&D (scaled by sales).[9] We include all NYSE,

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[7] To construct a baseline to compare this 70% against, we simulate our data using the parameters of our data (i.e., assuming a world with the exact same number of firms, and using the same rolling windows for these firms), but with R&D and sales replaced with standard normal variables. We run 1,000 simulations, and the averages of the 1,000 simulations are reported in the Internet Appendix Table A1. Comparing this simulated ability measure's persistence to the actual data, the 70% persistence in our high ability quintile is significantly higher than would be expected by chance: e.g., the Monte Carlo simulation results in Appendix Table A1 indicate that one should expect a firm in the top quintile to remain in the top quintile in the following year only 54% of the time; thus the 70% persistence of our actual ability measure is roughly 30% larger in magnitude than the simulated persistence expected by chance.

[8] This level of persistence stands in contrast to the lack of persistence shown in the mutual fund performance literature (see, for example, Brown, Goetzmann, Ibbotson, and Ross (1992), Malkiel (1995), Wermers (1997), Carhart (1997), and Daniel et al. (1997)) and the modest persistence shown in the hedge fund performance literature (see, for example, Agarwal and Nail (2000, 2004), Fung, Hsieh, Nail, and Ramadorai (2008), Kosowski, Nail, and Teo (2007), and Teo (2011)).

[9] In order to further test the robustness of our measure, we perform a number of falsification exercises. First, if we replace R&D with a non-negative random variable with the same time-series mean and stand deviation as the typical stock's R&D in the sample (keeping every other aspect of the sample the same), we find virtually no spread in returns. Also, if we just remove R&D from the ability estimation altogether (and simply use 1/sales instead), we again find no spread in returns. Finally, if we use raw R&D when estimating ability instead of scaled R&D, we still find significant (although slightly smaller) portfolio spreads (=43 basis points, t=1.81). These results indicate that our findings are not driven by our choice of

AMEX, and Nasdaq stocks from July 1978 to December 2009 with lagged share prices above $5 into these portfolios, and rebalance the portfolios yearly.

We characteristically-adjust returns (as in Daniel et al. (1997)) using either 25 size/book-to-market benchmark portfolios, or 125 (5x5x5) size/book-to-market/momentum benchmark portfolios. We also compute three- and four-factor alphas (as in Fama and French (1996), and Carhart (1997)) by running time-series regressions of excess portfolio returns on the market (MKT), size (SMB), value (HML), and momentum (UMD) factor returns. In addition to these risk adjustments, we also calculate an industry benchmark-adjusted return. If the ability measure is somehow sorting on industry (so the High Ability firms are disproportionately from one industry), we may be inadvertently sorting on an industry characteristic unrelated to our ability explanation. To combat this potential problem, each month we compute each firm's return subtracting out its industry's return over the same month. Thus, these industry excess returns will control for any characteristic of a firm (High or Low Ability) shared by its industry, and isolate only its abnormal returns relative to other firms in the same industry.[10] Lastly, as we will compare the returns of two firms that have *both* been spending a large amount on R&D (but with varying abilities), we have no selection bias in terms of firms that decide to engage (or not) in R&D. This also rules out any general story that there has been an unexpected positive trend for innovative firms over the past 30 years, as that would show up in all high R&D firms. Equivalently, we compare the returns within High Ability firms, varying levels of R&D, to rule out the possibility of High Ability sorting an unobserved risk.

Table III reports average stock returns for monthly portfolio sorts, and illustrates our first main result: stocks that exhibit high ability in the past and that spend a large amount on R&D (i.e., stocks in the $\text{Ability}_{\text{high}}$ / $\text{R\&D}_{\text{high}}$ portfolio, which we will call the "GoodR&D" portfolio) outperform in the future. This result holds for both equal- and value-weight portfolio returns, and for excess returns, characteristically-adjusted returns, industry-adjusted returns, and 3- and 4-factor alphas. Further, the magnitude of this outperformance is large: Panel A shows that the GoodR&D portfolio earns 135 basis

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scaling variable, but instead suggest we are capturing an important aspect of R&D spending.

[10] We assign firms into 17 industries, as defined in Fama and French (1997). Running it using the 10-, 12-, 30-, or 49-industry defined portfolios has no effect on the magnitude or significance of the results.

points per month (t=2.76) in equal-weight excess returns, and 122 basis points per month (t=2.61) in value-weight excess returns, which translates to 17.5% and 15.7% annually, respectively. In addition, the long-short portfolio spread (Spread) between stocks in the GoodR&D portfolio and those stocks that exhibit *low* ability in the past but which continue to spend a large amount on R&D (i.e., stocks in the $\text{Ability}_{\text{low}}$ / $\text{R\&D}_{\text{high}}$ portfolio, which we will call the "BadR&D" portfolio), is large and significant. For example, Panels A and B shows that the raw equal-weight spread is 73 basis points per month (t=2.61), and the raw value-weight spread is 90 basis points per month (t=2.30), which translates to 9.1% and 11.4% annually, respectively. Again this result holds for both equal- and value-weight portfolio returns, and for characteristically-adjusted returns, industry-adjusted returns, and 3- and 4-factor alphas. Note that the two components of this spread portfolio (i.e., the GoodR&D portfolio vs. the BadR&D portfolio) are very similar on other characteristics (e.g., in percentiles, the average size (0.46 vs. 0.43), book-to-market (0.31 vs. 0.38), leverage (0.26 vs. 0.25), momentum (0.56 vs. 0.53), volatility (0.53 vs. 0.49), turnover (0.72 vs. 0.69), and past R&D growth (0.65 vs. 0.69) are virtually the same for both portfolios).

Panel C of Table III presents additional characteristics of these portfolios. Specifically, the four-factor loadings in Panel C suggest that the GoodR&D portfolio loads negatively on value and momentum and positively on size, meaning that the stocks in this portfolio are typically large, growth stocks with poor past returns. Meanwhile the spread portfolio has no significant loadings on any of the four factors, indicating that the returns to this portfolio do not covary with any of these well-known factors. In addition, while Panel C reveals that the High Ability-High R&D portfolio contains an average of only 10 stocks per month, the percentage of combined market capitalization in this portfolio (0.71% of the stock market's annual value on average) is larger than that of the "small value" portfolio (0.50% of the stock market's annual value on average) that is featured prominently in the literature.

The results here are not sensitive to the particular breakpoints chosen; sorting based on quintiles or quartiles produces very similar (sometimes even a bit stronger) results. For example, the equal-weighted DGTW characteristically adjusted-spread return using 5x5 sorts is 120 basis points per month (t=2.29), while Appendix Tables A4 show that this same spread return using 4x4 sorts is 95 basis points per month (t=3.57). We have additionally tried coarser sorts, as in Appendix Table A3, where we simply split by median level of R&D. These sorts, while having less power to distinguish between R&D spending levels, again yield the same result: High Ability firms that engage in more R&D spending outperform Low Ability firms that also are above median spenders on R&D. The analogous DGTW spread portfolio returns 55 basis points per month (t=3.70). Further, the High Ability-High R&D contains an average of 29 stocks per month, with an average market capitalization of 1.93%. This is larger than the combined market capitalization of value quintile portfolios #1-3 (which together account for 1.71% [=0.50+0.49+0.72] of total market capitalization on average, and which collectively account for most (80%) of the value premium from 1963-2009).[11] Lastly, we also present results in Appendix Table A9 using "conditional sorts" (as opposed to the independent sorts we use for most of the paper) which sort stocks based on Ability, and *then* by R&D within each Ability bin. This approach forces the number of stocks to be equal in each portfolio bin, and by doing so increases the number of stocks in the "High-High" portfolio. Appendix Table A9 shows that for 5x5, 4x4, and 3x3 conditional sorts, the number of stocks in this portfolio increases significantly (up to 74 stocks per month), and our results remain robustly large and significant.

It is also important to note here that firms only report R&D expenses once per year, and we only calculate Ability once per year. Thus, although we report monthly returns in this table, we only rebalance our portfolios *once* per year.

We also find virtually no reversal of the abnormal returns we document here. Panel A of Figure 1 plots the spread portfolio (GoodR&D-BadR&D) of Cumulative Abnormal Returns (CARs) following portfolio formation at time 0 through the first eighteen months, and Panel B plots the GoodR&D portfolio. Both equal- and value-weighted CARs are shown, which are the size-BM-momentum-adjusted returns each month. Returns of the spread (and GoodR&D) portfolios are large and significant in the first year (documented in Table IV), and then returns drift up slightly but basically

[11] This 1.93% is also larger than the combined market share of the "Loser portfolio" (Decile 1) from the momentum anomaly (Jegadeesh and Titman (1993)), which comprises an average of 1.81% of total market capitalization each year, and accounts for roughly two-thirds (65%) of the profits to the (Winner-Loser) momentum strategy.

plateau. Importantly, even continuing on into the second and third years, there is no reversal in returns. This suggests that we are not capturing a form of overreaction, but instead that the embedded information about innovation that the market is misvaluing is important for fundamental firm value.

Figure 2 graphs the equal-weight yearly returns to the spread portfolio.[12] Figure 2 shows that the annual returns to the strategy are fairly stable across time, and the average annual return to the spread portfolio across the 29 years in our sample is 10.8% (t=2.29). In Appendix Table A2 we also split our sample into three distinct sub-periods, and show that no single sub-period drives our results. For example, the value-weight L/S spread is 46 basis points per month (t=1.01) in the 1980s, 115 basis points per month (t=2.45) in the 1990s, and 142 basis points per month (t=1.85) in the 2000s; the equal-weight equivalents are 25 basis points per month (t=0.55) in the 1980s, 121 basis points per month (t=3.67) in the 1990s, and 135 basis points per month (t=2.78) in the 2000s. Further, the annual correlation of these spread portfolio returns with the excess market return is low: 0.29 for the equal-weight, and 0.11 for the value-weight.[13]

In Table IV we demonstrate that simple sorts on R&D or Ability alone yield no pattern in average returns. In Panel A, we present monthly portfolio returns for quintiles based on R&D (scaled by sales).[14] We group stocks with no R&D ($R\&D_{zero}$) into a separate portfolio.[15] Panel A indicates that excess returns across the various groups are very similar, and that the spread in returns between $R\&D_{high}$ and $R\&D_{low}$, and also between $R\&D_{high}$ and $R\&D_{zero}$ are small and insignificant. We also characteristically-adjust returns (as in Daniel et al. (1997)) using 125 value-weight size/book-to-market/momentum benchmark portfolios. Again we see no pattern in the abnormal return spreads of portfolios sorted on R&D. Note that these results are not sensitive to the particular breakpoints chosen, to the particular risk-adjustment procedure employed, or to the particular scaling variables used (except for market equity, of course, which

[12] The analogous value-weight version of this figure can be found in the Appendix, as Figure A1.

[13] Monthly return correlations with the monthly excess market return are even lower: 0.09 for the equal-weight and 0.03 for the value-weight.

[14] The results are the same if we use the three-way sorts used in Table III.

[15] We separate out the $R\&D_{zero}$ to show any differences that may arise in this portfolio (as these make up roughly 25% of the firms that report R&D). Table IV shows that these stocks do not have significantly different returns. Further, including these in the interaction (or excluding them) does not materially affect the results (i.e., Table V actually does this comparison in Columns 3 and 4, and the results are nearly identical in magnitude and significance).

mechanically produces a scaled price effect when used as a denominator irrespective of numerator (see Fama and French (1996)).

Panel B of Table IV presents the average monthly portfolio returns associated with simple sorts on our ability measure. As with the simple sorts on R&D, these sorts on ability yield no obvious pattern in excess returns or abnormal returns, and the spread between $\text{Ability}_{\text{high}}$ and $\text{Ability}_{\text{low}}$ is always near zero and insignificant. Lastly, the correlation of R&D and Ability is -0.04. In other words, they seem to be picking up quite different information about firms.[16]

In summary, the results in Tables III and IV demonstrate that our simple classification scheme, which is designed to isolate high-ability firms solely based on their past success in converting R&D into future sales, produces a large spread in future abnormal returns that is not present when looking at simple sorts on R&D, or simple sorts on ability alone. This finding highlights the fact that even though two firms may spend an equal amount on research and development, it is critical to understand the likely effectiveness of these expenditures, and that one can estimate this effectiveness by simply looking at a firm's past experience. Thus our approach offers an ex-ante method for identifying future innovation that is likely to be successful, which we show is in fact the case in Section III.

