The R&D Anomaly: Risk or Mispricing?

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ABSTRACT

We offer new evidence on the risk versus mispricing explanations for the R&D anomaly. Return covariance with a characteristic-based factor captures the cross-sectional return variation on R&D portfolios not explained by asset pricing models. This is consistent with both covariance risk and mispricing. Under the framework of the ICAPM, we find little economic justification that an R&D factor is a proxy for innovations to a state variable. The characteristic subsumes the factor loading in direct tests, providing support to the mispricing hypothesis. Investigating the mispricing explanation further, we reject the assertion that the R&D anomaly arises from the correction of stocks mispriced by investor sentiment. A natural experiment exploiting the pilot program under Regulation SHO shows no evidence that the anomaly persists due to limits to arbitrage in the form of short sale constraints.

Keywords: R&D anomaly; Covariance risk; ICAPM; Mispricing.

JEL Classification: G12; G14.

1. Introduction

Research and Development (R&D) is an important driver of innovation, firm value and long-term economic growth. R&D investment earns significant positive stock returns that asset pricing models are unable to explain. The longevity of the R&D anomaly represents a complex and important challenge to asset pricing models. Despite a large literature confirming the anomaly, there is far less consensus on why it persists. Some studies attribute it to investor mispricing, while others argue that it reflects a premium to compensate systematic risk. We present new evidence on this debate by performing more direct tests to distinguish between these competing hypotheses.

Mispricing implies that R&D stocks are undervalued, earning higher returns when the mispricing corrects. This may be due to limits to arbitrage or many potential psychological traits. In a frictionless and efficient market, an arbitrage strategy would eliminate the anomaly. However, frictions make the costs and risks of arbitrage prohibitive, leading to persistent mispricing (Shleifer and Vishny, 1997). Lamont and Thaler (2003) argue that one of the most significant limits to arbitrage is short-sale constraints, under which, arbitrageurs are unable to engage the short leg of the arbitrage, allowing mispricing to persist. Some behavioral explanations are as follows. First, hard to value stocks, of which R&D intensive stocks are examples, may be relatively more sensitive to speculative investment flows subject to investor sentiment. According to Baker and Wugler (2006), following high (low) sentiment states, R&D stocks are overvalued (undervalued) by sentiment driven speculative demand, which subsequently correct when the sentiment reverses. Second, investors have limited attention (Barber and Odean, 2008). Since R&D projects are long-term whilst investors' horizons are short-term, investors with limited attention may fail to incorporate the longer-term benefits of R&D into current financial information, causing R&D-intensive stocks to be undervalued. When the benefits are subsequently realized, the mispricing is corrected delivering strong returns. Third, mispricing may arise due to investor over-optimism or over-pessimism, founded on their erroneous extrapolation of recent firm performance (Lakonishok et al., 1994). Investors are misled by the conservative accounting treatment of R&D, which understates earnings when R&D expenditure is increased. Since R&D intensive firms appear less profitable, investors are over-pessimistic of the firm's prospects. Fourth, investors overreact or underreact to information according to representativeness and conservatism heuristics (Barberis et al, 1998). For R&D, conservatism suggests that investors are slow to update their analysis of the benefit of R&D investment, the corresponding underreaction in stock prices then correct as investors update. Finally, investors react differently to tangible and intangible information (Daniel and Titman, 2006). Intangible returns, the proportion of stock returns not arising from accounting information, predict future stock returns negatively. This implies that the R&D anomaly may be driven not by R&D information, but lower prior intangible returns.

A convincing systematic risk explanation for the R&D anomaly requires theoretical motivation, which originates from the dynamic, multistage, real option model of Berk et al. (2004). The key property of the model is that the option-like characteristics of R&D ventures magnifies their systematic risk so they command a higher premium compared to standard cash generating projects. At each stage of development, the firm decides whether to continue to invest in R&D or to suspend the project. This decision rests on whether the expected cash flows from completion meet an appropriate threshold. The uncertainty of the potential cash flows from the project and their sensitivity to the stochastic discount factor generate the systematic risk of R&D.

Berk et al. (2004) derive the dynamics of the risk premium. Specifically, the premium falls between lower and upper bounds. On completion, R&D is analogous to a conventional project generating stochastic cash flows and so earns the premium at the lower bound, which is equivalent to that of non-R&D firms. Prior to completion, the premium on R&D increases above this lower bound reflecting the option to suspend. The more likely is suspension of the venture, the higher is the systematic risk embedded in R&D options and the greater the premium on R&D.

Resolution of the risk versus mispricing debate relies on rigorous empirical testing. Much of the existing evidence is based on inference from indirect tests or is implied by the elimination of one side of the argument. The risk-based explanation requires a proxy for a latent state variable, the innovations to which should capture the dispersion of returns in the cross section. This is a necessary condition, but is not sufficient for two important reasons. First, the ad hoc addition of variables to multifactor models does not guarantee the resulting factor structure will capture the economic risk associated with the anomaly (Hirschelifer et al., 2012; Maio and Santa-Clara, 2012). Therefore, adding a new factor based on R&D should be supported by an economic justification. Second, latent state variables are often proxied by firm characteristics. The innovations to the state variable are then captured by returns to portfolios sorted by the characteristic (Fama and French, 1993, 2015; Carhart, 1997). Adding such variables to multifactor models can appear to work well in modelling covariance and eliminating the anomaly. But, since the return-based factor correlates highly with the characteristic by construction, there is no way to reject characteristic mispricing with confidence (Hirschleifer et al, 2012).

Our first contribution to the literature performs more direct tests on the R&D anomaly that resolve these two issues. We follow the empirical asset pricing literature to create an R&D factor based on the anomaly, which seems to perform well. We then test whether this factor meets the strict conditions of the Intertemporal CAPM (ICAPM) (Merton, 1973), which is a necessary condition to support a risk explanation. Specifically, candidate factors should predict future investment opportunities, factor loadings should be priced in the cross section with the appropriate sign and must ensure an economically plausible equity market risk premium in a multifactor model (Maio and Santa-Clara, 2012). We are unable to support the economic motivation for the R&D factor as an ICAPM state variable. Second, we adopt the methodology of Daniel and Titman (1997) to distinguish risk versus mispricing directly. A covariance risk explanation requires that future return patterns from characteristic balanced portfolios are predicted by preformation factor loadings. Triple sorting stocks by their size, R&D and preformation R&D factor loadings, we find that the R&D factor loading does not predict future returns. Next, we use these portfolios in cross sectional regressions that include both the covariance and characteristic as regressors. The covariance is subsumed by the characteristic. This evidence rejects the factor risk pricing explanation for the R&D anomaly in favor of mispricing.

Our second contribution to the literature investigates the mispricing explanation in greater depth. We begin by examining the effect of investor sentiment on the R&D anomaly. Baker and Wurgler (2006) argue that shifts in investor sentiment have cross-sectional effects on returns that reveal the correction of mispricing. Certain stocks that are hard-to-value and more costly to arbitrage, such as R&D intensive stocks, may be subject to larger mispricing in relation to the degree of R&D investment. Overvaluation during high sentiment states and undervaluation during low sentiment states should correct as investor sentiment shifts to the opposite state. Contrary to this prediction, we find that sentiment has no effect on R&D portfolios. Specifically, we find no evidence for the correction of overvaluation, but show the correction of undervaluation following both sentiment states. Controlling for factor risk using the Carhart (1997) and Fama and French (2015) models, we document stronger evidence to refute investor sentiment as the explanation for R&D mispricing.

Next, we examine whether limits to arbitrage affect the R&D anomaly. In an efficient market, mispricing is arbitraged away quickly. However, market frictions could make the costs and risks of arbitrage prohibitive, providing the conditions for mispricing to persist (Shleifer and Vishny, 1997). One of the most important limits to arbitrage is short-sale constraints (Lamont and Thaler, 2003). However, identifying the effects of short-sale constraints on stock prices is difficult because existing proxies are imperfect and are likely to correlate with pricing factors and firm characteristics that drive returns. To circumvent these challenges, we exploit the plausibly exogenous variations in short-sale restrictions provided by the pilot program under Regulation SHO and estimate a difference-in-differences model for identification. In 2004, the Securities and Exchange Commission (SEC) initiated a pilot program under Regulation SHO to study how short-sale price tests affect the stock market and designated a random sample of stocks from the Russell 3000 index as pilot stocks. The pilot stocks were exempt from short-sale restrictions over the period from June 2005 to July 2007 and were therefore easier to short sell. Our difference-in-differences analysis compares the high-minus-low R&D return spread between pilot and non-pilot stocks, before and after the implementation of the pilot program. We decompose the long and short legs of the anomaly to isolate the effect of lifting short sale constraints. The short leg shows no effect from the pilot so we find no evidence that short sale constraints contribute to R&D mispricing.

There is a long history documenting significant positive returns related to R&D expenditure (Chan et al., 1990), capital (Lev and Sougiannis, 1996), intensity (Chan et al., 2001) and growth (Penman and Zhang, 2002; Eberhart et al., 2004; Lev et al., 2005). Meanwhile, the literature has inferred potential explanations for its persistence. In support of behavioral mispricing, investors fail to value the benefits of long term R&D investment due to limited attention (Hall, 1993; Lev et al., 2005), are pessimistic on R&D intensive stocks that have poor past performance (Chan et al., 2001), underreact to the conservative reporting of R&D (Penman and Zhang, 2002) and underreact to the benefits of R&D increases (Eberhart et al., 2004). On the other hand, R&D fully or partially subsumes the book-to-market effect, R&D returns are not explained by the Fama and French (1993) model, an R&D factor contributes to explaining the cross sectional variation in R&D returns and R&D returns show some state dependence (Lev and Sougiannis, 1999; Al-Horani et al., 2003), which are interpreted as consistent with the risk explanation.

Chambers et al. (2002) seek to distinguish between the competing hypotheses. They show that excess R&D returns are not removed by Fama and French (1993) risk controls, they persist for up to ten years, and are related to dispersion in analyst forecast and post-investment earnings, all of which are consistent with the notion that risk is not adequately controlled for in R&D intensive stocks. However, they fail to rule out entirely the mispricing arising from investor underreaction to the conservative accounting treatment of R&D. The remaining literature delves deeper into the information contained in R&D expenditure. Li (2011) and Gu (2016) reinforce the risk hypothesis that abnormal R&D returns stem from the real options within R&D projects. They argue that the systematic risk arising from the inherent leverage in the options to suspend or abandon reveals itself when interacting R&D with financial constraints (Li, 2011) and product market competition (Gu, 2016). R&D intensive stocks earn higher future returns in relation to these other characteristics.