B. Cross-Sectional Regressions

Our next set of tests employ monthly Fama and Macbeth (1973) cross-sectional regressions each month to further assess the predictive power of our ability classification. To control for the well-known effects of size (Banz (1981)), book-to-market ((Rosenberg. Reid, and Lanstein (1985), Fama and French (1992)), and momentum (Jegadeesh and Titman (1993), Carhart (1997)), we include controls for these as independent variables. Additionally, we include controls on the right-hand side for one-month past returns (to capture the liquidity and microstructure effects documented by Jegadeesh (1990)), volume (the average daily share turnover during the previous 12 months), and return volatility (the standard deviation of daily returns over the previous 12 months). Lastly,

[16] We have also calculated the correlation of the $\text{R\&D}_{\text{high}}$ and $\text{Ability}_{\text{high}}$ categorical variables, which is -0.25, again suggesting that neither heavily investing in R&D, nor having a high Ability using this measure, implies much about the other.

we include industry fixed effects to control for any industry level characteristic that may be driving our results. Our variable of interest is the interaction between our measure of high ability ($Ability_{high}$) and R&D. Analogous to Table IV, $Ability_{high}$ is a dummy vsriable equal to one for stocks in the highest quintile of ability each year, and zero otherwise. We include specifications with both a continuous measure of scaled R&D (i.e., log(1+(R&D/Sales))), as well as a categorical variable ($R\&D_{high}$) equal to one for stocks above the 70th percentile in scaled R&D each year.[17] We have also run all of the regressions in this paper using pooled regressions with month or firm fixed effects, and the results are very similar to those reported here.

The monthly cross-sectional regression estimates in Table V confirm our earlier portfolio results: firms that exhibit high ability in the past and that continue to spend a large amount on R&D outperform in the future. In Column 1, the coefficient on the variable of interest, $Ability_{high}$*$R\&D_{high}$, is 0.627 (t=2.41), which is similar in magnitude to the portfolio return results in Table IV. Columns 2-4 show that including controls and industry fixed effects has no effect on this finding. Further, the coefficients in Column 4 indicate that the equivalent of the spread portfolio from Table IV in these regressions (i.e., $Ability_{high}$*$R\&D_{high}$ - $Ability_{low}$*$R\&D_{high}$) is 99 basis points per month (78.5 – (-20.8)), again similar in magnitude to the Table IV spread portfolio results. In Columns 5-8, we present a similar result, but this time focusing on the interaction of ability with a continuous measure of R&D. Column 5 reports that the coefficient on $Ability_{high}$* log(R&D) is positive and significant (=5.433, t=2.14); to get an idea of the magnitude of this result, a one-standard-deviation increase in log(1+(R&D/Sales)) (=.07) implies that future returns are 38 basis points higher for high ability firms relative to all other firms.

C. Out-of Sample Tests: International Evidence and Pre-1980 U.S. Evidence

To further investigate the robustness of our results, we also conduct a series of out-of-sample tests. In particular, we check if our main findings hold both internationally and in the period prior to our original sample period. We report these results in Table VI. This table presents monthly Fama-MacBeth (1973) regressions of returns on R&D and

[17] The benefit of the categorical variable interaction terms is that the coefficient can be interpreted directly as the future abnormal return (controlling for all other variables), of the High Ability firms with large spending on R&D.

Ability for an international sample of stocks (UK, Japan, and Germany) and an early U.S. sample period (1974 to 1980).[18] For the international sample, the R&D and ability breakpoints are computed separately for each country. Returns, market capitalization figures, and prices are converted to U.S. dollars for the international sample. We also include country fixed effects in the pooled international regressions of Columns 1 and 2. In all samples we exclude lagged low price stocks: 5th price percentile (by month) for international stocks, and $5 for the U.S. stocks. The sample period is July 1995 to December 2010 for the international sample, and July 1974 to June 1980 for the U.S. sample.

Columns 1-5 of Table VI indicate that our classification of high R&D ability firms investing in R&D is also predictive of future returns in this international sample of stocks. For example, Column 2 of Table VI reports a coefficient on $R\&D_{high}$*$ability_{high}$ of 0.501 (t=2.24), which is both economically and statistically significant. Columns 3-5 then show this separately for each of the three countries. These columns indicate that our results are strongest for the UK, but that all three countries reveal a meaningful spread in magnitude; specifically, the spread (R&Dhigh*Abilityhigh - R&Dhigh*Abilitylow) is 106 basis points (92-(-14)) per month in the UK, 37 basis points (41-4) per month in Japan, and 34 basis points (-14-(-48)) per month in Germany.

Columns 5 and 6 of Table VI show that the early-period U.S. sample also delivers similar results. For instance, Column 4 reports a coefficient on $R\&D_{high}$*$ability_{high}$ of 0.581 (t=1.05); this estimate is statistically insignificant due to the small number of firms in these tests, but the magnitudes are again large and similar to those found in our baseline sample and in the international sample. We choose to start the baseline sample in 1980 as the accounting treatment of R&D expense reporting was not standardized by FASB until 1974 (Financial Accounting Standards Board Statement No. 2), as also noted in Eberhart et al. (2004). Given that we need at least 6 years of prior data to estimate ability, this places our starting date at 1980.

Taken as a whole, these out-of-sample results confirm the key findings from Table V (which uses our baseline US-sample from 1980-2008), and help to alleviate any concern

[18] The data before 1974 (or more formally, 1968, given our six year ability classification period) are too thin to employ our regression-based classification scheme.

that our results are due to data mining.

D. Controlling for Other R&D-Related Effects

Next we examine the extent to which our findings are related to previous R&D-related patterns that are known to exist in the cross-section of stock returns. Specifically, we now directly compare our results to the findings in Eberhart et al. (2004), Daniel and Titman (2006), and Hirshleifer et al. (2010), and test if our results are distinct and add to the findings in these papers.

To do so, we re-run our baseline regressions from Tables V and VI, and specifically control for the effects documented in these papers. We present the results of these tests in Table VII.[19] The first four columns of Table VII illustrate the additional impact of our findings relative to those in Eberhart et al. (2004). Specifically, following the approach in Eberhart et al. (2004), who find that large increases in R&D expenditures predict positive future abnormal returns, we construct variables called "$\Delta R\&D^{large}_{t-1}$" and "$\Delta R\&D^{large}_{t-5,t-1}$" designed to capture large increases in R&D that took place last year and over the past five years (taking an average), respectively. As in Eberhart, et al. (2004), we identify a "large change" if: i) raw R&D increased by 5%; ii) the level of R&D (divided by lagged assets) is greater than 5%; and iii) the change in R&D (divided by lagged assets) is greater than 5%. As columns 1-4 demonstrate, we find evidence consistent with the results reported in Eberhart et al. (2004), namely that large increases in R&D predict higher future returns. However, the inclusion of these variables has no impact on our main result, and our result remains roughly 3 times larger in magnitude: e.g., in column 4, the future return spread on ($R\&D_{high}$*$ability_{high}$ minus $R\&D_{high}$*$ability_{low}$) =0.975=(0.742-(-0.233), F-stat=10.15), while the coefficient on $\Delta R\&D^{large}_{t-5,t-1}$ (which shows the most predictive ability for future returns in our tests) is 0.324. Thus we conclude that our results are essentially orthogonal to those in Eberhart et al. (2004).

The last four columns of Table VIII illustrate the additional impact of our findings

[19] In addition, when we control for the effect of R&D divided by lagged market capitalization (documented in Chan, Lakonishok, and Sougiannis (2001)) on future returns, our results are unchanged. For example, the future return spread on ($R\&D_{high}$*$ability_{high}$ minus $R\&D_{high}$*$ability_{low}$) =0.955=(0.738-(-0.223), F-stat=9.97) in the regressions from Table V, while the coefficient on [$(R\&D/MktCap)_{high}$ minus $(R\&D/MktCap)_{low}$]=0.562=(0.298-(-0.264)), F-stat= 23.88.

relative to those in Daniel and Titman (2005), who find that the book-to-market effect is largely driven by overreaction to intangible information, and Hirshleifer et al. (2010), who show that a firm-level measure of innovative efficiency is positively related to future returns. Hirshleifer et al. (2010) measure innovative efficiency as patents divided by lagged raw R&D. Again we are able to replicate the findings in both of these papers in our sample, but find that our effect remains unchanged by their inclusion. For example, in Columns 5 and 6 we observe the negative predictive effect of intangible information on future returns when we compute the return to tangible versus intangible information as in Daniel and Titman (2006), but our result is unchanged by the inclusion of this measure. We also replicate the effect documented in Hirshleifer et al. (2010), but find that our effect is again roughly 3 times larger in magnitude: e.g., in column 8, the future return spread on ($R\&D_{high}$*$ability_{high}$ minus $R\&D_{high}$*$ability_{low}$) =0.971=(0.749-(-0.222), F-stat=10.03), while the future return spread on [$(Patents/RD)_{high}$ minus $(Patents/RD)_{low}$] =0.321=(0.032-(-0.297), F-stat=5.48). In addition, the predictive ability of the Hirshleifer et al. (2010) measure appears to be coming primarily from the poor future performance of low patent intensity firms, whereas our effect comes primarily from (high ability/high R&D) firms earning high future returns.

Collectively, these findings suggest that our approach is picking up a new and previously undetected pattern in the cross-section of stock returns associated with the market's misvaluation of high R&D ability firms.

E. Robustness: Using a Non-Regression Based Measure of Ability

Our final robustness check utilizes a different, non-parametric method for classifying R&D Ability. Rather than using the first-stage regressions described in Section II in order to determine Ability, we employ simple cross-sectional sorts of scaled measures of output per unit of R&D. We use both profit/lagged R&D and sales/lagged R&D as measures. Here, lagged R&D represents an average of the last 1-5 years of R&D, to be flexible to the lead time of turning R&D into sales (and profit). This alternate, non-parametric approach is meant to address any potential concerns that our regression framework may introduce into how the Ability coefficients are determined. Appendix Table A6 shows that the equal-weight (value-weight) excess returns on the spread portfolio derived from sorts on sales/lagged R&D—the analog of the excess return rows in both panels in Table III--is 103 basis points per month, t=2.28 (83 basis points per month, t=1.46).

III. Mechanism

In this section, we provide a series of additional tests aimed at isolating the mechanism driving our main result. In particular, we examine several implications of our results, and also try to pinpoint why the market does not recognize the information in past R&D track records.

A. Real Outcomes: Patents and Products

First we explore real outcomes associated with our high ability firms. The goal here is to assess if the firms that we classify as high ability and that invest heavily in R&D, which we saw in Section III experience high future returns, also produce tangible results with their research and development efforts. An alternative explanation for our results thus far is that the firms that we classify as high ability firms may simply anticipate higher sales growth in the future, and hence may ramp up R&D and other firm-level activities in advance of sales growth; therefore the high first-stage correlation between R&D and future sales growth that defines our high ability firms may not be due to actual skill at conducting R&D, but rather skill at predicting future sales growth. To begin to rule out this alternative story, we first explore whether R&D spending by high ability firms leads to tangible outcomes, in the form of additional patents (and patent citations) in the future, as well as additional new products in the future.

To examine the real effects of firm-level R&D, we explore patents and patent citations using data from the NBER's U.S. Patent Citations Data File (when matching to our data, this gives a sample of 1980-2006). The idea behind exploring patents is that they represent a successful outcome measure of past research and development efforts. Patents enable firms to maintain a competitive advantage for a lasting period of time, and as such are intrinsically valuable from a firm's point of view. We analyze both the number of patents (using both the stock and annual flow of firm-level patents), and the number of patent citations (again using a stock and flow-based measure).[20] Following Hall, Jaffe, and Trajtenberg (2001), using patent citations enables one to create indicators of the "importance" of individual patents. Our approach is motivated by a vast literature (see, for example, Griliches (1981), Griliches (1984), Pakes (1985), Jaffe (1986), Griliches, Pakes, and Hall (1987), Connolly and Hirschey (1988), Griliches, Hall, and Pakes (1991), Hall (1993a), Hall (1993b), and Hall, Jaffee, and Trajtenberg (2005)) showing that patents, and particularly patent citations, are viable measures of R&D "success."

Table VIII presents annual Fama-MacBeth cross-sectional regressions of future (log) patents and (log) patent citations on past R&D ability. All these dependent variables are measured relative to the application year of the patent (rather than the grant year). Specifically, our explanatory variable of interest is again the interaction between our measure of high ability ($\text{Ability}_{\text{high}}$) and R&D. Analogous to Table IV, $\text{Ability}_{\text{high}}$ is a categorical vsriable equal to one for stocks in the highest quintile of ability each year, and zero otherwise. For R&D, we include specifications with continuous measures of one- and five-year averages of past R&D (i.e., $\log(1+(\text{R\&D/Sales}))_{-1}$ and $\log(1+(\text{R\&D/Sales}))_{-5,-1}$.[21] We also include lagged control variables for size ($\log(\text{ME}_{t-1})$), book-to-market ratio ($\log(\text{BE}_{t-1}/\text{ME}_{t-1})$), leverage ($\log(1+(\text{D}_{t-1}/\text{BE}_{t-1}))$), institutional ownership, and firm age (measured in years since a firm's first appearance on CRSP). We also include industry fixed effects (in each annual regression of the Fama-MacBeth framework) where indicated.

Column 1 of Table VIII reveals a positive and significant coefficient (=11.96, t=7.20) on the interaction term ($\text{Ability}_{\text{high}} * \log(1+(\text{R\&D/Sales}))$), indicating that firms with high past ability that continue to do R&D produce more patents in the future than other firms. To get a sense of the magnitude of this effect, a one-standard deviation move in R&D by a high ability firm leads to an additional 0.84 patents in the stock of patents for that firm (the median firm's stock of patents is 2.56, so this represents an increase of 33%). In column 2 of Table VI, using the stock of patent citations as the

[20] Citations are calculated using the HJT procedure described in Hall et al. (2001).
[21] We have also tried using a categorical variable ($\text{R\&D}_{\text{high}}$) equal to one for stocks above the 70th percentile in R&D each year, in place of these continuous measures of R&D, and the results are similar to those presented here in magnitude and significance.

dependent variable, we find that firms with high past ability that continue to do R&D also receive significantly more citations on their patents. Again the magnitude of this result is large: a one-standard deviation increase in R&D by a high ability firm leads to an additional 1.17 citations in the stock of patent citations for that firm (the median firm's stock of citations is 5.02, so this represents an increase of over 23%).[22]

Columns 3 and 4 present similar results, but this time using the annual flow of firm-level patents and patent citations, as opposed to the stock variables. High ability firms that continue to do R&D produce more patents per year (=9.07, t=7.10) and receive more patent citations per year (=14.87, t=6.80) than other firms. The corresponding magnitudes are again large; a one-standard deviation increase in R&D by a high ability firm translates into 0.63 more patents per year (a 58% increase) and 1.04 more patent citations per year (a 52% increase). And as Table VIII shows, including additional control variables, adding industry fixed effects, or using five-year averages of past R&D in Panel B (in place of last year's R&D) makes no difference to these results.

Table IX presents another test of the real, direct impact of R&D by exploring the impact of high ability firms' R&D efforts on the development of new firm-level products. We use the segment-level Product Database from the Compustat Segment File to compute the number of products per year for each firm; we exclude geographic and operating segment breakdowns, and focus on business segment breakdowns in order to capture true firm-level product innovations. The Compustat Segment file records a unique product number for each new product and carries that product number through time (e.g., iPod is product number 10 for Apple, starting in 2004), and is available from 2000-2008; by computing the maximum product number in each year, we can get a sense of how many products a firm has produced at any given point in time (this is analogous to the patent stock measure used in Table VIII). In our tests, we report specifications using this maximum product number as our outcome measure, but we have analyzed a variety of different measures of product-level innovation, such as the total number of products listed in a given year, the change in the number of total products listed in a

[22] We have also run the regressions in Table VIII controlling for past lagged values of patents and citations (essentially first-differencing). The magnitudes of the effects are similar (and remain statistically significant), implying roughly 70-95% increases in patents and citations for high ability firms that have a one standard deviation increase in R&D expenditures.

given year, etc., and the results are similar to those presented here.

Table IX presents the results of annual Fama-Macbeth cross-sectional regressions of our firm-level (log) product measure on the interaction of high ability and level of R&D (constructed exactly as in Table VIII). We control for the average of each firm's maximum product number over the past five years on the right-hand side of these regressions, and include the same control variables and fixed effects as in Table VIII.

The estimates in Table IX indicate that high ability firms' continuing R&D efforts are positively related to the development of new firm-level products. In column 1, the positive and significant coefficient (=4.41, *t*=2.74) on the interaction term ($\text{Ability}_{\text{high}}$ * log(R&D)) implies a 20% increase in the number of additional products for a one-standard deviation increase in R&D by a high ability firm. Including additional control variables, adding industry fixed effects, or using five-year averages of past R&D (in place of last year's R&D) again makes no difference to these results.

Taken together, the findings in Tables VIII and IX suggest that high ability firms are not simply ramping up R&D in advance of higher-than-average sales growth, as an anticipation story would suggest. Instead, the firms we identify as high-ability firms appear to be investing in research and development activities that yield tangible, successful outcomes in the form of increased numbers of patents, patent citations, and new product innovations.

B. Heterogeneity in Information Provision by Firms

Next we analyze the information environment of firms, in order to test the hypothesis that information opacity may help explain why the market fails to properly understand the information embedded in firms' past track records. Under the assumption that firms that provide more earnings guidance are also likely to provide more information to investors more generally (as in Jones (2007)), we explore the impact of managerial guidance on our key result. If firm opacity is impacting whether investors are able to decipher firm ability, then more open firms should have less of the return predictability that we document. Specifically, we test if the returns are lower for high ability firms who provide more earnings guidance relative to high ability firms who provide less earnings guidance. We find precisely this pattern in the data: in Panel A of

Table X, we show that the triple interaction of ($R\&D_{high}$*$ability_{high}$*$Guidance_{high}$) is strongly negative and but not quite significant in our main regression specification, indicating that information asymmetry is may be related to the return predictability we observe.

C. Founder Effects

On the issue of what drives persistence in R&D skill within a given firm over time, one plausible hypothesis is that some firms (e.g., Apple) may have had the benefit of a unique "founder effect," which could persist for many years but then diminish after the founder leaves. Under this story, founder-led firms might tend to underperform after their founder leaves the firm. We test this idea directly by comparing non-founder-led firms to founder-led firms, and find marginally significant evidence that high-ability founder-led firms have larger impacts on future returns than non-founder-led firms. Specifically, Table X Panel B shows that the marginal effect of having a founder is almost 3 times the main effect; we view this result as suggestive evidence of founder effects in firm-level R&D ability.[23]

D. Variation in Financial Constraints

Continuing on the issue of interpretation, we next exploit variation in firm-level financial constraints, with the idea that financially constrained firms will likely only be able to increase R&D when they have exceptionally good R&D projects to invest in. Hence, those firms that are limited in their ability to raise financing would be hesitant to waste resources on R&D and to simply ramp up all spending in anticipation of perceived growth. Therefore, even amongst those firms that have high ability at R&D, comparing a financially constrained firm and an unconstrained firm, we may expect a stronger signal from the R&D spending of the financially constrained firm.

We test this notion in Panel C of Table X when we interact our measure of GoodR&D ($R\&D_{high}$ * $Ability_{high}$) with the Kaplan and Zingales (1997) "KZ-index" of

[23] We also tried to exploit within-firm variation in firms before and after a founder leaves to identify the impact of a founder at a firm-specific level, but we did not have enough power to detect any meaningful effects given the tiny number of observations available for this additional test.

financial constraints, and re-run our basic return predictability regression test from Table IV. Specifically we form dummy variables of the KZ-index based on the same Fama and French (1996) 30/40/30 breakpoints across all firms each month. We then interact these three dummy variables with our GoodR&D measure. We examine the return predictability of GoodR&D firms within these three categories of financial constraints (GoodR&D*KZ_{high}, GoodR&D*KZ_{low}, GoodR&D*KZ_{mid}) in Table X. Panel C indicates that our result is indeed strongest among firms that are financially constrained (=1.865=(0.450+1.415), *t*-stat=2.27). Similarly, using financial constraints measured by cash balances of the firm provides the same intuition (highest coefficient for most constrained (lowest cash) firms =1.159=(0.732+0.427), *t*-stat=1.50).

E. What Happens to Firms that Ramp Up All Operations?

We run a final test to pinpoint the mechanism behind our results by examining the future returns of high past R&D ability (Ability_{high}) firms that continue to ramp up all firm operations. The idea behind this test is to specifically rule out the alternative explanation that our interaction measure simply picks up firms that are: i.) good at predicting their future growth (through Ability_{high}), ii.) ramping up all firm operations, including R&D (through $\text{R\&D}_{high}$). Instead, of course, we would like to pinpoint specifically the impact of firms with *specific* ability at R&D, translating high *R&D* expenditures into future value for the firm. We test this by taking those firms who we identify as having high ability at R&D, and seeing what happens when they ramp up all other types of spending. For example, we look at large increases in capital expenditures (CAPEX_{high}) and large increases in total operating expenditures (OPEX_{high}) by these firms, rather than just large increases in R&D (as in Tables III-V).

Again, if the high future returns we observe are a consequence of firms simply ramping up all expenditures in advance of future sales, then the interaction of our ability measure with *any* type of expenditure should predict high returns. We test this in Panels E and F of Table X, where we replicate our Table V regressions, but include interactions with high ability and high spending on capital expenditures (CAPEX_{high}), or high total expenses (OPEX_{high}), in place of high spending on R&D ($\text{R\&D}_{high}$). Panels E and F indicate that both interaction terms (both in Column 1 of the respective panels) are near zero and insignificant, in contrast to the strong positive predictive power of GoodR&D ($R\&D_{high}$ * $Ability_{high}$) documented earlier.

Collectively, the findings in Table X reinforce the idea that our empirical approach isolates a set of firms with predictable, persistent R&D skill, and not simply a set of firms with skill at predicting future firm growth. We also find suggestive evidence that R&D skill is positively related to the presence of a founder. Lastly, we show that the market's failure to understand the implications of R&D track records is related to heterogeneity in information provision by firms.

IV. Discussion

In this section, we discuss two important aspects of our methodology. The first has to do with the determinants (and optimality) of firm-level R&D. We are agnostic in the paper as to what drives the variation between firms in the level of their R&D investment. In other words, one could make the argument that all firms should be individually solving for the optimal level of R&D expenditure. Given their (privately known) ability at research and development, a firm will continue R&D expenditures until the value of the marginal dollar of R&D is equal to its opportunity cost. If each firm does this, then we simply observe (through R&D expenditures) the optimal amount of research that each firm is undertaking. On the other hand, perhaps because of financial constraints, other frictions, or even errors in firm decision-making, firms may have sub-optimal levels of research expenditures. However, whether the amount of R&D is optimal or not, the market should still be expected to value the firm's chosen R&D level.

This brings up a second important aspect of our findings. Namely, in either case above (optimal investment or not), as long as the market correctly extracts the information about a given firm's level of R&D along with its R&D ability, there should be no predictability. More generally, even if the market is always incorrect about the effect of R&D on future value for every firm, there would still be no implied return predictability, as the market would sometimes overvalue, and sometime undervalue, the impact of R&D on future firm value. Only in the case that the market is consistently incorrect in an ex-ante identifiable and *predictable* manner, would the market's misvaluation of innovation translate into return predictability. This is, in fact, precisely what we show is happening across the universe of firms and innovation expenditures undertaken. Collectively, the results of the paper suggest that the market fails to incorporate the information in past successes when evaluating the likely efficacy of today's investments. In doing so, we provide evidence of a new friction in the response of capital to trading opportunities.

V. Conclusion

In this paper we demonstrate that firm-level innovation is predictable, persistent, and relatively simple to compute, and yet the stock market ignores the implications of publicly available information when setting prices. Our approach is based on the simple idea that some firms are likely to be skilled at certain activities, and some are not, and this skill may be persistent over time. Hence, past track records associated with a given activity represent a straightforward way to gauge the future prospects of firms. Using this idea as the starting point for our analysis, we examine the predictability of firm-level R&D track records for future returns and future real outcomes. We show that despite the uncertainty typically associated with R&D investment, substantial return predictability exists by exploiting the information in these firm-level track records. We find that a long-short portfolio strategy that takes advantage of the information in past track records yields abnormal returns of 11 percent per annum. In doing so, we add to a growing literature showing that the market appears to underreact to the information contained in R&D investments. Our tests pinpoint a specific channel through which the market under-reacts to firm-level R&D investments by highlighting the importance of the interaction between a successful past track record and current R&D activity.