In contrast, Cohen et al. (2013) show that R&D intensive firms that have completed projects successfully in the past earn significantly higher future returns than firms that have been less productive for the same R&D intensity. Rather than R&D itself, it is the information relating to the predictability of its likely success that attention limited investors consistently underreact to. Hirshleifer et al. (2013) also investigate innovation success, but in the form of the efficiency of R&D, measured as the number of patents and their citations in proportion to R&D investment. Following the same reasoning, investors are unable to decipher the predictive information in innovation efficiency between R&D intensive firms. Therefore, innovation efficient firms are relatively undervalued and earn high future returns.

To further complicate matters, Donelson and Resutek (2012) suggest that R&D is neither mispriced nor impacts systematic risk directly. Extending the methodology of Daniel and Titman (2006), they decompose returns into R&D and non-R&D components that are orthogonal to each other. The R&D component captures the level of R&D and its growth, thereby capturing the information investors see in R&D expenditure, but this characteristic does not determine returns, which refutes the mispricing explanation. Rather, the non-R&D component that encompasses all other value relevant information forecasts future returns, but with a negative sign. Analogous to Daniel and Titman (2006), Donelson and Resutek (2012) interpret abnormal R&D returns as emanating not from information in R&D, but from intangible information unrelated to R&D, but present in R&D firms. This non-R&D component of returns maps onto variables that relate to the value anomaly.

We contribute to this ongoing risk versus mispricing debate in several ways. First, we extend the literature that relies on asset pricing factors by subjecting the data to more stringent tests. We construct an R&D factor based on the anomalous returns, but we seek an economic motivation for it under the restrictive conditions of the ICAPM (Maio and Santa-Clara, 2012). Next, we test covariance versus the characteristic directly by triple sorting stocks into portfolios, analyzing characteristic balanced portfolios and examining predictive Fama and MacBeth (1973) regressions at the portfolio and individual stock levels (Daniel and Titman, 1997; Hirshleifer et al., 2012). We find little evidence to support the systematic risk argument. The R&D factor returns do not meet the criteria demanded by the ICAPM, the R&D factor loadings do not predict future returns after controlling for the characteristic, and this covariance is subsumed by the characteristic.

In light of this, we extend the literature that already asserts the mispricing hypothesis (Cohen et al., 2013; Hirshleifer et al., 2013) by investigating two further issues. We follow Baker and Wugler (2006) to assess the role of investor sentiment on the correction of the mispricing of R&D stocks. We find no effect. Finally, we perform a difference-in-differences analysis to test whether the lifting of short sale constraints on a random selection of stocks under the SEC's Regulation SHO pilot scheme allowed investors to take advantage of the arbitrage opportunity implied by the R&D anomaly. We find no evidence that the pilot corrected any mispricing due to short sale constraints. Our findings, therefore, suggest that it is the characteristic that drives the R&D anomaly.

The remainder of the paper is organized as follows. Section 2 confirms the R&D anomaly. Section 3 establishes an R&D factor that proxies for innovations to a state variable. Section 4 seeks a fundamental economic justification for the R&D factor in the form of an ICAPM state variable. Section 5 tests the predictive power of the R&D factor loading against the R&D characteristic in a direct evaluation of the characteristic versus covariance hypothesis. Section 6 presents evidence on the impacts of investor sentiment and limits to arbitrage on the R&D anomaly and Section 7 concludes.

2. The R&D Anomaly

Our first task is to confirm that the R&D anomaly is a persistent feature of stock returns that cannot be explained by existing asset pricing factors. We construct a sample consisting of all NYSE, AMEX, and NASDAQ stocks with accounting data available from COMPUSTAT and securities data from the Centre for Research in Security Prices (CRSP) from July 1975 to June 2013. Stocks with a share code of 10 or 11 are included. All accounting variables as at fiscal year-end in calendar year *t-1* are matched with monthly returns from July *t* to June *t+1*, allowing sufficient time for public information to be made available to investors. Any unmerged data and firm-month observations with negative book values of equity are discarded and financial stocks are excluded. We adjust returns for stock delisting to avoid survivorship bias following Shumway (1997).[1] Our final sample consists of 1,945,179 stock-month observations (17,694 firms), with 774,072 stock-month observations (7,788 firms) having non-zero R&D expenditure.

Consistent with the literature, we measure R&D intensity as the ratio of R&D expenditure to market value (*RD-MV*) and this is for several reasons. First, prior studies show that *RD-MV* is associated

[1] When a stock delists, the last return is the delisting return if it is available. Following Shumway (1997), if this is not available, we assign a return of -30 percent for stocks that delist for performance reasons and -100 percent for those that delist for other reasons.

with greater anomalous returns than alternative measures such as R&D expenses to total assets (*RD-A*) or total sales (*RD-S*) (Chan et al., 2001; Al-Horani et al., 2003). Second, *RD-MV* is analogous to price multiples and can therefore be readily applied to practical investment analysis. Third, *RD-MV* is not as volatile across time and sectors as *RD-S*, is not as persistent as *RD-A*, and is less likely to be influenced by creative accounting.[2]

To test for the R&D anomaly, we assign stocks with non-zero R&D expenditure into 2×5=10 portfolios according to market capitalization (*Size*) as at December of year *t-1* and *RD-MV* using independent sorts. We then compute their equal and value-weighted average returns in excess of the 1-month Treasury bill rate to compare the effects of weighting method. To reduce the dispersion in size across R&D ranks, we average (with equal weights) the R&D portfolio returns across the size portfolios to produce R&D quintiles and report these in Table 1. The average firm characteristics for these portfolios can be found in Table IA.1 of the online appendix.

Insert Table 1 about here

Panel A in Table 1 shows a monotonic increase of equally weighted average returns with *RD-MV*. The spread between the 1.67 percent return for Portfolio 5 and 0.43 percent return for Portfolio 1 represents a statistically and economically significant return on the zero-cost portfolio (*5-1*) of 1.24 percent per month. The anomaly persists in estimated alphas when adjusting for the conventional Carhart (1997) (*C-4*) and Fama and French (2015) (*FF-5*) factors. The zero-cost spread portfolio yields a *C-4* alpha of 1.09 percent and a *FF-5* alpha of 1.18 percent per month, both significant at the 1 percent level. In Panel B we report value-weighted returns and again find that average excess returns, and *C-4* and *FF-5* alphas increase monotonically with *RD-MV*. Although smaller than in Panel A, the *5-1* portfolio return,

[2] We perform a range of robustness checks on our empirical analysis in sections 2, 3 and 5. These include RD-A, RD-S and RDC-MV measures. Following Chan et al. (2001), we measure the stock of R&D capital using the perpetual inventory method as follows: $RDC_{i,t} = RD_{i,t} + 0.8\times RD_{i,t-1} + 0.6\times RD_{i,t-2} + 0.4\times RD_{i,t-3} + 0.2\times RD_{i,t-4}$. We also exclude R&D stocks with prices smaller than \$1 and larger than \$1000, or with prices smaller than \$5 and larger than \$1000, at the portfolio formation. Finally, the *RD-HML* factor is robust to variations in the methods of its construction including adjustments for size, size and book-to-market, Daniel et al. (1997) characteristics matching, independent and dependent portfolio sorting, value weighting and the use of alternative breakpoints. All our results are robust. This analysis is not reported, but is available on request.

C-4 alpha and *FF-5* alpha all remain significant at the 1% level with value-weighted average excess returns of 0.81 percent, 0.56 percent and 0.62 percent per month respectively.

We check the patterns of loadings on the factors across R&D quintiles, but do not report the results for brevity. The loadings on *SMB* and *CMA* increase with *RD-MV*, while those on *HML5* and *RMW* decrease. Under the *FF-5* model, the zero-cost spread portfolio loads significantly on all factors except for *HML5*. These patterns suggest that R&D-intensive stocks display at least some similar covariance structure to small, growth, weak operating profitability and conservative investment firms.[3]

We confirm the presence of the R&D anomaly and show that it cannot be explained by popular empirical asset pricing factors, including the relatively newer investment and profitability factors.[4] We proceed to test whether this R&D anomaly represents mispricing or a factor risk premium.

3. Constructing an R&D Factor (*RD-HML*)

We begin by extracting an empirical factor from the R&D anomaly by forming a factor-mimicking portfolio based on the anomaly itself. This follows the well-known empirical asset pricing literature that replicates a state variable that is highly correlated with the anomaly. Stocks that are most exposed to the anomaly load more heavily onto this factor, and this occurs even when the latent risk factor is unobserved.[5]

At the end of June of year *t*, we sort R&D stocks independently into 2×3=6 portfolios according to *Size* (median breakpoint) and *RD-MV* (breakpoints at the 30^{th} and 70^{th} percentiles) and compute their value weighted average returns. The R&D factor, which we denote *RD-HML*, is computed as the high minus low *RD-MV* returns. To adjust for *Size*, the high and low *RD-MV* portfolios are equally weighted across the two *Size* groups. More formally, $RD\text{-}HML = (S/H + B/H)/2 - (S/L + B/L)/2$. The summary

[3] The unabridged version of these estimation results can be found in Table IA.2 of the online appendix.
[4] Our results are comparable to those of Hou et al. (2015). Furthermore, greater abnormal returns for equal than value weighting tests are entirely consistent with Loughran and Ritter (2000) who argue that the former does not obscure mispricing that is likely greater among smaller firms. This is pertinent to our study because R&D-intensive stocks tend to be smaller in size.
[5] See Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003) and Hirshleifer et al. (2012).

statistics, pairwise correlations and factor spanning tests of the *RD-HML* factor on the Carhart (1997) and Fama and French (2015) factors are reported in Table 2.

Insert Table 2 about here

Panel A reports summary statistics for our pricing factors. The R&D factor yields an average premium of 0.68 percent per month, which is the highest among all the factors and double those of the *FF-5* model. This high return relative to the standard deviation of 3.59 delivers an ex-post Sharpe ratio of 0.19, which is also the largest of all the factors. These simple statistics demonstrate the importance of the R&D anomaly. Panel B shows generally moderate pairwise correlations between *RD-HML* and the other factors. Only *Size* (*SMB3* and *SMB5*) and *RMW* show meaningful correlations of 0.58, 0.56 and -0.55 respectively. These are consistent with the estimated factor loadings in Table IA.2 (in the online appendix), which suggest that R&D portfolio returns are related to these existing factors.[6] More importantly, Panel C examines the covariance structure of factor returns. The factor spanning tests regress *RD-HML* on other risk factors based on the CAPM, *FF-3*, *C-4,* and *FF-5* models. We find that regardless of the model specifications, the intercepts are positive and significant, and the adjusted R-squared of the models are quite low (36.8 percent for *FF-3*, 37.2 percent for *C-4* and 47.5 percent for *FF-5* respectively). These indicate that the R&D anomaly generates significant abnormal returns and considerable return variation beyond those predicted by established factors.[7]

Our results show that the *RD-HML* portfolio is capturing some incremental covariance structure arising from the R&D anomaly and improves the pricing of these stocks. Intuitively, this supports the systematic risk explanation of Berk et al. (2004). If firms with higher (lower) R&D intensity share characteristics that make them more (less) sensitive to stochastic future cash flows, then we expect their

[6] The high correlation of *RD-HML* with the size factor is in line with Al-Horani et al. (2003) who document a correlation coefficient of 0.49 between their R&D factor and the size factor.