We show that the firms we classify as high ability based on their past track records also produce tangible results with their research and development efforts. In particular, R&D spending by high ability firms leads to increased numbers of patents, patent citations, and new product innovations by these firms in the future. The same level of R&D investment by low ability firms does not. Additionally, we document that high R&D ability firms that continue to spend substantial amounts on *other* activities, such as capital expenditures or total expenses as opposed to R&D, do not experience high future returns. These results suggest that our findings are unlikely to be driven by firms that simply anticipate higher sales growth in the future, and hence ramp up R&D and other firm-level activities in advance of sales growth. Rather, our findings are consistent with the idea that the firms we define as high ability are in fact truly skilled at R&D, and that future firm-level innovation by these firms is unanticipated by the market.

Given the substantial shift in the funding of research and development from the public sector to the private sector over the past few decades, the extent to which the stock market properly values investments in R&D is increasingly important. Our findings suggest that while R&D investment is indeed associated with considerable uncertainty, it is possible to identify potential winners and losers solely based on publicly available information. The fact that the stock market fails to adequately incorporate this type of information raises important questions about the efficiency of R&D investment in the economy.

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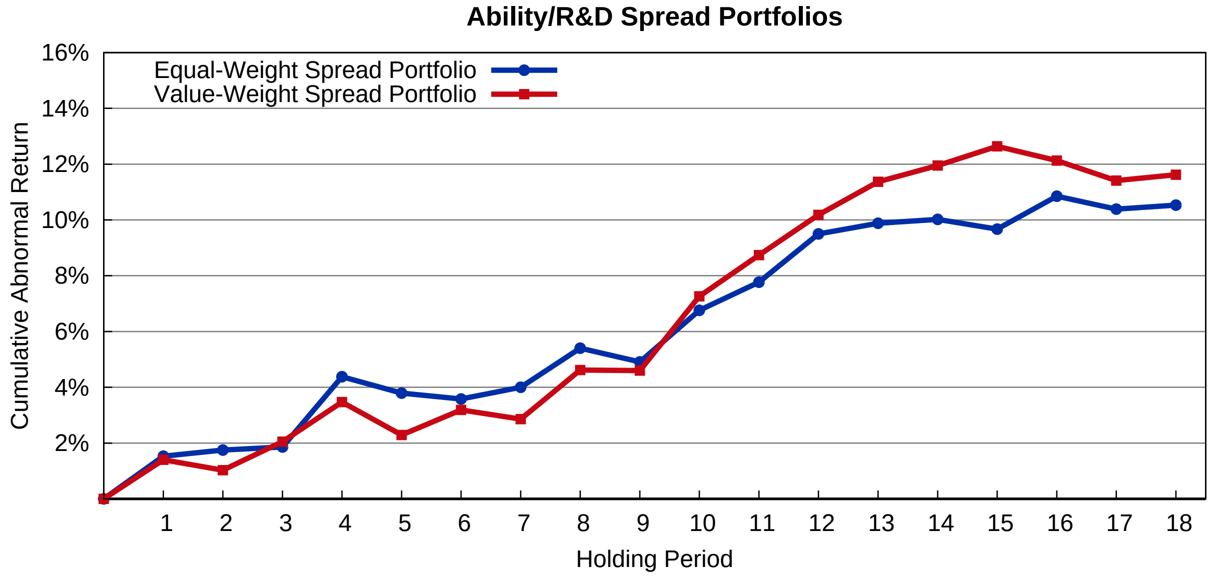
Figure 1

Returns to Correctly Valuing Innovation, Event-time Abnormal Returns

This figure shows the size-B/M-mom adjusted cumulative abnormal returns to portfolios that follow high Ability/high R&D and low Ability/high R&D firms in the 18 months following formation. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are double sorted into portfolios using quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in Table II. The high Ability/high R&D (low Ability/high R%D) portfolio is formed from the intersection of the top 20% (bottom 20%) of ability and top 30% of R&D. The top graph shows the abnormal return spread between high Ability/high R&D and low Ability/high R&D portfolios. The bottom graph shows the abnormal return on the high Ability/high R&D portfolio. abnormal returns are computed by adjusting returns using 125 size/book-to-market/momentum portfolios (formed as in DGTW (1997)). The sample period is July 1980 to December 2009.



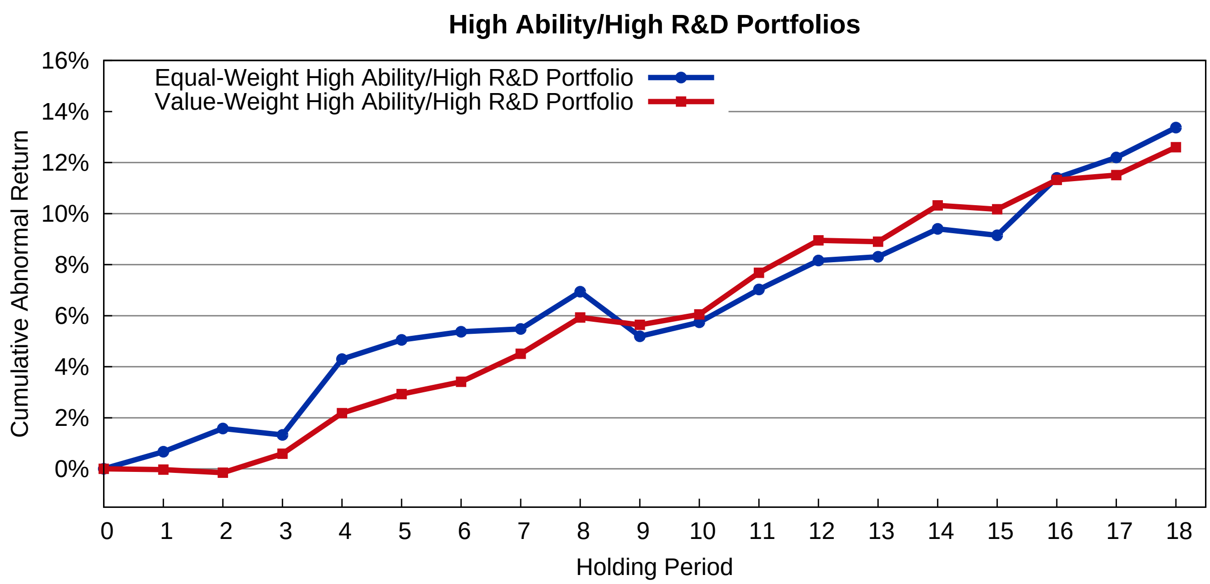


Figure 2
Annual Returns to Equal-Weight Ability/R&D Spread Portfolio

This figure shows annual returns to high Ability/high R&D minus low Ability/High R&D spread portfolios. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in Table II. The high Ability/high R&D (low Ability/high R&D) portfolio is formed from the intersection of the top 20% (bottom 20%) of ability and top 30% of R&D. The figure also show the annual excess return on a proxy for the market portfolio (VW portfolio of CRSP common stocks), and recession periods (as defined by the NBER) are denoted by the gray shaded areas.

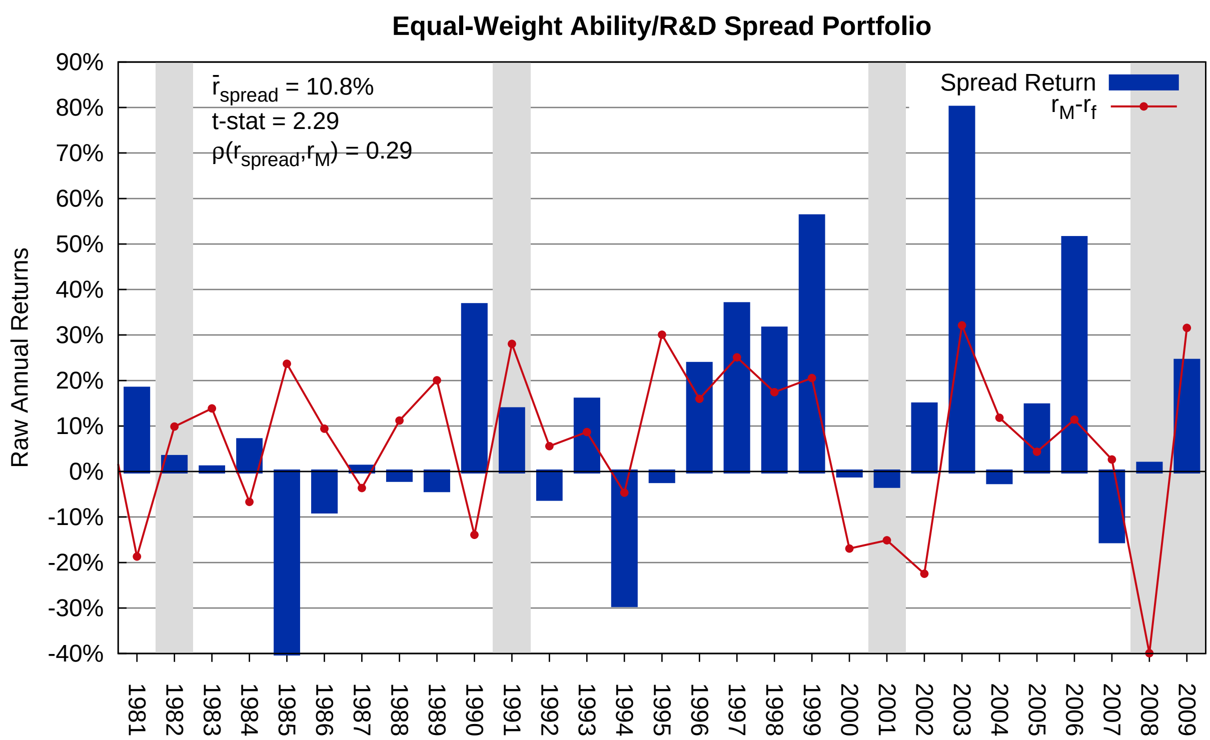


Table I
Summary Statistics: R&D-Ability Sample Compared to CRSP Stocks

This table compares the R&D-Ability sample of stocks with a sample of all CRSP common stocks. The R&D-Ability sample is comprised of CRSP common stocks, and non-missing R&D Ability estimates. Ability is computed as described in Table II. R&D is scaled by sales. Each year in July the percentile ranks of market-cap, B/M, leverage, $r_{-12,-2}$, volatility, and turnover for every stock are computed. The table reports pooled summary statistics of the percentile ranks. Market-cap is the market capitalization of the firm from the end of June. B/M is book equity to market equity and is computed as in Fama and French (1993). Leverage is long term debt divided by book equity where book equity is computed as in Fama and French (1993). Both B/M and leverage are from the fiscal year that ended in calendar year $t-1$. $r_{-12,-2}$ is the return from month $t-12$ (previous July) to $t-2$ (May). Volatility is the standard deviation of daily returns computed over the past year (250 trading days). Turnover is average daily share turnover during the last year (250 trading days). The sample period is 1980 to 2009.

	Panel A: All CRSP Common Stocks			
	Breakpoints	Mean	Median	St. Dev
Percentile Market-Cap	NYSE	0.22	0.10	0.27
Percentile B/M	NYSE	0.47	0.46	0.31
Percentile Leverage	NYSE	0.38	0.31	0.32
Percentile $r_{-12,-2}$	All	0.50	0.50	0.29
Percentile Volatility	All	0.50	0.50	0.29
Percentile Turnover	All	0.50	0.50	0.29

	Panel B: R&D/Ability Sample			
	Breakpoints	Mean	Median	St. Dev
Percentile Market-Cap	NYSE	0.31	0.17	0.32
Percentile B/M	NYSE	0.43	0.39	0.30
Percentile Leverage	NYSE	0.32	0.24	0.28
Percentile $r_{-12,-2}$	All	0.52	0.52	0.28
Percentile Volatility	All	0.49	0.49	0.27
Percentile Turnover	All	0.56	0.57	0.27

Table II
R&D Ability Summary Statistics and Persistence in Ability

Panel A reports pooled summary statistics for Ability, R&D (scaled by sales), and sales growth. R&D ability is computed for each firm every year using five ($j = 1 \dots 5$) time series regressions of sales growth on past R&D:

$$\log(\frac{Sales_{it}}{Sales_{it-1}}) = \gamma_0 + \gamma_j log(1 + R\&D_{it-j}) + \epsilon_{it}.$$

A back window of 6-8 years of non-missing data is required. An additional requirement is that at least half of the R&D observations are non-zero. Ability is computed as the average of the five slope coefficients (γ_j). Panel B reports the fraction of stocks that are in ability quintile x in year t given they are in ability quintile x in year $t - lag$. Specifically, panel B reports means of the time series of these fractions for each quintile. The sample period is 1980 to 2009.

	Panel A: Ability Summary Statistics		
	Mean	Median	St. Dev
Ability	3.26	3.29	11.11
$log(1 + R\&D)$	0.18	0.17	0.07
$log(sales_t/sales_{t-1})$	0.07	0.07	0.28

Panel B: Mean Annual Persistence in Ability					
$Prob(Quintile = i)$, $year = t$ if $Quintile = i$, $year = t - lag$					
Ability Quintiles					
Lag	Low	2	3	4	High
1	0.66	0.50	0.51	0.49	0.70
2	0.48	0.37	0.40	0.36	0.55
3	0.38	0.32	0.35	0.29	0.46
4	0.30	0.30	0.32	0.26	0.39
5	0.26	0.28	0.30	0.24	0.36

Table III
Double Sorts on R&D and Ability: Monthly Portfolio Returns

This table presents monthly portfolio returns (in %) for double sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in table II. Characteristic abnormal returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (computed as in DGTW (1997)), 25 size/book-to-market portfolios (computed as in Fama and French (1993)), and 17 industry portfolios (as in Fama and French (1997)). The benchmark portfolios' weighting match the weighting of the R&D/Ability portfolios. All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). Average abnormal returns are also computed using the three factor model (Fama and French (1993)) and four factor model (Carhart (1997)).

$$r_i - r_f = \alpha_i + b(r_M - r_f) + sSMB + hHMB + e_i$$
$$r_i - r_f = \alpha_i + b(r_M - r_f) + sSMB + hHMB + uUMD + e_i$$

The sample period is July 1980 to December 2009.

Panel A: Equal-Weight Portfolios							
		Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
Excess Returns							
Mean	0.81	0.75	0.62	0.80	0.83	1.35	0.73
T-stat	3.04	2.61	1.48	3.00	2.81	2.76	2.61
Size-B/M-Mom Adjusted Returns							
Mean	-0.07	-0.04	-0.10	-0.03	0.08	0.79	0.89
T-stat	-0.86	-0.43	-0.50	-0.42	0.90	2.84	3.32
Size-B/M Adjusted Returns							
Mean	0.02	0.08	-0.04	0.04	0.15	0.88	0.92
T-stat	0.27	0.94	-0.18	0.57	1.79	2.84	3.33
Industry Adjusted Returns							
Mean	0.15	0.12	-0.03	0.18	0.22	0.81	0.84
T-stat	1.35	1.05	-0.16	1.58	2.17	2.97	3.03
Three Factor Model α							
α	0.04	0.02	-0.02	0.02	0.14	0.72	0.74
T-stat	0.38	0.21	-0.09	0.20	1.45	2.52	2.59
Four Factor Model α							
α	0.10	0.10	0.14	0.12	0.25	0.90	0.76
T-stat	0.88	0.90	0.75	1.18	2.51	3.11	2.59

Panel B: Value-Weight Portfolios							
	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
Excess Returns							
Mean	0.73	0.60	0.32	0.56	0.72	1.22	0.90
T-stat	2.79	2.18	0.81	2.18	2.25	2.61	2.30
Size-B/M-Mom Adjusted Returns							
Mean	0.16	-0.05	-0.20	-0.06	0.21	0.72	0.92
T-stat	1.52	-0.40	-0.91	-0.63	1.67	2.30	2.64
Size-B/M Adjusted Returns							
Mean	0.11	-0.02	-0.10	0.02	0.16	0.68	0.78
T-stat	0.84	-0.13	-0.41	0.16	1.06	1.99	2.10
Industry Adjusted Returns							
Mean	0.16	0.01	-0.32	0.04	0.17	0.63	0.95
T-stat	1.43	0.07	-1.48	0.42	1.52	2.02	2.61
Three Factor Model α							
α	0.19	-0.04	-0.16	-0.01	0.12	0.89	1.05
T-stat	1.36	-0.26	-0.62	-0.04	0.87	2.64	2.64
Four Factor Model α							
α	0.14	0.06	-0.15	0.01	0.19	0.78	0.93
T-stat	0.95	0.35	-0.56	0.09	1.33	2.27	2.30

Panel C: Equal Weight Portfolios Four Factor Loadings							
	Low Ability			High Ability			
	$R\&D_{low}$	2	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
b	0.99	1.00	1.11	0.99	1.01	1.18	0.06
t(b)	38.52	40.16	24.86	40.82	43.82	17.25	0.93
s	0.42	0.57	0.89	0.40	0.59	0.91	0.01
t(s)	11.95	16.88	14.63	11.92	18.61	9.75	0.15
h	0.43	0.23	-0.37	0.42	0.09	-0.51	-0.13
t(h)	11.30	6.25	-5.58	11.65	2.48	-4.98	-1.30
u	-0.06	-0.08	-0.17	-0.10	-0.11	-0.18	-0.02
t(y)	-2.46	-3.41	-4.18	-4.81	-5.16	-3.03	-0.29
# Stocks	84	69	25	114	60	10	

Table IV
Monthly R&D and Ability Portfolio Returns

This table presents monthly portfolio returns (in %) for sorts on Ability and R&D. Ability is computed as described in Table II. R&D is scaled by sales. In panel A we form R&D quintiles. The R&D used to form the portfolios is R&D for the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June (as in Fama and French (1993)). In panel B we form Ability quintiles. The Ability used to form the portfolios is the Ability estimate from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June. Characteristic abnormal returns are computed by adjusting returns using 125 value-weight size/book-to-market/momentum portfolios (formed as in DGTW (1997)). All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5. The sample period is July 1980 to December 2009.

Panel A: *R&D* Portfolios							
	$R\&D_{zero}$	$R\&D_{low}$	2	3	4	$R\&D_{high}$	$High - Zero$
Equal-Weight: Excess Returns							
Mean	0.63	0.70	0.67	0.83	0.79	0.29	-0.33
T-stat	2.11	2.56	2.36	2.35	1.82	0.58	-0.90
Equal-Weight: Size-B/M-Mom adjusted returns							
Mean	-0.18	-0.11	-0.07	0.15	0.24	-0.09	0.09
T-stat	-1.63	-1.56	-1.03	1.71	1.66	-0.41	0.31
Value-Weight: Excess Returns							
Mean	0.72	0.59	0.51	0.61	0.64	0.47	-0.25
T-stat	2.41	2.47	1.92	2.16	1.97	1.01	-0.62
Value-Weight: Size-B/M-Mom adjusted returns							
Mean	0.13	0.02	-0.04	0.15	0.10	0.15	0.01
T-stat	1.00	0.27	-0.55	2.14	1.04	0.72	0.05
Number of Stocks							
Mean	278	308	296	278	268	198	

Panel B: Value-Weight *Ability* Portfolios						
	$Ability_{low}$	2	3	4	$Ability_{high}$	$High - Low$
Equal-Weight: Excess Returns						
Mean	0.77	0.77	0.81	0.86	0.83	0.07
T-stat	2.77	2.39	2.25	2.76	3.02	1.09
Equal-Weight: Size-B/M-Mom adjusted returns						
Mean	-0.06	0.09	0.17	0.13	0.03	0.09
T-stat	-0.87	1.03	1.39	1.56	0.60	1.50
Value-Weight: Excess Returns						
Mean	0.63	0.58	0.62	0.59	0.58	-0.04
T-stat	2.59	2.11	2.13	2.12	2.22	-0.34
Value-Weight: Size-B/M-Mom adjusted returns						
Mean	0.06	0.06	0.05	0.12	0.04	-0.03
T-stat	0.99	0.70	0.50	1.49	0.52	-0.31
Number of Stocks						
Mean	188	170	155	174	194	

Table V
Fama-MacBeth Regressions of Monthly Returns on R&D and Ability

This table presents monthly Fama-MacBeth (1973) regressions of returns on R&D and Ability. The R&D (Ability estimate) used in the regression is the R&D (Ability estimate) from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June (as in Fama and French (1993)). Ability is computed as described in Table II. $ability_{high}$ ($ability_{low}$) equals one if a stock is in the top (bottom) quintile for a given month. $R\&D_{high}$ ($R\&D_{low}$) equals one for a stock if its ability estimate is greater than the 70^{th} (not greater than the 30^{th}) percentile in a given month. $R\&D_{zero}$ equals one if $R\&D = 0$. $log(ME)$ is the log of month $t-1$ market-cap, and $log(B/M)$ is log book to market defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is the return from month $t-12$ to month $t-2$. r_{-1} is the one month lagged return. $turnover$ is average daily share turnover ($\times 100$) over the past year. σ is the standard deviation of daily returns over the past year. Some regressions includes industry dummies (using Fama and French's (1997) 17-industry classification scheme). The regressions only include stocks with lagged price greater than 5. The sample period is July 1980 to December 2009. T-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{high} * ability_{high}$	0.627	0.649	0.758	0.785				
	(2.41)	(2.46)	(2.86)	(3.04)				
$R\&D_{high} * ability_{low}$		-0.140	-0.214	-0.208				
		(-0.77)	(-1.17)	(-1.15)				
$\log(1 + R\&D) * ability_{high}$					5.433	5.786	9.547	
					(2.14)	(2.25)	(3.62)	
$\log(1 + R\&D) * ability_{low}$						0.881	0.809	-0.038
						(0.52)	(0.50)	(-32.00)
$ability_{high}$	-0.048	-0.103	-0.055	-0.016	-0.142	-0.213	-0.267	0.027
	(-0.83)	(-1.44)	(-0.95)	(-0.27)	(-1.48)	(-1.83)	(-2.92)	(51.02)
$ability_{low}$		-0.143	-0.101	-0.070		0.881	0.809	-0.038
		(-1.90)	(-1.62)	(-1.11)		(0.52)	(0.50)	(-32.00)
$R\&D_{high}$	0.109	0.093	0.134	0.094				
	(0.64)	(0.56)	(1.13)	(0.82)				
$R\&D_{low}$			-0.170	-0.176				
			(-2.38)	(-2.50)				
$R\&D_{zero}$			-0.861	-1.040				
			(-2.39)	(-2.85)				
$\log(1 + R\&D)$					0.803	0.479	1.267	0.012
					(0.91)	(0.53)	(1.39)	(11.49)
$\log(ME)$	-0.028	-0.026	-0.041	-0.049	-0.026	-0.025	-0.035	0.000
	(-0.73)	(-0.69)	(-1.19)	(-1.38)	(-0.69)	(-0.66)	(-1.01)	(15.76)
$\log(B/M)$	0.247	0.257	0.220	0.277	0.258	0.263	0.230	-0.001
	(3.55)	(3.75)	(3.58)	(4.85)	(3.62)	(3.83)	(3.74)	(-12.85)
$r_{-12,2}$	0.775	0.766	0.788	0.749	0.811	0.796	0.803	0.000
	(3.59)	(3.57)	(4.02)	(3.93)	(3.63)	(3.62)	(4.06)	(0.64)
r_{-1}			-3.771	-4.046			-3.810	0.000
			(-8.42)	(-9.24)			(-8.40)	(1.47)
$turnover$			-0.308	-0.320			-0.318	0.001
			(-1.71)	(-1.85)			(-1.79)	(12.92)
σ			-0.123	-0.114			-0.111	0.001
			(-1.87)	(-1.79)			(-1.65)	(13.28)
Industry Fixed Effects				Yes				Yes
Number of Months	354	354	354	354	354	354	354	354
Total Observations	290272	290272	283031	283031	290272	290272	283031	283031

Table VI
Fama-MacBeth Return Regressions: International and Early U.S. Sample

This table presents monthly Fama-MacBeth (1973) regressions of returns on R&D and Ability for an international sample of stocks (UK, Japan, and Germany) and an early U.S. sample period (July 1974 to June 1980). The R&D (Ability estimate) used in the regression is the R&D (Ability estimate) from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June. Ability is computed as described in Table II. $ability_{high}$ ($ability_{low}$) equals one if a stock is in the top (bottom) quartile for a given month . $R\&D_{high}$ ($R\&D_{low}$) equals one for a stock if its ability estimate is in the top (bottom) quartile in a given month. $R\&D_{zero}$ equals one if $R\&D = 0$. For the international sample, the R&D and ability breakpoints are computed separately for each country. $log(ME)$ is the log of month $t-1$ market-cap, and $log(B/M)$ is log book to market defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is the return from month $t-12$ to month $t-2$. r_{-1} is the one month lagged return. σ is the standard deviation of daily returns over the past year. *turnover* is average daily share turnover ($\times 100$) over the past year. Returns, market-caps, and prices are converted to U.S. dollars for the international sample. We include country fixed effects in the international regressions. In both samples we exclude lagged low price stocks: 5th price percentile (by month) for international stocks, and for $5 the U.S. stocks. The sample period is July 1995 to December 2010 for the international sample and July 1974 to June 1980 the U.S. sample. T-statistics are in parenthesis.