[7] A complementary test augments these traditional models with the *RD-HML* factor, which we include in Table IA.3 in the online appendix for completeness. Analyzing the value-weighted portfolio returns, we find intercepts indistinguishable from zero and monotonically increasing factor loadings of R&D portfolio returns on the *RD-HML* factor that are expected by construction. By adding the *RD-HML* factor, the loadings of R&D portfolio returns on other factors maintain their significance, but any patterns across the quintiles are no longer present.

returns to demonstrate higher (lower) co-movement with the level of R&D intensity. However, co-movement alone meets only the necessary condition for a factor risk explanation for the anomaly. Since the factor correlates with the characteristic by construction, this evidence of covariation on its own does not allow us to attribute the R&D anomaly to risk as opposed to mispricing. To distinguish between the underlying explanations, we perform more stringent tests.

4. Is the *RD-HML* Factor Consistent with the ICAPM?

Many multifactor asset pricing models are motivated by the Intertemporal CAPM (ICAPM) (Merton, 1973). In addition to the market portfolio, new state variables such as R&D can be identified if their factor loadings help to explain the patterns of cross sectional portfolio returns, as demonstrated in the previous section. However, adding candidate risk factors can be rather ad hoc if we ignore the theoretical restrictions that the ICAPM implies (Maio and Santa-Clara, 2012). Furthermore, constructing the R&D factor from the R&D characteristic itself can lead us to mistakenly interpret R&D as a risk factor when it is really a proxy for mispricing (Hirshleifer et al., 2012). Under the motivation of ICAPM, therefore, a sufficient condition to support the risk explanation requires the *RD-HML* factor to adhere to its restrictions.

Maio and Santa-Clara (2012) identify the three requirements for a potential state variable. First, it should forecast changes in the investment opportunity set and thus should forecast future aggregate market returns (and variance). Second, innovations to the state variable should be priced in the cross section with the correct sign. Third, the estimate of the market risk premium must be economically plausible.

To test whether *RD-HML* meets the first restriction, we follow Maio and Santa-Clara (2012) and proxy the investment opportunity set using the aggregate equity market, captured by the monthly return on the CRSP value-weighted index. We perform predictive regressions across several horizons to analyze whether the R&D state variable has significant forecasting power over future expected market returns. Specifically, we estimate the following time-series regressions:

$$R_{t,t+q} = a_q + b_q Z^{R\&D}{}_t + u_{t,t+q} \quad (1)$$

where $R_{t,t+q} = R_{t+1} + \ldots + R_{t+q}$ is the continuously compounded market index return over q periods, $Z^{R\&D}{}_t$ is the current value of the R&D related state variable and $u_{t,t+q}$ is the error term. We analyze forecasting horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The sample runs from July 1975 to June 2013 (456 months), but q observations are lost for each q-month ahead predictive regression. We evaluate statistical significance based on Newey and West (1987) robust standard errors with q lags. If the R&D state variable ($Z^{R\&D}{}_t$) is consistent with the ICAPM, we should find a positive and significant estimates of b_q.

The R&D state variable warrants explanation. We follow Maio and Santa-Clara (2012) and construct an empirical proxy for the state variable, which is analogous to their *M/B* ratios, but with an adjustment for R&D investment. Specifically, we sort stocks independently into 2×3=6 portfolios by *Size* and *RD-MV* and compute the market capitalization to book equity plus R&D expenses ratio for each portfolio and denote this *TMV-TBVRD*. To adjust for the size effect, we average the ratio across the size portfolios for the top and bottom R&D portfolios. *RD-HML** then represents the state variable measured as the size-adjusted *TMV-TBVRD* for high R&D stocks minus that for low R&D stocks. We find that *RD-HML* ≈ Δ*RD-HML**, meaning that our measure is a reasonable proxy for the state variable and the return captured by *RD-HML* is a good approximation for its innovations.[8]

Table 3 reports the estimation results for the univariate predictive regressions for *RD-HML**, which forecasts future market returns positively and significantly and its predictive power increases with the horizon q. The R&D state variable satisfies the first requirement of the ICAPM.

Insert Table 3 about here

[8] We experiment with alternative proxies for the state variable as suggested by the referee. These include the sum of *RD-HML* in rolling windows, and the high minus low spreads in *RD-MV*, *MV-RD* and *MV-BV* in *Size* portfolios, which are then averaged across the *Size* groups. We opt for our measure since it delivers stronger predictability of future market returns. It also provides a closer approximation of *RD-HML* ≈ Δ*RD-HML** than the alternatives, which is important since it is the *RD-HML* return that is used later in cross sectional pricing tests. Results based on these alternative proxies can be found in Table IA.4 of the online appendix.

For robustness, we estimate multivariate predictive regressions that also control for the size, value, and momentum state variable proxies in R&D augmented versions of the *FF-3* and *C-4* models.[9] As shown in Table 4, while the predictive power of *RD-HML** is generally reduced after controlling for these additional state-variable proxies, it is significant for forecasting positive future aggregate market returns from q=12 onward. Consistent with Maio and Santa-Clara (2012), *SMB** does not predict future market returns in multivariate regressions while *CUMD* forecasts them positively. Conditional on *RD-HML** and in our smaller sample of R&D stocks, *HML** loses its forecasting power.

Insert Table 4 about here

The second requirement for ICAPM consistency is that the R&D factor loadings are priced in the cross section with the correct sign. To test this, we follow Maio and Santa-Clara (2012) and use 25 *Size-BM*, 25 *Size-Momentum* and 25 *Size-RD-MV* portfolios as test assets. We use a 60-month rolling window to estimate the loadings of each portfolio on the factors. We then examine whether the estimated loadings are correctly priced in the cross-section of subsequent excess returns using Fama and MacBeth (1973) cross-sectional regressions with Newey and West (1987) adjusted standard errors. Table 5 reports these pricing results.

Insert Table 5 about here

Panels A and B show results based on the *Size-BM* and *Size-Momentum* portfolios respectively, to test risk pricing in the full cross section. In Panel A, the risk prices of *SMB*, *HML* and *UMD* are positive, but only significant for *HML*. Adding *RD-HML* loadings produces only minor changes to the results; the significance of *HML* increases and the risk price on *UMD* decreases. However, although not significant, the price of risk on *RD-HML* is negative. For portfolios sorted by size and momentum in Panel B, *SMB* retains positive yet insignificant coefficients. However, *HML* conveys a negative and insignificant price of risk, while that on momentum is positive and significant, as expected given the test assets. More notably, the price of R&D risk is positive, and significantly so in the *C-4* model, which is encouraging for

[9] We focus on these factor models because Maio and Santa-Clara (2012) show that they perform best in their candidate models in consistently satisfying the ICAPM conditions.

a risk explanation for the R&D anomaly. To check the robustness of this result to errors-in-variables problems, we perform two-pass tests that estimate factor loadings for the full sample in the first stage and one cross-sectional regression in the second stage with Shanken (1992) corrected standard errors (reported in Table IA.5). The significant price of R&D risk is robust.[10] In Panel C, no factor is priced other than R&D. Moreover, throughout Table 5, the intercepts are significant implying inadequate pricing performance.

The final ICAPM restriction requires the price of market risk to be economically plausible. We find that these estimates are negative in all columns and are statistically significant in some cases. When applying the Shanken (1992) methodology, the coefficients are positive in only 5 out of 12 estimations, but these are never significant. This important finding means that these models are inconsistent with the ICAPM, meaning that we fail to support a fundamental economic justification for the R&D factor, which is not consistent with a rational risk pricing explanation for the R&D anomaly.

5. Covariance vs. Characteristics

As argued by Berk et al. (2004), the leverage embedded in the real options of R&D projects make R&D firms more sensitive to common risk factor(s) affecting the likelihood of future cashflows to the projects, such that they earn positive systematic risk premia. Alternatively, R&D stocks may be mispriced because of limits to arbitrage or psychological biases. The *RD-HML* factor constructed in section 3 captures the abnormal return to R&D intensive stocks, but this premium could just as well be driven by mispricing as covariance risk. The evidence in section 4 fails to support a risk factor explanation under the framework of ICAPM.

Daniel and Titman (1997) accept that it would be very difficult for characteristics-based portfolios to satisfy the conditions required for consistency with ICAPM. Therefore, in this section, we are less focused on whether the R&D factor meets these strict conditions, but are more concerned with the

[10] Indeed, this alternative method shows other changes that suggest more promising pricing performance. For *Size-BM* portfolios, the *UMD* factor shows a significant positive price of risk. Analogously, for *Size-Momentum* portfolios, *HML* has a positive and significant price of risk.

more fundamental issue of whether the R&D anomaly is related to a factor loading at all. We employ the methodology of Daniel and Titman (1997), which investigates the ability of factor loadings to explain the cross sectional patterns in average portfolio returns *after controlling for* the characteristic that determines the anomaly. This allows us to distinguish between the risk and mispricing explanations for the R&D anomaly directly.

We begin by performing a triple sort of stocks into portfolios by *Size*, *RD-MV,* and pre-formation loadings on the *RD-HML* factor ($Pre\text{-}\beta_{RD\text{-}HML}$). We estimate a stock's $Pre\text{-}\beta_{RD\text{-}HML}$ by regressing stock returns on *RD-HML* during months t-60 to t-7 relative to the portfolio formation date (the end of June every year). These pre-formation R&D factor loadings instrument for future expected loadings. At the end of June each year, we sort stocks independently into 3×3=9 portfolios by *Size* and *RD-MV* (breakpoints at 30th and 70th percentiles). Within each of the nine portfolios, we sort further into three portfolios according to the pre-formation R&D factor loadings (breakpoints at the 30th and 70th percentiles) to create 27 portfolios. For each of the 27 portfolios, we calculate the equal and value-weighted excess portfolio returns, *Size*, *RD-MV* and $Pre\text{-}\beta_{RD\text{-}HML}$. We then regress the portfolio returns on the augmented *C-4* model, which includes the *RD-HML* factor, to estimate the portfolio alpha and post-formation R&D factor loadings ($\beta_{RD\text{-}HML}$). Panel A of Table 6 presents these statistics.