	ALL: UK, JPN,Ger		UK	JPN	Ger	Early U.S.: 74-80	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$R\&D_{high} * ability_{high}$	0.510	0.501	0.923	0.416	-0.138	0.572	0.661
	(2.32)	(2.24)	(1.37)	(1.69)	(-0.20)	(1.04)	(1.18)
$R\&D_{high} * ability_{low}$		-0.158	-0.139	0.043	-0.477		0.103
		(-0.84)	(-0.25)	(0.19)	(-0.60)		(0.15)
$ability_{high}$	-0.045	-0.064	-0.085	-0.099	0.634	-0.029	-0.077
	(-0.70)	(-0.85)	(-0.47)	(-1.18)	(2.03)	(-0.16)	(-0.37)
$ability_{low}$		-0.099	0.111	-0.187	0.379		-0.100
		(-1.18)	(0.63)	(-1.97)	(1.11)		(-0.50)
$R\&D_{high}$	0.199	0.145	0.339	0.045	0.468	0.073	0.029
	(1.94)	(1.39)	(1.39)	(0.43)	(1.13)	(0.32)	(0.12)
$R\&D_{low}$		-0.156	0.113	-0.247	-0.342		0.192
		(-1.48)	(0.63)	(-2.04)	(-1.14)		(0.87)
$R\&D_{zero}$		-0.230	-0.199	-0.331	-0.686		0.162
		(-0.73)	(-0.52)	(-0.84)	(-0.86)		(0.22)
$\log(ME)$	0.016	0.012	0.004	0.002	-0.086	-0.214	-0.215
	(0.34)	(0.27)	(0.07)	(0.03)	(-1.17)	(-2.13)	(-2.16)
$\log(B/M)$	0.251	0.265	0.203	0.318	0.028	0.535	0.512
	(3.09)	(3.31)	(1.70)	(2.80)	(0.14)	(1.91)	(1.81)
$r_{-12,2}$	0.001	0.001	0.008	-0.007	0.010	0.892	0.895
	(0.30)	(0.24)	(2.07)	(-1.52)	(1.40)	(1.51)	(1.53)
r_{-1}	-0.048	-0.048	-0.026	-0.064	-0.004	-8.207	-8.139
	(-5.77)	(-5.80)	(-2.37)	(-6.41)	(-0.22)	(-5.84)	(-5.94)
Country Fixed Effects	Yes	Yes					
Number of Months	186	186	186	186	126	73	73
Total Observations	185697	185697	33543	132019	17992	23601	23601

Table VII
Fama-MacBeth Return Regressions: Controlling for Other R&D Effects

This table presents monthly Fama-MacBeth (1973) return regressions. The R&D (Ability estimate) is the from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June. Ability is computed as in Table II. $ability_{high}$ ($ability_{low}$) equals one if a stock is in the top (bottom) quintile for a given month. $R\&D_{high}$ ($R\&D_{low}$) equals one for a stock if its ability estimate is greater than the 70^{th} ($\leq$ the 30^{th}) percentile in a given month. $R\&D_{zero}$ equals one if $R\&D = 0$. $\Delta R\&D^{large}_{t-1}$ ($\Delta R\&D^{large}_{t-5,t-1}$) refers to large increases in R&D over the past year (past five years) where the follow conditions define a large increase: raw $\Delta R\&D_t > 5\%$, $R\&D_t/assets_{t-1} > 5\%$, and $\Delta(R\&D_t/assets_{t-1}) > 5\%$. r_{book} ($r_{intangible}$) is the return on book equity (intangible assets) defined as in Daniel and Titman (2006). $Patents/R\&D$ is patents to lagged raw R&D (defined as in Hirshleiefer, Hsu, and Li (2011)). $\frac{Patents}{R\&D}_{high}$ ($\frac{Patents}{R\&D}_{low}$) refers to stocks in the top (bottom) 30% in a given month. $log(ME)$, $log(B/M)$. $r_{-12,-2}$, r_{-1}, $turnover$, and σ are defined as in table V. r_{-1}, $turnover$, and σ are controls in some regressions. The regressions only include stocks with $price_{t-1} > 5$. The sample period is July 1980 to December 2009. T-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{high} * ability_{high}$	0.615	0.721	0.603	0.741	0.676	0.780	0.629	0.747
	(2.31)	(2.71)	(2.30)	(2.80)	(2.49)	(2.87)	(2.38)	(2.81)
$R\&D_{high} * ability_{low}$	-0.147	-0.213	-0.198	-0.231	-0.125	-0.217	-0.152	-0.222
	(-0.81)	(-1.16)	(-1.09)	(-1.26)	(-0.68)	(-1.17)	(-0.84)	(-1.22)
$ability_{high}$	-0.093	-0.053	-0.036	-0.023	-0.111	-0.058	-0.092	-0.054
	(-1.33)	(-0.91)	(-0.55)	(-0.39)	(-1.56)	(-1.00)	(-1.29)	(-0.93)
$ability_{low}$	-0.134	-0.100	-0.083	-0.069	-0.146	-0.098	-0.135	-0.093
	(-1.84)	(-1.60)	(-1.23)	(-1.12)	(-1.95)	(-1.56)	(-1.80)	(-1.49)
$R\&D_{high}$	0.047	0.093	-0.058	-0.005	0.067	0.105	0.089	0.139
	(0.30)	(0.79)	(-0.42)	(-0.04)	(0.40)	(0.89)	(0.54)	(1.17)
$R\&D_{low}$		-0.153		-0.077		-0.181		-0.142
		(-2.21)		(-1.18)		(-2.55)		(-1.98)
$R\&D_{zero}$		-0.838		-0.770		-1.082		-0.968
		(-2.33)		(-2.15)		(-3.01)		(-2.66)
$\log(ME)$	-0.026	-0.041	-0.025	-0.042	-0.036	-0.046	-0.050	-0.060
	(-0.68)	(-1.18)	(-0.65)	(-1.20)	(-0.95)	(-1.30)	(-1.31)	(-1.75)
$\log(B/M)$	0.263	0.226	0.269	0.226			0.245	0.210
	(3.86)	(3.68)	(4.07)	(3.71)			(3.58)	(3.43)
$r_{-12,2}$	0.771	0.791	0.756	0.784	0.714	0.706	0.785	0.805
	(3.59)	(4.03)	(3.55)	(4.01)	(3.27)	(3.55)	(3.66)	(4.10)
$\Delta R\&D^{large}_{t-1}$	0.192	0.205						
	(1.72)	(2.01)						
$\Delta R\&D^{large}_{t-5,t-1}$			0.302	0.344				
			(2.75)	(3.89)				
$\log(B/M)_{t-5}$					0.092	0.091		
					(1.55)	(1.65)		
r_{book}					0.014	-0.002		
					(0.25)	(-0.03)		
$r_{intangible}$					-0.221	-0.189		
					(-2.72)	(-2.52)		
$\frac{Patents}{R\&D}_{high}$							-0.069	-0.062
							(-0.66)	(-0.56)
$\frac{Patents}{R\&D}_{low}$							-0.333	-0.322
							(-3.65)	(-3.86)
Other Controls		Yes		Yes		Yes		Yes
Number of Months	354	354	354	354	354	354	354	354
Total Observations	290272	283031	290272	283031	284098	277350	290272	283031

Table VIII
Annual Fama-MacBeth regressions of Logged Patents on R&D and Ability

The table presents annual Fama-MacBeth regressions of logged patents on R&D and R&D Ability. The patent dependent variables are the following: patent stock, cite stock, patent flow, and cite flow. Patent stock is the number of patents held by a firm in a given year (where year refers to application year). Patent flow is the number of new patents granted to a firm based on the application year of the patent. Cite refers to the number of citations, and cite stock and flow are defined analogously to patent stock and flow. The functional form of the dependent variables is the log of 1 + the raw variable. Ability is computed as described in Table II. The R&D (Ability) used in the regressions is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1. $ability_{high}$ equals one if a stock is in the top quintile for a given month. The regressions include the following control variables: log(ME), log(B/M), log(1+leverage), instown, and log(age). ME is market-cap at the end of the previous year. B/M is lagged book to market computed as in Fama and French (1993). *leverage* is book leverage divided by book equity lagged one year. *instown* is institutional ownership from the previous year expressed as a fraction of shares outstanding. Age is the age of the firm in years computed based on they firm's first appearance on CRSP. The sample period is 1980 to 2006. T-statistic are in parenthesis.

	Panel A: R&D lagged one period							
	Patent Stock	Cite Stock	Patent Flow	Cite Flow	Patent Stock	Cite Stock	Patent Flow	Cite Flow
$\log(1+R\&D)ability_{high}$	11.96	16.70	9.07	14.87	9.18	12.61	6.99	11.31
	(7.2)	(6.8)	(7.1)	(6.8)	(6.6)	(6.1)	(6.3)	(6.2)
$ability_{high}$	-0.63	-0.95	-0.45	-0.75	-0.52	-0.78	-0.37	-0.60
	(-19.8)	(-19.7)	(-13.4)	(-11.2)	(-18.2)	(-17.9)	(-12.1)	(-10.8)
$\log(1+R\&D)$	2.21	3.10	1.94	3.16	1.92	2.68	1.81	2.90
	(3.0)	(3.0)	(3.1)	(3.0)	(3.1)	(3.0)	(3.2)	(3.1)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects					Yes	Yes	Yes	Yes
$\overline{R}^2$	0.42	0.31	0.28	0.17	0.46	0.35	0.31	0.19
Number of Years	27	27	27	27	27	27	27	27
Total Observations	27464	27464	27464	27464	27464	27464	27464	27464

	Panel B: Average R&D from $t-5$ to $t-1$							
	Patent Stock	Cite Stock	Patent Flow	Cite Flow	Patent Stock	Cite Stock	Patent Flow	Cite Flow
$\log(1+R\&D)_{-5,1}ability_{high}$	16.51	22.69	12.41	20.30	12.33	16.43	9.45	15.15
	(9.2)	(9.5)	(10.4)	(9.8)	(8.6)	(8.5)	(9.6)	(9.6)
$ability_{high}$	-0.69	-1.05	-0.50	-0.83	-0.55	-0.83	-0.39	-0.65
	(-28.1)	(-24.6)	(-16.6)	(-13.2)	(-22.7)	(-19.0)	(-15.0)	(-12.9)
$\log(1+R\&D)_{-5,-1}$	1.94	2.62	1.62	2.63	1.78	2.42	1.55	2.52
	(3.1)	(2.9)	(3.0)	(2.9)	(3.2)	(3.1)	(3.2)	(3.1)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects					Yes	Yes	Yes	Yes
$\overline{R}^2$	0.45	0.34	0.32	0.20	0.48	0.37	0.35	0.22
Number of Years	27	27	27	27	27	27	27	27
Total Observations	28625	28625	28625	28625	28625	28625	28625	28625

Table IX
Annual Fama-MacBeth Regressions of New Products on R&D and Ability

This table presents annual Fama-MacBeth regressions of products on lagged R&D and lagged Ability. Products is the number of new products introduced by a firm in a given fiscal year. Ability is computed as described in Table II. $ability_{high}$ equals one if a stock is in the top quintile for a given month. The regressions include the following control variables: $\overline{products}_{-5,-1}$, $log(ME)$, $log(B/M)$, log(1+leverage), instown, and log(age). $\overline{products}_{-5,-1}$ is the log of 1 + the average yearly number of new products measured over the past five years. ME is market-cap at the end of the previous year. B/M is lagged book to market computed as in Fama and French (1993). *leverage* is book leverage divided by book equity lagged one year. *instown* is institutional ownership from the previous year expressed as a fraction of shares outstanding. Age is the age of the firm in years computed based on they firm's first appearance on CRSP. The sample period is 2000 to 2008. T-statistic are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+R\&D) * ability_{high}$	4.414	4.628	3.458			
	(2.73)	(2.67)	(2.36)			
$\log(1+R\&D)_{-5,-1} * ability_{high}$				0.515	0.455	0.436
				(7.54)	(6.01)	(3.17)
$ability_{high}$	-0.367	-0.466	-0.313	-0.048	-0.053	-0.048
	(-2.86)	(-3.29)	(-1.54)	(-3.49)	(-3.36)	(-2.51)
$\log(1+R\&D)$	-0.058	-0.021	-0.177			
	(-0.87)	(-0.26)	(-1.81)			
$\log(1+R\&D)_{-5,-1}$				-0.011	-0.013	-0.029
				(-1.20)	(-1.44)	(-3.04)
$\overline{products}_{-5,-1}$	1.281	1.261	1.250	1.022	1.010	1.001
	(47.90)	(46.42)	(45.94)	(107.45)	(95.76)	(96.35)
$\log(ME)$		0.152	0.163		0.012	0.013
		(6.63)	(6.68)		(5.86)	(5.83)
$\log(B/M)$		0.137	0.214		0.005	0.011
		(2.17)	(2.98)		(1.01)	(2.05)
$\log(1+leverage)$		0.291	0.307		0.028	0.032
		(2.85)	(2.75)		(2.27)	(2.17)
$\log(instown)$		0.599	0.754		0.074	0.098
		(2.03)	(2.41)		(1.66)	(1.92)
$\log(age)$		-0.256	-0.202		-0.022	-0.019
		(-3.35)	(-3.46)		(-5.13)	(-6.42)
Industry Fixed Effects			Yes			Yes
$\overline{R}^2$	0.87	0.87	0.87	0.81	0.82	0.82
Number of Years	9	9	9	9	9	9
Total Observations	6078	5992	5992	6185	6098	6098

Table X
Tests of Mechanisms

This table presents monthly Fama-MacBeth (1973) regressions. The R&D (Ability estimate) used in the regression is the R&D (Ability estimate) from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June (as in Fama and French (1993)). Ability is computed as described in Table II. $ability_{high}$ ($ability_{low}$) equals one if a stock is in the top (bottom) quintile for a given month. $R\&D_{high}$ ($R\&D_{low}$) equals one for a stock if its ability estimate is greater than the 70^{th} (not greater than the 30^{th}) percentile in a given month. $R\&D_{zero}$ equals one if $R\&D = 0$. $guidance$ is the number of times a firm issued earnings' guidance in the previous 12 months. $guidance_{high}$ equals one if the stock is in top 30% of $guidance$ for a given month. $founder$ equals one if the CEO is currently a founder. KZ is the Kaplan-Zingales four variable (we exclude Q from the measure) financial constraint measure (1997). KZ_{most} (KZ_{mid}) equals one if the stock is top 30% (middle 40%) of KZ for a given month. $cash$ is defined as cash and short term investmests divided by lagged total assets. $cash_{low}$. (KZ_{mid}) equals one if the stock is bottom 30% (middle 40%) of $cash$ for a given month. $CAPX$ is capital expenditures divided sales. $OPEX$ is operating expeditures divided by sales. The regressions use the following control variables: $log(ME)$, $log(B/M)$, $r_{-12,-2}$, r_{-1}, $turnover$ and σ. They are defined as in table V. The regressions only include stocks with lagged price greater than 5. The sample period is July 1980 to December 2009. T-statistics are in parenthesis.

Panel A: Pooled regressions: Opacity Interaction ($guidance$)

	$R\&D_{high}ability_{high}$	$R\&D_{high}ability_{high}guidance_{high}$	Controls
Estimate	1.553	-1.161	Yes
T-stat	(3.52)	(-1.53)	

Panel B: Pooled regressions: Founder Interaction

	$R\&D_{high}ability_{high}$	$R\&D_{high}ability_{high}founder$	Controls
Estimate	0.640	1.534	Yes
T-stat	(1.38)	(1.61)	

Panel C: Pooled Regressions: Financial Constraint Interaction (KZ_x)

	$R\&D_{high}ability_{high}$	$R\&D_{high}ability_{high}KZ_{mid}$	$R\&D_{high}ability_{high}KZ_{most}$	Controls
Estimate	0.450	0.692	1.415	Yes
T-stat	(1.31)	(1.20)	(1.62)	

Panel D: Pooled Regressions: Financial Constraint Interaction ($Cash$)

	$R\&D_{high}ability_{high}$	$R\&D_{high}ability_{high}cash_{mid}$	$R\&D_{high}ability_{high}cash_{low}$	Controls
Estimate	0.732	0.013	0.427	Yes
T-stat	(1.91)	(0.02)	(0.52)	

Panel E: F-M Regression of returns on Ability and CAPX

	$CAPX_{high}ability_{high}$	$ability_{high}$	$CAPX_{high}$	Controls
Estimate	-0.127	-0.109	-0.051	Yes
T-stat	(-1.05)	(-1.44)	(-0.61)	

Panel F: F-M Regression of returns on Ability and OPEX

	$OPEX_{high}ability_{high}$	$ability_{high}$	$OPEX_{high}$	Controls
Estimate	-0.070	-0.131	-0.269	Yes
T-stat	(-0.35)	(-1.87)	(-2.12)	

Appendix:
Misvaluing Innovation

Figure A1
Annual Returns to Value-Weight Ability/R&D Spread Portfolio

This figure shows annual returns to high Ability/high R&D minus low Ability/High R&D spread portfolios. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in Table II. The high Ability/high R&D (low Ability/high R&D) portfolio is formed from the intersection of the top 20% (bottom 20%) of ability and top 30% of R&D. The figure also show the annual excess return on a proxy for the market portfolio (VW portfolio of CRSP common stock), and recession periods (as defined by the NBER) are denoted by the gray shaded areas.

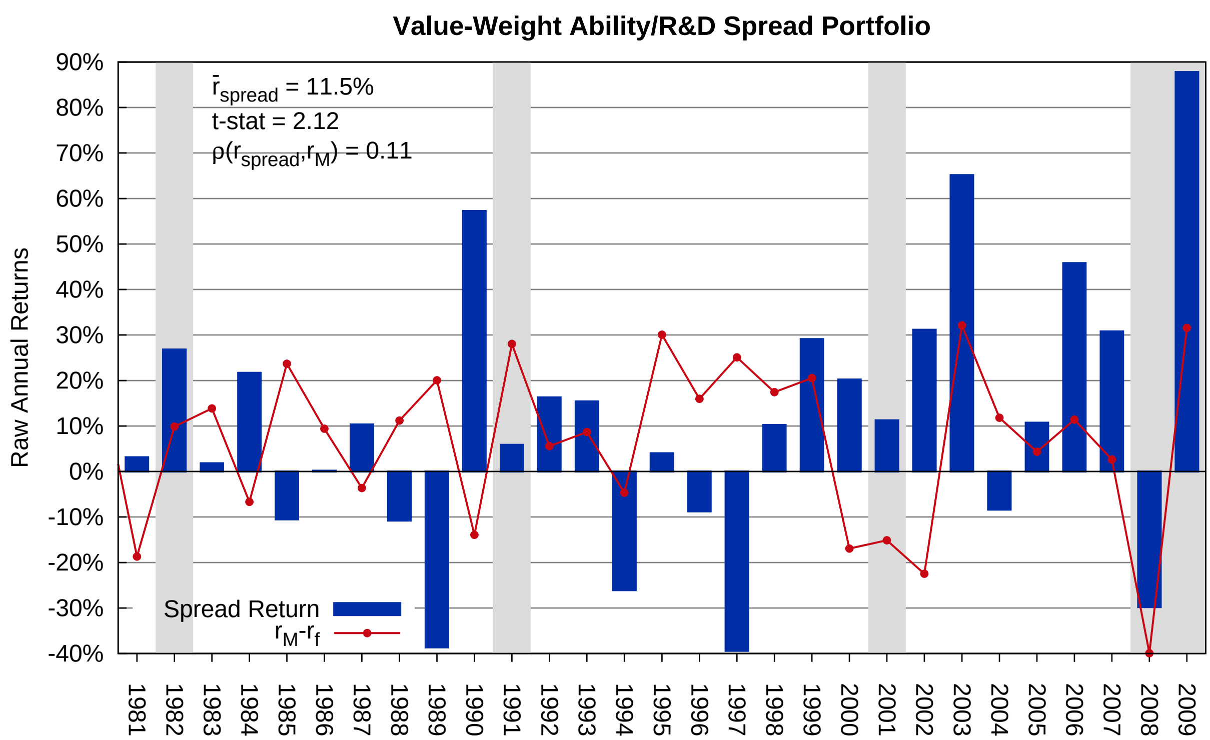


Table A1
Persistence in R&D Ability

The table reports the fraction of stocks that are in ability quintile x in year t given they are in ability quintile x in year $t - lag$. Sepcifically, it reports means of the time series of these fractions for each quintile. The table also reports results from a simulation of 1,000 trials where persistence is computed using an identical sample and methodology except R&D and sales growth are replaced with standard normal random variables (i.e., the ability estimation is just noise). R&D ability is computed for each firm every year using five ($j = 1 \ldots 5$) time series regressions of sales growth on past R&D:

$$\log(\frac{Sales_{it}}{Sales_{it-1}}) = \gamma_0 + \gamma_j log(1 + R\&D_{it-j}) + \epsilon_{it}$$

A back window of 6-8 years of non-missing data is required. An additional requirement is that at least half of the R&D observations are non-zero. Ability is computed as the average of the five slope coefficients (γ_j). The sample period is 1980 to 2009.

	Mean Annual Persistence in Ability $Prob(Quintile = i),\ year = t$ if $Quintile = i,\ year = t - lag$ Ability Quintiles				
Lag	Low	2	3	4	High
1	0.66	0.50	0.51	0.49	0.70
2	0.48	0.37	0.40	0.36	0.55
3	0.38	0.32	0.35	0.29	0.46
4	0.30	0.30	0.32	0.26	0.39
5	0.26	0.28	0.30	0.24	0.36
Lag	Simulation (runs=1,000): Ability Estimation is Noise				
1	0.54	0.40	0.38	0.40	0.54
2	0.39	0.33	0.32	0.33	0.39
3	0.29	0.29	0.29	0.29	0.29
4	0.24	0.27	0.28	0.27	0.24
5	0.21	0.25	0.27	0.26	0.21

Table A2
Double Sorts on R&D and Ability: Sub-Periods

This table presents monthly portfolio returns (in %) for sorts on Ability and R&D for various sub-periods of the sample. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in table II. Characteristic abnormal returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (computed as in DGTW (1997). The benchmark portfolios' weighting match the weighting of the R&D/Ability portfolios. All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). The sample period is July 1980 to December 2009.

Panel A: Equal-Weight Portfolios
Size-B/M-Mom Adjusted Returns

	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
			July 1980 - June 1990				
Mean	0.22	-0.04	-0.13	0.22	0.18	0.12	0.25
T-stat	1.91	-0.35	-0.60	2.22	1.60	0.28	0.55
			July 1990 - June 2000				
Mean	-0.23	-0.04	-0.08	-0.16	0.02	1.14	1.21
T-stat	-1.98	-0.30	-0.29	-1.59	0.18	3.17	3.67
			July 2000 - December 2009				
Mean	-0.03	0.06	-0.50	0.05	0.08	0.85	1.35
T-stat	-0.20	0.37	-1.30	0.36	0.47	1.72	2.78

Panel B: Value-Weight Portfolios
Size-B/M-Mom Adjusted Returns

	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
			July 1980 - June 1990				
Mean	0.28	-0.01	-0.34	-0.11	0.18	0.12	0.46
T-stat	1.62	-0.11	-1.70	-0.77	1.11	0.28	1.01
			July 1990 - June 2000				
Mean	0.10	-0.07	-0.12	-0.03	0.22	1.03	1.15
T-stat	0.75	-0.38	-0.40	-0.26	1.32	2.44	2.45
			July 2000 - December 2009				
Mean	0.16	0.27	-0.54	0.14	0.27	0.88	1.42
T-stat	0.78	1.37	-1.34	0.82	0.95	1.34	1.85

Table A3
Double Sorts on R&D and Ability: 5x2 Sort

The table presents monthly portfolio returns (in %) for sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 2 buckets based on median R&D. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in table II. Characteristic abnormal returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (computed as in DGTW (1997). The benchmark portfolios' weighting match the weighting of the R&D/Ability portfolios. All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). The sample period is July 1980 to December 2009.