Insert Table 6 about here

In each *Size-RD-MV* group (blocks of three rows in Panel A), we achieve the objective of the triple sorting, which is to produce variation in the factor loading (beta) whilst keeping the *Size* and *RD-MV* characteristics balanced. After controlling for the *RD-MV* characteristic, a risk explanation for the R&D anomaly should show a positive relation between pre-formation factor loadings and portfolio returns. Our results do not support this conjecture. For equally weighted portfolio returns, only the S/M *Size-RD-MV* group displays returns increasing with $Pre\text{-}\beta_{RD\text{-}HML}$. One group (B/M) shows the reverse, returns falling with higher loadings. Of the seven remaining categories, six show a humped pattern where returns increase from low to medium loadings, but see returns to high loadings diminish. The higher R&D loading portfolios struggle to earn a sufficient return to provide clear support to the risk explanation.

More importantly, in five of these six cases, the fall off produces a return to high $Pre\text{-}\beta_{RD\text{-}HML}$ portfolios that is lower than or very close to the return to low $Pre\text{-}\beta_{RD\text{-}HML}$ portfolios, meaning there is no premium for R&D covariance risk. The S/H group reveals a dipped pattern, returns falling from small to medium R&D loading and then increasing on the highest loading portfolio to earn a premium.

The value weighted returns confirm this lack of evidence for covariance risk driving the R&D anomaly. Again, only one *Size-RD-MV* category shows the increasing returns-loadings relation (B/H), although the difference in return between high and low R&D loading portfolios is small in this case. Two categories (M/L and M/M) reveal a decreasing pattern with $Pre\text{-}\beta_{RD\text{-}HML}$. The remaining six groups show a humped or dipped pattern, with only three of these showing a positive spread between high and low $Pre\text{-}\beta_{RD\text{-}HML}$. When controlling for the R&D characteristic, the returns to high R&D factor loading portfolios do not earn sufficient returns to suggest that the R&D anomaly is explained by covariance risk.

The alphas from the augmented *C-4* model are also illuminating. As noted by Hirshleifer et al. (2012), they should be zero if the patterns in returns across $Pre\text{-}\beta_{RD\text{-}HML}$ are explained by the factor model. For equally weighted returns, 14 out of 27 portfolios produce significant estimates of α at the 10% (11 at the 5% level). Similarly, 8 (5) out of 27 alphas are significant at the 10% (5%) level for value weighted returns. Irrespective of statistical significance, the absolute values of the alphas also tend to be quite large. These do not offer convincing support for the risk explanation. More important are the patterns that emerge in the α estimates for high and low $Pre\text{-}\beta_{RD\text{-}HML}$ portfolios, which manifest in the signs on the α's. Concentrating on the value weighted returns, the average estimated alphas of the nine high R&D loadings is -19.11 basis points per month, with 5 out of 9 estimates less than zero. In contrast, 8 out of 9 alphas for the low R&D loadings portfolios are positive with an average of 14.33 basis points per month. These findings are more suggestive of mispricing. A negative α on a high $Pre\text{-}\beta_{RD\text{-}HML}$ portfolio suggests the portfolio's return is insufficient relative to the factor model. Analogously, mispricing suggests higher abnormal returns on the low $Pre\text{-}\beta_{RD\text{-}HML}$ portfolio, as shown by a positive alpha (Hirshleifer et al. 2012).

Rather than relying on detecting patterns in Panel A, we test the risk versus mispricing hypotheses more formally by using the 27 triple-sorted portfolios to construct characteristics balanced portfolios. Within each of the nine *Size-RD-MV* groups, we calculate the return spread between the high and low *Pre-*$\beta_{RD\text{-}HML}$ portfolios, which isolates the premium on the R&D loading after controlling for characteristics. We also combine the nine characteristic balanced portfolios with equal weight into one portfolio to improve the power of the tests. Panel B of Table 6 reports the average returns and the estimated augmented *C-4* alphas. The average returns are negative for 9 of the 18 characteristic balanced portfolios, and for the combined portfolio in the final row. All portfolio returns are indistinguishable from zero. Therefore, when holding the R&D characteristic constant, the R&D factor loading fails to deliver a premium, which rejects the rational factor pricing model. Under a covariance risk explanation for the R&D anomaly, the estimated alphas should be zero. Alternatively, a mispricing explanation dictates that characteristic balanced portfolio returns are not driven by *Pre-*$\beta_{RD\text{-}HML}$ resulting in negative estimates of α. For the more relevant value weighted returns, all estimated intercepts are negative, though not often significant. More importantly, under value weighting, we find that the intercept on the combined portfolio is negative and significant, which is consistent with the mispricing hypothesis. Since all value weighted characteristic balanced portfolios deliver significant post-formation loadings on the R&D factor ($\beta_{RD\text{-}HML}$), our failure to reject the mispricing explanation is not likely due to a lack of statistical power (Hirshleifer et al., 2012).[11]

A more direct evaluation of the competing risk versus mispricing explanations for the R&D anomaly employs monthly Fama and Macbeth (1973) cross sectional tests, both at the portfolio and firm

[11] For robustness, we apply the *FF-5* model augmented with the R&D factor. We report the results in Table IA.6 of the online appendix. The alphas are generally small and insignificant, and are not often negative. With the exception of the S/H and B/L portfolios in Panel A, the augmented *FF-5* model seems to explain the returns on triple sorted portfolios and the characteristic balanced portfolios in Panel B. However, this is not to say that the model supports a risk explanation for the R&D anomaly since *Pre-*$\beta_{RD\text{-}HML}$ fails to provide the necessary premium to explain. Another possibility is that the alphas may be the manifestation of overfitting. More curiously, the post-formation $\beta_{RD\text{-}HML}$ does not always observe the patterns that we expect. For example, in Panel A for value weighted returns, the S/L and M/L blocks show that the $\beta_{RD\text{-}HML}$ from the highest *Pre-*$\beta_{RD\text{-}HML}$ are lower than the $\beta_{RD\text{-}HML}$ from the medium *Pre-*$\beta_{RD\text{-}HML}$. In these cases, the preformation loading does not deliver the necessary post-formation loadings. Furthermore, in Panel B and for value weighted returns, the post-formation $\beta_{RD\text{-}HML}$ are declining with the R&D characteristic for the portfolios of the smallest and biggest firms. This is contrary to the equal weighted returns, Table 6 and the findings of Daniel and Titman (1997) and Hirshleifer et al. (2012). Since the preformation loadings are estimated univariately, the failure of the augmented *FF-5* model to deliver appropriate post-formation loadings could signal some inter-relation between *RD-HML* and the other factors. This is perhaps not surprising given the correlations and factor spanning tests in Table 2.

levels. The test assets for the portfolio tests are the excess returns to the 27 characteristic balanced portfolios described above. The regressors are the average *RD-MV* for each portfolio (characteristic) and the factor loadings (covariance) estimated for each portfolio on the factors of the *C-4* and *FF-5* models. The factor loadings (β_i) are obtained using univariate time series regressions in 60-month rolling windows following Jagannathan and Wang (1996).[12,13] We report the time-series average of coefficients estimates along with their Newey and West (1987) robust *t*-statistics in Panel A of Table 7.

Insert Table 7 about here

In columns (1) and (5) $\beta_{RD\text{-}HML}$ explains the cross section of average returns with a positive and significant price of risk. This is not inconsistent with the risk explanation since this appears to suggest a risk premium for bearing systematic factor risk. However, given the correlation between *RD-HML* and the R&D characteristic, we are unable to rule out mispricing with this test alone. When replacing $\beta_{RD\text{-}HML}$ with *Avg. RD-MV* (the R&D characteristic) in columns (2) and (6), we find the same qualitative result. The characteristic also explains the cross section of average returns. Combining both the covariance and characteristic into the regressions, we perform the important direct test of the competing hypotheses. We show in columns (3) and (7) that the *RD-MV* characteristic maintains its significance and subsumes the explanatory power of the R&D factor loading. This result is maintained in the *FF-5* model in columns (4) and (8). Therefore, at the portfolio level, we reject the covariance risk hypothesis in favor of the mispricing explanation.

We adopt a similar approach in Panel B of Table 7, but use individual stock returns instead. This allows us to include a wider range of firm-level characteristics that explain cross sectional returns as control variables. However, firm level regressions also raise the errors-in-variables problem for the

[12] As discussed in Jagannathan and Wang (1998) and Eiling (2013), in a model with *multivariate beta*, adding a new factor will affect the values of all the other betas unless the new factor is uncorrelated with the existing ones. This makes the evaluation of adding a new factor on the model's performance difficult, which complicates model selection based on estimated factor risk premia. They argue that the use of *univariate beta* is more convenient and allows for a comparison of model performance. Additionally, since the matrix of *univariate betas* is a linear transformation of the matrix of *multivariate betas*, the errors and R-squared of the cross-sectional regressions are identical to those that use *multivariate betas*.

[13] Our results are qualitatively similar when *multivariate betas* are used instead, as shown in Table IA.7 of the online appendix.

estimates of factor loadings. To mitigate this, we follow the convention in the literature and estimate factor loadings for the 27 characteristics balanced portfolios based on 60-month rolling windows. We then allocate the more precise portfolio level factor loading to each firm in the portfolio.

Our control variables are extensive. Firm size (*ln(ME)*) is measured as the natural logarithm of the product of stock price and the number of shares outstanding at the end of June in year *t*. Following Fama and French (1993), the BM ratio (*BM*) is defined as book equity value at fiscal year-end in calendar year *t-1* divided by market equity at the end of December *t-1*. To control for price momentum (Jegadeesh and Titman, 1993), we construct a past return variable, *RET(-12,-2)*, computed as the compounded gross return from month *j-12* to *j-2*. Following Fama and French (2015), operating profitability (*OP*) is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expenses, all divided by book equity, and investment (*INV*) is the change in total assets from fiscal year *t-2* to *t-1*, divided by *t-2* total assets (*Inv*). Following Jegadeesh (1990), short-term reversal (*REV*) is defined as stock return in the prior month. Following Chordia et al. (2001), a stock's turnover ratio is share trading volume divided by the number of shares outstanding. We use the log turnover ratio of month *j-2* to explain returns in month *j* (*ln(Turn)*). Stock illiquidity is measured by the Amihud (2002) illiquidity measure (*ILLIQ*) and liquidity shocks (*LIQU*) is estimated following Bali et al. (2014). Monthly idiosyncratic volatility (*IVOL*) is estimated using daily stock returns within each calendar month following Ang et al. (2006). A stock's extreme positive return (*MAX*) is its maximum daily returns in the previous month following Bali et al. (2011). Following Eisfeldt and Papanikolaou (2013), organization capital intensity is estimated by capitalizing selling, general and administrative expenses using the perpetual inventory method, and then dividing the capitalized measure by total assets (*O-A*). Following Zhang (2006), a stock's information uncertainty (*ln(DISP)*) is measured as the natural logarithm of the cross-sectional standard deviation of analysts' one-year ahead earning per share forecasts over a fiscal year, divided by its stock price at the end of December in year *t-1*. Financial constraint is measured by the Kaplan and Zingales (1997) index (*KZ index*). Asset tangibility is measured as the ratio of net property, plant and equipment to total assets (*PPE-A*). Bankruptcy risk is captured by the Altman (1968) Z-score (*Z-score*).[14] The detailed definitions of these variables are provided in Appendix A.1.

Throughout Panel B of Table 7, our results support those of Panel A. On its own, the R&D factor loading ($\beta_{RD\text{-}HML}$) explains the cross section of stock returns, but its coefficient estimate is significant only at the 10% level. The *RD-MV* characteristic, on the other hand, is more important. When included jointly and with various combinations of control variables in columns (3) to (7), the *RD-MV* characteristic subsumes the R&D factor loading. We conclude that this evidence rejects the covariance risk explanation for the R&D anomaly in favor of the mispricing hypothesis. When adding the loadings on *RMW* and *CMA* in columns (8) and (9), the coefficient on the characteristic retains its magnitude and statistical significance, but we see the R&D factor loading significant at the 10% level. Given that this only occurs when these controls are added, and our concerns over the adequacy of the post-formation $\beta_{RD\text{-}HML}$ noted above, we speculate that this may arise from correlations between factors in the augmented *FF-5* model.[15]

6. Mispricing Tests

Our covariance versus characteristic results convincingly reject a factor risk explanation for the R&D anomaly, in favor of the mispricing explanation. In this final section, we investigate the extent to which two potential mechanisms permit the persistence of the R&D anomaly. First, hard to value stocks, of which R&D intensive stocks are examples, may be influenced by investor sentiment (Baker and Wugler, 2006). Following high sentiment states, R&D stocks are overvalued by sentiment driven speculative demand, which is corrected when the mispricing reverses. Analogously, after low sentiment states, R&D stocks are undervalued due to a lack of speculative demand, which later correct in the higher sentiment state. We test whether R&D returns are consistent with these predictions. Second, the mispricing of R&D

[14] We verify our results throughout to the inclusion of the liquidity risk factor of Pastor and Stambaugh (2003). Since this has no impact on our results, we do not report the analysis.

[15] For completeness, the estimated coefficients on other explanatory variables in Table 7 Panel B are consistent with prior literature. There is a significant negative size effect and positive value effect. Higher asset growth (*Inv*) (Cooper et al., 2008) and short-term reversal (*REV*) (Bali et al., 2014) are significantly and negatively related to stock returns, while higher organization capital (*O-A*) is associated with higher returns (Eisfeldt and Papanikolaou, 2013). The estimated loadings on empirical asset pricing factor loadings are not significantly priced in the cross section.

stocks may persist due to the inability of investors to arbitrage away the R&D anomaly (Shleifer and Vishny, 1997). Since one of the most significant limits to arbitrage is the constraint on short sales, this impinges on the short leg of the anomaly. We exploit the plausibly exogenous variation in short sale constraint provided by the SEC's Regulation SHO pilot program. Since stocks are assigned to the pilot program randomly, we employ a difference-in-differences analysis to identify the causal effect of short sale constraints on the R&D anomaly.

6.1. *Does Investor Sentiment Affect the R&D Anomaly?*

Baker and Wurgler (2006) argue that during high (low) sentiment states, hard-to-value and costly-to-arbitrage stocks are subject to more (less) speculative demand and mispricing. Switching between states, these stocks should observe subsequent correction of the mispricing, generating lower (higher) future returns in proportion to the degree of subjectivity over the firm's value. Therefore, a sentiment driven mispricing explanation of the R&D anomaly implies monotonically declining (increasing) returns to *RD-MV* quintile portfolios following high (low) sentiment states. Furthermore, the magnitude of the cross-sectional return patterns should be symmetric across sentiment states. However, Baker and Wurgler (2006) show increasing returns with R&D intensity following both sentiment states. The absence of a correction of returns following the high state is inconsistent with sentiment induced mispricing. Meanwhile, the increasing returns following low sentiment states are consistent with undervaluation from a lack of speculative demand, but also with the correction of mispricing emanating from other sources. We extend the analysis to control for other characteristics that may be present in R&D stocks to isolate the role of sentiment on R&D mispricing. We include the empirical factors of the *C-4* and *FF-5* models, which capture the covariance risk that may exist in R&D returns. Alternatively, these factors may also serve as proxies for other mispricing characteristics, such as small firms being more difficult to value (*SMB*), appearing as distressed (*HML*), or having performed poorly recently (*UMD*, *RMW*).

We use the Baker and Wurgler (2006) sentiment index proxy, defining high and low sentiment states according to its sample median. Subsequent equal and value-weighted returns to size-adjusted R&D

quintile portfolios are then averaged within sentiment states.[16] Panel A of Table 8 illustrates our results. We confirm a monotonic increase in both equal and value-weighted returns across R&D portfolios following both sentiment states, consistent with Baker and Wugler (2006). Hard-to-value stocks subject to sentiment effects should be overvalued during high sentiment states with returns correcting in subsequent periods. Since our pattern in returns is entirely opposite to this prediction, we find no evidence for the correction of sentiment driven overvaluation. Following low sentiment states, R&D quintile returns are much higher, consistent with underpricing. The 5-1 spread portfolio returns are significantly positive following both sentiment states, and they are almost identical when compared across sentiment states, which suggest that sentiment has little effect on the R&D anomaly. Panel A also shows that the differences between high and low sentiment returns are stable across the R&D quintiles, inconsistent with sentiment effects.

Stambaugh et al. (2012) offer an alternative approach in which short sale constraints are the specific impediments to eliminating sentiment related mispricing leaving overpricing as the source of the anomaly. Under this framework, following high sentiment versus low sentiment states, the 5-1 spread return should be higher, the long leg should not be different and the short leg should display lower returns. Contrary to these predictions, we find that the 5-1 spread portfolio return is not significantly higher following the high sentiment state and the long leg of the anomaly earns significantly different returns according to sentiment. Although the short leg generates lower returns following high sentiment as hypothesized by Stambaugh et al. (2012), this observation is not constrained to the short leg only, the return difference across sentiment states is consistent and significant across all R&D quintiles. Therefore our evidence does not support sentiment driven mispricing.

Insert Table 8 about here

Panels B and C report the estimated *C-4* and *FF-5* alphas. In both panels, the patterns of the alphas are largely consistent with Panel A and for both equally and value weighted returns, although the

[16] Specifically, sentiment state is measured at the end of year *t-1* and subsequent R&D portfolio returns are calculated from July of year *t* to June of year *t+1*. This maintains consistency with our earlier methods. Calculating returns for the twelve months from January of year *t* instead makes no difference to our results.

magnitude of the estimates are lower when value weighting. We find estimated alphas increasing across R&D portfolios following both sentiment states such that the intercept for the 5-1 spread portfolio return is not significantly related to sentiment. This suggests that, even after including appropriate controls, mispricing of undervalued R&D stocks are corrected and this occurs irrespective of sentiment state. Increasing alphas across quintiles following the high sentiment state is not consistent with sentiment driven mispricing. Furthermore, the alphas following high (low) sentiment states are lower (higher) than the corresponding estimates in Table 1. After adjusting for characteristics, high (low) sentiment reduces (accentuates) the abnormal returns in all quintiles. In contrast to the returns in Panel A, the alphas on the 5-1 spread portfolios are higher (lower) following high (low) sentiment states, but are not significantly different. This is partly due to the abnormal returns on the 4th and 5th R&D quintiles following low sentiment states, which are not as high as we might expect based on the return patterns in Panel A. This is not consistent with the sentiment hypothesis. At least some of the correction of the underpricing of the most R&D intensive stocks is captured by other characteristics.

6.2. *Do Short Sale Constraints Increase the R&D Anomaly?*

In the absence of sentiment driven mispricing, we next investigate whether limits to arbitrage affect the R&D anomaly. In a frictionless and efficient market, mispricing should be arbitraged away. However, frictions make the costs and risks of arbitrage prohibitive, leading to persistent mispricing (Shleifer and Vishny, 1997). One of the most significant limits to arbitrage is short-sale constraints (Lamont and Thaler, 2003), under which, arbitrageurs face significant costs or restrictions to short-selling. If the R&D anomaly reflects limits to arbitrage, we could expect short-sale constraints to supply the conditions for the R&D anomaly to persist.

The existing literature offers several indirect proxies for short-sale constraints, including the breadth of ownership, institutional ownership, short interest and costs of stock borrowing (Chen et al., 2002; Hirshleifer et al., 2011; Asquith et al., 2005; Drechsler and Drechsler, 2014). However, as noted by Fang et al. (2016), since these proxies are likely to be correlated with pricing factors and other risk-related firm characteristics, it may be difficult to isolate the true effect of short-sale constraints on asset prices. To address this challenge, we exploit the plausibly exogenous variation in the restriction on short-selling provided by the pilot program under Regulation SHO and perform a difference-in-differences analysis to identify the causal effect of limits to arbitrage on the R&D anomaly.

In July 2004, the SEC initiated a pilot program under Regulation SHO to facilitate research into the effects of short-sale price tests on stock markets. Under the pilot program, a random sample of stocks was selected and a short-sale restriction on these stocks was removed over a designated period. Specifically, within the Russell 3000 index constituents as at June 2004, Regulation SHO selected every third stock ranked by trading volume within each Exchange as a pilot stock. The pilot stocks were exempted from the uptick rule (called the bid price test) from May 2, 2005 to August 6, 2007 and were therefore easier to sell short relative to the non-pilot stocks. Because the pilot program is a randomized experiment, the plausibly exogenous variation in short-sale restrictions allows us to identify the effect of short sale constraints on the R&D anomaly.

We begin with 986 pilot stocks and 1,966 non-pilot stocks in the Russell 3000 index obtained from Fang et al. (2016).[17, 18] However, to ensure the balance of covariates between the treatment and control groups, we only include the pilot and non-pilot stocks that are within our R&D sample. This sample consists of 446 pilot R&D stocks and 922 non-pilot R&D stocks. Our sample period remains the same and covers the period July 1975 to June 2013.

While existing studies show that the assignment of pilot stocks is random (Chu et al., 2016; Fang et al., 2016), our sampling requirement of non-zero R&D expenditure firms may introduce selection bias. Therefore, we evaluate the balance of covariates between the pilot and non-pilot stocks at the end of 2003, prior to the announcement of Regulation SHO. Panel A of Table 9 compares the average characteristics between the pilot and non-pilot stocks (Full) and the averages in the top 20% of *RD-MV*

[17] The list of 986 pilot stocks is published by the SEC (2004). Among the non-pilot stocks, Fang et al. (2016) use Thomson Reuters Securities Data Company (SDC) Platinum database, the Compustat database and CRSP monthly files to identify firms that went public, had spinoffs or were not exchange-listed after April 30, 2004. These stocks are excluded from the non-pilot sample. See Fang et al. (2016) for further details.