Panel A: Equal-Weight Portfolios					
	Low Ability		High Ability		
	$R\&D_{low}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{high}$	Spread
Excess Returns					
Mean	0.77	0.75	0.79	1.19	0.43
T-stat	2.89	2.14	2.92	3.18	2.76
Size-B/M-Mom Adjusted Returns					
Mean	-0.09	0.01	-0.04	0.56	0.55
T-stat	-1.14	0.06	-0.58	3.66	3.70
Number of Stocks					
Mean	123	54	155	29	

Panel B: Value-Weight Portfolios					
	Low Ability		High Ability		
	$R\&D_{low}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{high}$	Spread
Excess Returns					
Mean	0.71	0.55	0.58	0.98	0.44
T-stat	2.86	1.73	2.23	2.68	1.76
Size-B/M-Mom Adjusted Returns					
Mean	0.12	-0.04	-0.03	0.54	0.58
T-stat	1.40	-0.29	-0.37	3.04	2.81
Number of Stocks					
Mean	123	54	155	29	

Table A4
Double Sorts on R&D and Ability: 4x4 Sort

This table presents monthly portfolio returns (in %) for sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quartiles for *Ability* and quartiles for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed as described in table II. Characteristic abnormal returns are computed by adjusting returns using 125 (5x5x5) size/book-to-market/momentum portfolios (computed as in DGTW (1997). The benchmark portfolios' weighting match the weighting of the R&D/Ability portfolios. All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). The sample period is July 1980 to December 2009.

Panel A: Equal-Weight Portfolios							
	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
Excess Returns							
Mean	0.83	0.74	0.57	0.78	0.84	1.27	0.70
T-stat	3.14	2.57	1.29	2.94	2.85	2.46	2.61
Size-B/M-Mom Adjusted Returns							
Mean	-0.07	-0.05	-0.17	-0.05	0.05	0.78	0.95
T-stat	-0.72	-0.60	-0.90	-0.67	0.72	2.67	3.57
Number of Stocks							
Mean	77	113	29	108	106	13	

Panel B: Value-Weight Portfolios							
	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
Excess Returns							
Mean	0.66	0.66	0.40	0.60	0.59	1.11	0.71
T-stat	2.50	2.71	0.98	2.39	1.89	2.45	1.79
Size-B/M-Mom Adjusted Returns							
Mean	0.12	0.11	-0.14	-0.07	0.06	0.70	0.84
T-stat	1.11	1.28	-0.69	-0.69	0.63	2.38	2.43
Number of Stocks							
Mean	77	113	29	108	106	13	

Table A5
Double Sorts on R&D and Ability: Alternate Regression Ability Measure

The table presents monthly portfolio returns (in %) for sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (Ability estimate) used to form the portfolios is the R&D (Ability estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. Ability is computed for each firm every year using the time series regressions of $sales\ growth_{it}$ on $\overline{R\&D}_{i,t-1,t-5}$. A back window of 6-8 years of non-missing data is required. Ability is defined as the slope coefficient from the regression. An additional requirement is that at least half of the R&D observations are non-zero. All portfolios also contain the restriction that lagged price must be greater than $5. The sample period is July 1980 to December 2009.

Panel A: Equal-Weight Portfolios							
		Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
			Excess Returns				
Mean	0.87	0.72	0.52	0.75	0.89	1.24	0.72
T-stat	3.22	2.45	1.16	2.77	2.92	2.48	2.51
			Size-B/M-Mom Adjusted Returns				
Mean	0.00	-0.12	-0.15	-0.11	0.10	0.78	0.93
T-stat	0.04	-1.20	-0.69	-1.44	1.14	2.72	3.15

Panel B: Value-Weight Portfolios							
		Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
			Excess Returns				
Mean	0.64	0.52	-0.09	0.55	0.71	1.14	1.23
T-stat	2.49	1.72	-0.18	2.16	2.16	2.33	2.80
			Size-B/M-Mom Adjusted Returns				
Mean	0.12	-0.16	-0.22	-0.09	0.20	0.60	0.82
T-stat	1.06	-1.13	-0.80	-0.88	1.54	2.09	2.11

Table A6
Double Sorts on R&D and Ability: Non-Regression Ability Measure

This table presents monthly portfolio returns (in %) for sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D used to form the portfolios is the R&D from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). Ability is lagged one year relative to R&D. R&D is scaled by sales. Ability is computed as follows:

$$Ability = \frac{1}{8}\sum_{j=1}^{8} \frac{\log\left(\frac{Sales_{t-j}}{Sales_{t-j-1}}\right)}{\overline{[R\&D/Sales]}_{t-j-1,t-j-6}}$$

All portfolios also contain the restriction that lagged price must be greater than \$5. The sample period is July 1980 to July 2008.

Panel A: Equal-Weight Portfolios							
		Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
				Excess Returns			
Mean	0.83	0.78	0.30	0.73	0.69	1.33	1.03
T-stat	2.95	2.30	0.57	2.92	2.04	2.13	2.28
			Size-B/M-Mom Adjusted Returns				
Mean	0.01	-0.01	-0.18	-0.11	-0.02	0.42	0.61
T-stat	0.06	-0.05	-0.70	-1.49	-0.26	1.09	1.49

Panel B: Value-Weight Portfolios							
		Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
				Excess Returns			
Mean	0.80	0.66	0.54	0.63	0.40	1.37	0.83
T-stat	2.67	2.31	1.13	2.49	1.06	2.03	1.46
			Size-B/M-Mom Adjusted Returns				
Mean	0.12	0.06	-0.02	-0.05	-0.10	0.55	0.58
T-stat	0.63	0.46	-0.09	-0.58	-0.63	1.27	1.20

Table A7
Double Sorts on R&D and Ability: Full 3x5

This table presents monthly portfolio returns (in %) for double sorts on Ability and R&D. Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quintiles for *Ability* and 30%/40%/30% breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (*Ability* estimate) used to form the portfolios is the R&D (*Ability* estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. *Ability* is computed as described in Table II. Characteristic abnormal returns are computed by adjusting returns using 25 size/book-to-market portfolios' (computed as in Fama and French (1993)). The benchmark portfolios weighting match the weighting of the R&D/Ability portfolios. All portfolios (including the benchmark portfolios) also contain the restriction that lagged price must be greater than $5 (breakpoints are computed before imposing the lagged price restriction). The sample period is July 1980 to December 2009.

Panel A: Excess Returns of Equal Weight Portfolios

Ability	Mean			T-stats		
Quintile	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$
Low	0.81	0.75	0.62	3.04	2.61	1.48
2	0.87	0.85	0.73	2.96	2.86	1.74
3	0.70	0.83	0.79	2.19	2.71	1.77
4	0.74	0.91	0.80	2.58	3.06	1.90
High	0.80	0.83	1.35	3.00	2.81	2.76
Spread			0.73			2.61

Panel B: Size-B/M-Adjusted Returns of Equal Weight Portfolios

Ability	Mean			T-stats		
Quintile	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$
Low	-0.07	-0.04	-0.10	-0.86	-0.43	-0.50
2	-0.01	0.13	0.13	-0.05	1.35	0.81
3	0.03	0.10	0.25	0.14	1.01	1.19
4	-0.10	0.15	0.22	-0.84	1.56	1.29
High	-0.03	0.08	0.79	-0.42	0.90	2.84
Spread			0.89			3.32

Panel C: Number of Stocks

Ability	Mean		
Quintile	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$
Low	83	69	25
2	24	70	65
3	16	58	73
4	36	85	43
High	114	60	10

Table A8
Double Sorts on R&D and Ability: International Stocks

This table presents monthly portfolio returns (in %) for double sorts on *Ability* and R&D for an international sample of stocks (UK, Japan, and Germany). Each month stocks with positive lagged R&D and non-missing lagged *Ability* are sorted into quartiles for *Ability* and quartile breakpoints for R&D. Portfolios are formed every month from the intersection of these two sorts. The R&D (*Ability* estimate) used to form the portfolios is the R&D (*Ability* estimate) from the fiscal year ending in calendar year t-1 from July to December and calendar year t-2 from January to June (as in Fama and French (1993)). R&D is scaled by sales. $ability_{high}$ ($ability_{low}$) equals one if a stock is in the top (bottom) quartile for a given month. $R\&D_{high}$ ($R\&D_{low}$) equals one for a stock if its *Ability* estimate is in the top (bottom) quartile in a given month. For this international sample, the R&D and *Ability* breakpoints are computed separately for each country. All portfolios also contain the restriction that lagged price must be greater than the 5th percentile (by month). Average abnormal returns are also computed using the four factor model (Carhart (1997)). We use Ken French's international factors in the factor model regressions. The sample period is July 1995 to December 2010 (except for the case of German stocks, for which the sample period is July 2007 to December 2010).

Panel A: Equal-Weight International Portfolios

	Low Ability			High Ability			
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	Spread
	Excess Returns						
Mean	0.26	0.49	0.39	0.27	0.52	1.23	0.84
T-stat	0.64	1.19	0.91	0.61	1.26	2.84	3.21
	Global Four Factor Model α						
α	-0.20	0.10	0.05	-0.18	0.06	0.68	0.63
T-stat	-0.62	0.37	0.16	-0.51	0.23	2.15	2.37

Panel B: Number of Stocks

	Low Ability			High Ability		
	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$	$R\&D_{low}$	$R\&D_{mid}$	$R\&D_{high}$
Mean	97	73	56	78	44	20

Table A9
F-M Regressions Using Condtional Ability and R&D Sorts

This table presents monthly Fama-MacBeth (1973) regressions of returns on R&D and Ability. The R&D (Ability estimate) used in the regression is the R&D (Ability estimate) from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June (as in Fama and French (1993)). Ability is computed as described in Table II. $ability_{high}$ equals one if a stock is in the top quintile/quartile/30% percent for a given month. $R\&D_{high}$ equals one for a stock if its R&D is in the top quartile/quintile/30% percent breakpoint of the respective ability portfolio bin (conditional sorting). $log(ME)$ is the log of month $t-1$ market-cap, and $log(B/M)$ is log book to market defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is the return from month $t-12$ to month $t-2$. r_{-1} is the one month lagged return. *turnover* is average daily share turnover ($\times 100$) over the past year. σ is the standard deviation of daily returns over the past year. The regressions only include stocks with lagged price greater than 5. The sample period is July 1980 to December 2009. T-statistics are in parenthesis.

	5x5 Sort		4x4 Sort		3x3 Sort	
$R\&D_{high} * ability_{high}$	0.403	0.428	0.413	0.394	0.296	0.254
	(2.29)	(2.51)	(2.81)	(2.68)	(2.32)	(2.02)
$ability_{high}$	-0.107	-0.134	-0.112	-0.142	-0.072	-0.107
	(-1.31)	(-1.97)	(-1.49)	(-2.23)	(-1.02)	(-1.78)
$R\&D_{high}$	0.027	0.105	0.002	0.077	0.089	0.163
	(0.15)	(0.74)	(0.01)	(0.59)	(0.53)	(1.27)
log(ME)	-0.031	-0.039	-0.031	-0.041	-0.031	-0.043
	(-0.80)	(-1.14)	(-0.81)	(-1.17)	(-0.79)	(-1.23)
log(B/M)	0.242	0.198	0.241	0.196	0.246	0.196
	(3.37)	(3.20)	(3.39)	(3.15)	(3.48)	(3.17)
$r_{-12,2}$	0.787	0.797	0.783	0.793	0.769	0.792
	(3.55)	(4.01)	(3.54)	(3.99)	(3.49)	(3.98)
r_{-1}		-3.735		-3.729		-3.749
		(-8.22)		(-8.20)		(-8.27)
turnover		-0.299		-0.292		-0.292
		(-1.65)		(-1.61)		(-1.62)
σ		-0.106		-0.110		-0.117
		(-1.56)		(-1.62)		(-1.73)
Number of Months	354	354	354	354	354	354
Total Observations	290271	283030	290271	283030	290271	283030
Stocks per month in $R\&D_{high} * ability_{high}$	33	32	52	50	74	72