[18] We are extremely grateful to Professor Vivian Fang for sharing the list of pilot and non-pilot stocks with us.

(Long) and bottom 20% of *RD-MV* firms (Short) across the groups. There are very few differences between the two groups. Firms in the treatment group have smaller average *ln(BM)* and lower tangible assets in the short leg. Since it is the spread between the high and low R&D stocks that drives the anomaly, comparing the Long and Short spread in *RD-MV* is essential to ensure that the treatment and control groups are comparable for our test.[19] The treatment group contains firms with lower average *RD-MV* by only 2.1% (unreported tests show the medians are not different from each other). Average *RD-MV* of the long and short legs are not significantly different across the treatment and control groups, suggesting that the Long-Short spreads in *RD-MV* are unlikely to be significantly different. These statistics show that the observables are in general similar across the two groups, which likely satisfies the parallel trend assumption (Roberts and Whited, 2012).

Insert Table 9 about here

To examine the effect of short sale constraints on the R&D anomaly, we form two sets of quintile portfolios based on year *t-1 RD-MV*, one for the pilot sample and one for the non-pilot stocks. Specifically, to improve the test, we apply the R&D breakpoints from the full sample to the quintile portfolio sorts in this analysis. For each set of quintiles, we calculate the equal and value-weighted average monthly returns for the zero-cost portfolio that goes long the high-R&D portfolio and short the low-R&D portfolio (Long-Short), which captures the anomalous R&D returns. We then estimate the following difference-in-differences model:

$$RET_{it} = \alpha_t + \beta_1\, Pilot_i + \beta_2\, Pilot_i \times During_t + \beta_3\, Pilot_i \times Post_t + \varepsilon_{it}\ , \qquad (2)$$

where RET_{it} is the average monthly portfolio returns on the Long-Short portfolio. We also separate the Long and Short legs of the spread portfolio for deeper analysis. $Pilot_i$ is a treatment dummy variable equal to one if stock i is a pilot stock, and zero otherwise. $During_t$ is a dummy variable equal to one if month t falls during the pilot program from June 2005 to July 2007. Therefore, β_2 captures the average treatment effect of the removal of the short-sale restriction on the R&D anomaly. Specifically, it compares the Long-Short return difference before and after the implementation of the pilot program, and between the

[19] We are very grateful to the referee for this and many other suggestions that have improved this section.

pilot and non-pilot stock samples. Furthermore, we investigate whether the effect on returns of lifting the short-sale restriction disappears after the program ended in August 2007 by including the interaction between *Pilot*$_i$ and *Post*$_t$. *Post*$_t$ is a dummy variable equal to one if month *t* is on or after August 2007. We also include monthly dummy variables to account for economy-wide shocks that may drive stock returns. We estimate equation (2) for *Long-Short*, *Long* and *Short* portfolio returns separately. Panels B to C of Table 9 report the coefficient estimates and their Newey and West (1987) robust *t*-statistics. Both panels show estimation results for raw portfolio excess returns and *C-4* and *FF-5* adjusted returns.

To the extent that limits to arbitrage enable periods of mispricing, we would expect the removal of a short-sale restriction under the pilot program to facilitate arbitrage and reduce the R&D anomaly. We find no empirical support for this prediction. In Panel B where equal weighted portfolio returns are analyzed, we find no significant coefficient estimates for *Pilot*×*During* in the zero-cost spread portfolio or the long and short legs, inconsistent with a mispricing explanation. In addition, the estimates for *Pilot*×*Post* are also insignificant, suggesting that the R&D anomaly does not change significantly after the SHO program ended. Examining value-weighted portfolio returns in Panel C, we again find that the critical coefficient estimate on *Pilot*×*During* is insignificant in all model specifications. Interestingly, our tests reveal that *Pilot*×*Post* enters negatively and significantly into the zero cost spread portfolio, suggesting that the R&D anomaly reduces significantly after the program had ended. Such results persist after accounting for characteristics in the *C-4* and *FF-5* models. However, this is only observed in the long, but not in the short leg. While this evidence may be driven by potential confounding effects occurring at the time of the short-sale ban removal, our finding that the short leg is unaffected maintains the interpretation that the R&D anomaly is not related to limits to arbitrage in the form of short sale constraints.

A potential concern of this analysis is that the R&D anomaly may be more relevant to those R&D stocks that are not in the Russell 3000 and so were not eligible for the pilot. We repeat this analysis to compare the pilot stocks against the remaining R&D stocks.[20] Unsurprisingly, there are more characteristics showing significant differences. More importantly, the average *RD-MV* 21% higher in the non-Russell 3000 group in the top R&D quintile, but our results are similar to those reported in Table 9. Therefore, the assignment of treatment status is not random, and, these additional results likely suffer from selection issues.

Finally, we test the joint effects of sentiment driven mispricing and short sale constraints on the R&D anomaly. During the Regulation SHO sub-sample, we follow the methodology of Stambaugh et al. (2012) to investigate the role of sentiment on the anomaly for pilot and non-pilot stocks. Since our analysis finds no convincing effect of sentiment on the anomaly and no differences between the groups to suggest any effect from the lifting of short sale constraints, we do not report the results for brevity, but conclude that these issues do not explain the mispricing in R&D stocks.[21] More details relating to these tests can be found in Tables IA.9 and IA.10 of the online appendix.

7. Conclusion

There is considerable evidence of a significant positive relation between R&D investment and future stock returns, which is not explained by empirical asset pricing models. A common explanation is mispricing, which argues that limits to arbitrage or behavioral traits cause R&D stocks to be undervalued. When these market frictions or psychological heuristics are resolved, the mispricing is corrected and strong positive returns are earned. Alternatively, abnormal R&D returns may represent rational compensation for bearing systematic risk, which emanates from the real options embedded in R&D projects and is not captured in conventional pricing models. Resolution of this debate relies on rigorous empirical methods.

[20] We do not report the results for brevity, but show them in Table IA.8 of the online appendix.

[21] The only potential effect we find is a significantly positive alpha to the short leg of the anomaly following periods of high sentiment for the pilot stocks under the *FF-5* model. This could indicate that sentiment driven overpricing of low R&D stocks may have been eliminated by short sellers during high sentiment states, with the stocks correcting subsequently as short positions were covered when the sentiment state switched from high to low. However, without corroborating evidence from the non-pilot stocks, this interpretation is tentative.

We contribute to the literature by providing more stringent and direct tests that can eliminate one of the assertions. We show that the R&D characteristic is more important than the loading on a R&D factor for predicting the cross section of future returns, so we reject the covariance risk explanation in favor of the mispricing hypothesis. Motivated by this evidence, we test for the correction of R&D mispricing using the cross-sectional effects of investor sentiment and a natural experiment on the limits to arbitrage. Our results are consistent with the significant undervaluation of R&D stocks, but this is not related to investor sentiment. Finally, we estimate a difference-in-differences analysis to identify the causal effect of short selling constraints on the R&D anomaly. We find that lifting short sale constraints under the SEC's Regulation SHO pilot program has no significant effect on the R&D anomaly. In sum, our evidence is consistent with mispricing, but we do not identify any mechanisms, incremental to extant studies such as Cohen et al. (2013) and Hirshleifer et al. (2013), that cause the mispricing to persist.

There are two particular features of our findings that motivate deeper analysis in future. In relation to systematic risk, the correlation between the returns on the R&D factor and those on size, value, profitability and investment factors may induce overfitting. Second, R&D is known to interact with financial constraints (Li, 2011) and product market competition (Gu, 2016). Third, Donelson and Resutek (2012) suggest that the R&D anomaly is part of the larger value anomaly. Teasing out these correlation and interactions present a formidable challenge. On the mispricing argument, the positive relation between the R&D, value and profitability factors present great potential to extend the ideas of Daniel and Titman (2006) and Donelson and Resutek (2012) to distinguish the under reaction to intangible information heuristic from the pessimistic extrapolation of poor performance (Lakonishok et al., 1994). Alternatively, researchers may focus on investors' interpretations of the uncertainty of R&D, or their prior beliefs regarding the probability of success of R&D investment.

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TABLE 1
Size-Adjusted R&D Quintile Portfolio Returns

This table reports the details of the size-adjusted *RD-MV* sorted quintile portfolios. We sort stocks independently into 2×5 *Size-RD-MV* portfolios and compute their equal and value-weighted average returns. Within each *RD-MV* rank, we average the portfolio returns across the big and small portfolios. Panels A and B report the size-adjusted equally-weighted (EW) and value-weighted (VW) average monthly simple (*RET*) and risk-adjusted stock returns. *C-4 α* and *FF-5 α* are the estimated intercept of time-series regressions based on the Carhart (1997) four-factor and Fama and French (2015) five-factor models. We also report the zero-cost portfolio that goes long Portfolio 5 and short Portfolio 1. The *t*-statistics in brackets are calculated based on Newey and West (1987) robust standard errors.

	1 (Low)	2	3	4	5 (High)	5-1
Panel A. Equally weighted portfolio returns						
EW RET	0.43%	0.77%	1.03%	1.29%	1.67%	1.24%
	[1.336]	[2.280]	[2.917]	[3.265]	[3.519]	[5.238]
EW C-4 α	-0.16%	0.16%	0.38%	0.60%	0.93%	1.09%
	[-1.311]	[1.263]	[3.731]	[4.087]	[4.326]	[5.188]
EW FF5 α	-0.17%	0.14%	0.39%	0.65%	1.01%	1.18%
	[-1.236]	[1.049]	[3.968]	[4.970]	[4.907]	[5.636]
Panel B. Value-weighted portfolio returns						
VW RET	0.37%	0.57%	0.76%	1.00%	1.18%	0.81%
	[1.421]	[1.986]	[2.579]	[2.941]	[2.887]	[3.538]
VW C-4 α	-0.28%	-0.11%	0.07%	0.23%	0.28%	0.56%
	[-3.728]	[-1.376]	[0.937]	[2.100]	[1.637]	[2.979]
VW FF5 α	-0.16%	-0.03%	0.15%	0.39%	0.47%	0.62%
	[-2.054]	[-0.298]	[2.240]	[3.749]	[2.667]	[3.147]

TABLE 2
The *RD-HML* Factor

This table summarizes the *RD-HML* factor and its relationship to other pricing factors. Panel A reports the summary statistics and Panel B reports the pairwise correlations between the pricing factors and the corresponding *p*-values. In panel C, the *RD-HML* factor is regressed on other pricing factors. The model specifications of rows (1), (2), (3) and (4) follow the *CAPM*, *FF-3*, *C-4* and *FF-5* models. *SMB3* and *HML3* are the *FF-3* size and value factors, whereas *SMB5* and *HML5* denote the *FF-5* size and value factors.

Panel A. Summary statistics

	Obs.	Mean	Stdev	Sharpe ratio	5%	25%	Median	75%	95%
RD-HML	456	0.68%	3.59%	0.19	-4.33%	-1.22%	0.60%	2.34%	5.74%
MKT	456	0.58%	4.52%	0.13	-7.26%	-1.96%	1.03%	3.54%	7.19%
SMB3	456	0.26%	3.05%	0.08	-4.02%	-1.33%	0.16%	2.05%	4.83%
HML3	456	0.36%	2.97%	0.12	-4.19%	-1.18%	0.34%	1.74%	5.22%
SMB5	456	0.28%	2.97%	0.09	-4.13%	-1.33%	0.13%	2.09%	4.96%
HML5	456	0.36%	2.97%	0.12	-4.19%	-1.18%	0.34%	1.74%	5.22%
UMD	456	0.67%	4.46%	0.15	-6.84%	-0.78%	0.72%	2.85%	6.73%
RMW	456	0.34%	2.26%	0.15	-2.58%	-0.75%	0.26%	1.39%	3.75%
CMA	456	0.35%	1.94%	0.18	-2.70%	-0.89%	0.24%	1.52%	3.43%

Panel B. Correlation With Pricing Factors

Correlation	*RD-HML*	*MKT*	*SMB3*	*HML3*	*UMD*	*SMB5*	*HML5*	*RMW*	*CMA*
RD-HML	1.000								
	—								
MKT	0.315	1.000							
	0.000	—							
SMB3	0.581	0.253	1.000						
	0.000	0.000	—						
HML3	-0.228	-0.314	-0.272	1.000					
	0.000	0.000	0.000	—					
UMD	-0.022	-0.087	0.085	-0.169	1.000				
	0.642	0.064	0.071	0.000	—				
SMB5	0.559	0.233	0.986	-0.159	0.066	1.000			
	0.000	0.000	0.000	0.001	0.162	—			
HML5	-0.228	-0.314	-0.272	1.000	-0.169	-0.159	1.000		
	0.000	0.000	0.000	0.000	0.000	0.001	—		
RMW	-0.547	-0.270	-0.485	0.224	0.098	-0.423	0.224	1.000	
	0.000	0.000	0.000	0.000	0.036	0.000	0.000	—	
CMA	-0.004	-0.379	-0.126	0.700	0.004	-0.057	0.700	0.029	1.000
	0.939	0.000	0.007	0.000	0.935	0.227	0.000	0.540	—

Panel C. Factor Spanning Tests

Variables	Mean	α	*MKT*	*SMB3*	*HML3*	*UMD*	*SMB5*	*HML5*	*RMW*	*CMA*	R^2	N
(1)	0.68%	0.0054	0.2497								0.099	456
t-stat	[3.716]	[3.146]	[6.341]									
(2)		0.0046	0.1358	0.6224	-0.0363						0.368	456
t-stat		[2.974]	[2.609]	[4.902]	[-0.383]							
(3)		0.0050	0.1277	0.6275	-0.0510	-0.0484					0.372	456
t-stat		[3.324]	[2.685]	[4.910]	[-0.534]	[-0.716]						
(4)		0.0058	0.1350				0.4480	-0.2619	-0.4797	0.4474	0.475	456
t-stat		[3.932]	[3.301]				[7.044]	[-2.780]	[-3.525]	[2.979]		

TABLE 3
ICAPM Tests: Single Predictive Regressions for Market Returns

This table reports the results for single variable predictive regressions for the monthly continuously compounded return of the CRSP value-weighted market index, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variable is the current values of the R&D state variable proxy (*RD-HML**). To estimate this state variable, we first sort stocks independently into 2×3=6 portfolios by *Size* and *RD-MV*. For each portfolio, we compute the sum of market capitalization and book equity plus R&D expenses. We then divide the total market value by total book equity plus R&D expenses to obtain the ratio *TMV-TBVRD*. To adjust for the size effect, we equal average the ratio across the size portfolios for the top and bottom R&D portfolios. *RD-HML** is the high-minus-low size-adjusted *TMV-TBVRD*. For each regression, we report the coefficient estimates, Newey and West (1987) robust standard errors adjusted using *q* lag (in parentheses) and R-squared.

Predictor	*q=1*	*q=3*	*q=12*	*q=24*	*q=36*	*q=48*	*q=60*
*RD-HML**	0.0065*	0.0195**	0.0867***	0.1873***	0.3097***	0.4432***	0.5600***
	(0.0037)	(0.0096)	(0.0332)	(0.0554)	(0.0499)	(0.0577)	(0.0749)
Obs.	455	453	444	432	420	408	396
R^2	0.83%	2.33%	10.34%	22.28%	32.05%	38.27%	38.34%

TABLE 4
ICAPM Tests: Multivariate Predictive Regressions for Market Returns

Panels A to G of this table report the results of multivariate predictive regressions for the monthly continuously compounded return of the CRSP value-weighted market index at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variable of interest is the current value of the R&D state variable proxy (*RD-HML**). We control for other state variables associated with the *SMB*, *HML*, and *UMD* factors by constructing their proxies following Maio and Santa-Clara (2012). *SMB** is the difference between the monthly BM-adjusted market-to-book ratios of small and big stocks; *HML** is the difference between the monthly size-adjusted market-to-book ratios of value and growth stocks. C*UMD* is the cumulative sum of the monthly UMD factor over the last 60 months. Rows labelled (1) and (2) indicate *FF-3* and *C-4* models. For each regression, we report the coefficient estimates, the Newey and West (1987) robust standard errors adjusted for *q* lags (in parentheses) and R-squared.

Row	*SMB**	*HML**	*CUMD*	*RDHML**	Obs.	R^2
Panel A. *q*=1						
(1)	0.0067	0.0019		0.0023	455	0.0095
	(0.0162)	(0.0042)		(0.0078)		
(2)	0.0047	0.0028	-0.0047	0.0010	455	0.0103
	(0.0164)	(0.0046)	(0.0079)	(0.0085)		
Panel B. *q*=3						
(3)	0.0225	0.0042		0.0087	453	0.0260
	(0.0401)	(0.0116)		(0.0210)		
(4)	0.0186	0.0057	-0.0089	0.0063	453	0.0268
	(0.0410)	(0.0124)	(0.0198)	(0.0223)		
Panel C. *q*=12						
(5)	0.0878	-0.0080		0.0781	444	0.1088
	(0.1752)	(0.0321)		(0.0523)		
(6)	0.1174	-0.0197	0.0780	0.0973*	444	0.1222
	(0.1674)	(0.0300)	(0.0764)	(0.0547)		
Panel D. *q*=24						
(7)	0.1923	-0.0492		0.2137**	432	0.2441
	(0.3373)	(0.0543)		(0.0931)		
(8)	0.2965	-0.0798*	0.2734**	0.2627***	432	0.3163
	(0.2907)	(0.0446)	(0.1228)	(0.0928)		
Panel E. *q*=36						
(9)	0.0279	-0.0930		0.4410***	420	0.3405
	(0.4258)	(0.1065)		(0.1213)		
(10)	0.2327	-0.1146	0.5011***	0.4641***	420	0.4545
	(0.3633)	(0.0876)	(0.1695)	(0.1079)		
Panel F. *q*=48						
(11)	-0.2458	-0.1068		0.6603***	408	0.4045
	(0.4418)	(0.1347)		(0.1689)		
(12)	0.2311	-0.1135	0.7938***	0.6027***	408	0.5255
	(0.2926)	(0.1104)	(0.2579)	(0.1505)		
Panel G. *q*=60						
(13)	-0.2234	-0.1499		0.8443***	396	0.4008

	(0.4468)	(0.1873)		(0.2826)		
(14)	0.3482	-0.1174	0.9414***	0.7062**	396	0.5028
	(0.3314)	(0.1648)	(0.2784)	(0.2864)		

TABLE 5
Factor Pricing in the Cross Section

This table examines prices of covariance risk in the cross section. Panel A (Panel B) [Panel C] uses value-weighted returns to 25 portfolios sorted by size and book-to-market equity ratio (momentum) [*RD-MV*] as test assets. To estimate the factor loadings, we estimate the *FF-3* and *C-4* model augmented with the *RD-HML* factor using a 60-month rolling window and examine whether the estimated factor loadings explain the cross section of subsequent average returns using Fama-MacBeth regressions. We report the estimated coefficients, Newey and West (1987) robust *t*-statistics, the average R-squared, and the number of months.

Panel A. 25 Size and BM Sorted Portfolios

	FF-3		*C-4*	
	(1)	(2)	(3)	(4)
β_{MKT}	-0.0066*	-0.0061*	-0.0071*	-0.0069**
	[-1.901]	[-1.942]	[-1.903]	[-1.969]
β_{SMB}	0.0006	0.0006	0.0008	0.0008
	[0.408]	[0.389]	[0.563]	[0.530]
β_{HML}	0.0035*	0.0037**	0.0037**	0.0038**
	[1.892]	[2.047]	[1.981]	[2.119]
β_{UMD}			0.0021	0.0008
			[0.505]	[0.205]
$\beta_{RD\text{-}HML}$		-0.0001		-0.0008
		[-0.026]		[-0.288]
Intercept	0.0131***	0.0126***	0.0135***	0.0132***
	[3.555]	[4.002]	[3.490]	[3.804]
Average R^2	0.497	0.550	0.550	0.598
Number of months	396	396	396	396

Panel B. 25 Size and Momentum Sorted Portfolios

	FF-3		*C-4*	
	(1)	(2)	(3)	(4)
β_{MKT}	-0.0102***	-0.0086**	-0.0049	-0.0026
	[-2.637]	[-2.174]	[-1.480]	[-0.790]
β_{SMB}	0.0023	0.0026	0.0017	0.0018
	[1.326]	[1.502]	[0.962]	[1.072]
β_{HML}	-0.0031	-0.0022	-0.0017	-0.0010
	[-1.290]	[-0.904]	[-0.766]	[-0.458]
β_{UMD}			0.0056**	0.0055**
			[2.327]	[2.244]
$\beta_{RD\text{-}HML}$		0.0043		0.0063**
		[1.291]		[2.002]
Intercept	0.0166***	0.0147***	0.0122***	0.0097***
	[4.871]	[4.521]	[4.063]	[3.582]
Average R^2	0.497	0.550	0.550	0.598
Number of months	396	396	396	396

Panel C. 25 Size and *RD-MV* sorted portfolios

	FF-3		*C-4*	
	(1)	(2)	(3)	(4)
β_{MKT}	-0.0063	-0.0041	-0.0051	-0.0032
	[-1.484]	[-1.055]	[-1.208]	[-0.815]
β_{SMB}	-0.0002	0.0004	0.0000	0.0004
	[-0.113]	[0.226]	[0.009]	[0.203]
β_{HML}	-0.0002	-0.0005	-0.0008	-0.0014
	[-0.101]	[-0.233]	[-0.367]	[-0.651]
β_{UMD}			-0.0044	-0.0033
			[-1.197]	[-0.896]
$\beta_{RD\text{-}HML}$		0.0069***		0.0070***
		[3.130]		[3.134]
Intercept	0.0132***	0.0091**	0.0114**	0.0075*
	[2.758]	[2.115]	[2.392]	[1.748]
Average R^2	0.310	0.410	0.350	0.445
Number of months	396	396	396	396

TABLE 6
Covariance vs. Characteristics: Portfolio Evidence

This table reports the results examining whether covariance or characteristics explain the R&D anomaly. In Panel A, we first sort R&D stocks independently into 3×3 *ME* and *RD-MV* portfolios at their respective 30th and 70th breakpoints. In each of the 9 portfolios, we further divide stocks into 3 portfolios (at 30th and 70th breakpoints) according to the estimated preformation R&D factor loadings ($Pre\text{-}\beta_{RD\text{-}HML}$). To estimate the preformation R&D factor loadings, we follow Daniel and Titman (1997) and regress stock returns on the RD-HML factor over the previous 60 months (skipping the most recent 6 months) before the portfolio formation date. Panel A reports the equal and value-weighted characteristics (size, RD-MV, $Pre\text{-}\beta_{RD\text{-}HML}$, and excess returns) for each of the 27 portfolios. In the first column, the three letters denote the rank for *ME*, *RD-MV*, and $Pre\text{-}\beta_{RD\text{-}HML}$. S/M/B denote small, medium, and big stocks; L/M/H denote low, middle, and high portfolios. We also report the estimated post-formation alpha and RD-HML factor loadings from estimating the augmented C-4 model with the RD-HML factor. Panel B presents results from the 9 characteristics-balanced portfolios, which are the spread portfolios between the high and low preformation R&D factor loadings portfolios within each size and *RD-MV* categories. We then equal average the 9 characteristics-balanced portfolios to arrive at a combined portfolio for an overall test.

Panel A. 27 Portfolios

	Equal weighted portfolios									Value weighted portfolios								
	ME	*RD-MV*	$Pre\text{-}\beta_{RD\text{-}HML}$	*RET*	*t(RET)*	α	*t*(α)	$\beta_{RD\text{-}HML}$	$t(\beta_{RD\text{-}HML})$	*ME*	*RD-MV*	$Pre\text{-}\beta_{RD\text{-}HML}$	*RET*	*t(RET)*	α	*t*(α)	$\beta_{RD\text{-}HML}$	$t(\beta_{RD\text{-}HML})$
S/L/L	27.03	1.09%	-0.45	0.61%	[1.425]	0.26%	[0.821]	-0.179	[-2.006]	34.81	1.25%	-0.42	0.12%	[0.294]	-0.30%	[-1.065]	-0.277	[-3.342]
S/L/M	28.40	1.13%	0.80	0.97%	[2.034]	0.33%	[1.132]	0.182	[1.263]	35.70	1.20%	0.81	0.65%	[1.683]	0.05%	[0.204]	0.005	[0.053]
S/L/H	28.39	1.14%	2.31	0.81%	[1.492]	0.26%	[0.627]	-0.070	[-0.506]	35.94	1.40%	2.30	0.25%	[0.458]	-0.54%	[-1.515]	0.061	[0.480]
S/M/L	24.19	4.71%	-0.22	1.10%	[2.792]	0.67%	[2.511]	-0.044	[-0.536]	33.54	4.59%	-0.18	0.76%	[2.007]	0.19%	[0.839]	-0.052	[-0.684]
S/M/M	28.13	4.84%	0.94	1.20%	[2.751]	0.68%	[2.067]	0.053	[0.465]	36.96	4.92%	0.95	0.88%	[2.126]	0.17%	[0.876]	0.133	[1.798]
S/M/H	27.25	4.95%	2.54	1.43%	[2.459]	0.90%	[2.077]	0.332	[1.774]	36.20	5.82%	2.54	0.77%	[1.391]	0.07%	[0.230]	0.353	[2.185]
S/H/L	19.90	22.18%	-0.04	1.99%	[4.067]	1.19%	[4.223]	0.480	[3.674]	30.57	17.14%	0.02	1.56%	[3.166]	0.59%	[2.167]	0.602	[5.471]
S/H/M	23.52	24.33%	1.26	1.97%	[3.691]	1.16%	[3.932]	0.554	[4.384]	33.26	19.34%	1.26	1.59%	[3.010]	0.57%	[2.461]	0.600	[6.554]
S/H/H	25.94	28.80%	2.93	2.08%	[3.080]	1.08%	[2.735]	0.904	[5.363]	35.07	22.61%	2.89	1.37%	[2.119]	0.23%	[0.782]	0.902	[6.957]
M/L/L	221.96	1.09%	0.02	0.49%	[1.531]	-0.02%	[-0.115]	-0.304	[-5.833]	294.69	1.04%	0.04	0.58%	[1.923]	0.05%	[0.346]	-0.343	[-5.347]
M/L/M	226.29	1.13%	0.91	0.51%	[1.449]	-0.06%	[-0.426]	-0.132	[-3.129]	298.35	1.11%	0.91	0.54%	[1.584]	-0.11%	[-0.994]	-0.098	[-2.842]
M/L/H	216.42	1.16%	2.21	0.27%	[0.571]	-0.14%	[-0.398]	-0.010	[-0.082]	285.55	1.30%	2.19	0.06%	[0.145]	-0.50%	[-2.289]	-0.001	[-0.007]
M/M/L	211.64	4.45%	0.22	0.90%	[2.619]	0.16%	[1.156]	0.013	[0.261]	292.25	4.02%	0.24	0.92%	[2.791]	0.11%	[0.841]	0.022	[0.457]
M/M/M	220.76	4.69%	1.19	0.94%	[2.476]	0.23%	[1.982]	0.164	[3.934]	297.86	4.36%	1.18	0.88%	[2.401]	0.02%	[0.145]	0.266	[6.468]
M/M/H	212.64	4.94%	2.56	0.75%	[1.416]	-0.01%	[-0.064]	0.466	[5.326]	286.69	4.97%	2.50	0.65%	[1.297]	-0.26%	[-1.653]	0.488	[7.552]
M/H/L	168.95	16.87%	0.49	1.23%	[2.887]	0.32%	[1.628]	0.368	[5.431]	237.34	13.01%	0.51	1.12%	[2.653]	0.10%	[0.571]	0.373	[6.304]
M/H/M	183.88	17.05%	1.56	1.50%	[2.873]	0.50%	[2.471]	0.655	[9.074]	259.54	13.71%	1.56	1.43%	[2.730]	0.26%	[1.455]	0.802	[10.214]
M/H/H	165.76	19.51%	2.94	0.91%	[1.432]	-0.22%	[-0.967]	0.881	[8.056]	233.53	15.39%	2.90	0.72%	[1.208]	-0.57%	[-2.436]	0.915	[11.601]
B/L/L	16671.12	1.01%	-0.04	0.61%	[2.614]	0.19%	[1.718]	-0.244	[-4.307]	87881.59	0.91%	-0.15	0.60%	[2.778]	0.24%	[2.047]	-0.303	[-5.410]
B/L/M	6710.00	1.12%	0.67	0.66%	[2.286]	0.19%	[2.010]	-0.159	[-4.241]	66532.32	1.09%	0.61	0.57%	[1.997]	0.20%	[1.726]	-0.181	[-2.691]
B/L/H	3662.06	1.19%	1.61	0.58%	[1.448]	0.03%	[0.155]	0.197	[2.677]	20041.87	1.15%	1.51	0.69%	[1.699]	0.10%	[0.520]	0.221	[3.499]

B/M/L	11182.34	4.01%	0.27	0.95%	[3.845]	0.35%	[3.405]	0.003	[0.055]	51164.40	3.56%	0.22	0.72%	[3.389]	0.21%	[1.851]	0.043	[0.991]
B/M/M	6561.57	4.28%	0.97	0.91%	[2.867]	0.24%	[2.552]	0.174	[3.995]	40936.17	3.93%	0.95	0.79%	[2.493]	0.10%	[0.930]	0.408	[6.807]
B/M/H	3151.45	4.69%	2.08	0.80%	[1.739]	0.02%	[0.105]	0.565	[9.239]	18102.81	4.10%	1.89	0.78%	[1.837]	0.00%	[0.015]	0.553	[8.583]
B/H/L	5289.92	13.37%	0.55	1.17%	[3.687]	0.33%	[1.684]	0.344	[2.931]	19231.04	11.77%	0.56	0.90%	[3.047]	0.10%	[0.447]	0.540	[5.093]
B/H/M	4017.48	14.54%	1.41	1.34%	[3.294]	0.32%	[1.941]	0.692	[11.007]	13474.28	13.54%	1.38	1.06%	[2.590]	-0.23%	[-1.119]	0.944	[13.608]
B/H/H	2110.00	16.14%	2.56	1.19%	[2.082]	0.03%	[0.111]	0.969	[10.691]	6632.48	13.27%	2.42	1.09%	[1.863]	-0.25%	[-0.838]	1.099	[9.999]

Panel B. 9 Characteristics-Balanced Portfolios

	Equal weighted portfolios						Value-weighted portfolios					
	RET	*t(RET)*	α	*t*(α)	$\beta_{RD\text{-}HML}$	$t(\beta_{RD\text{-}HML})$	*RET*	*t(RET)*	α	*t*(α)	$\beta_{RD\text{-}HML}$	$t(\beta_{RD\text{-}HML})$
S/L	0.20%	[0.542]	0.01%	[0.017]	0.109	[0.818]	0.13%	[0.345]	-0.24%	[-0.607]	0.337	[2.546]
S/M	0.33%	[0.917]	0.24%	[0.648]	0.376	[2.293]	0.00%	[0.006]	-0.13%	[-0.431]	0.405	[2.580]
S/H	0.09%	[0.307]	-0.11%	[-0.367]	0.424	[3.141]	-0.19%	[-0.651]	-0.36%	[-1.174]	0.301	[2.591]
M/L	-0.22%	[-0.764]	-0.13%	[-0.333]	0.294	[2.026]	-0.51%	[-1.728]	-0.55%	[-1.992]	0.342	[2.758]
M/M	-0.16%	[-0.537]	-0.17%	[-0.728]	0.453	[4.557]	-0.27%	[-0.889]	-0.37%	[-1.862]	0.467	[6.070]
M/H	-0.32%	[-1.048]	-0.55%	[-2.291]	0.512	[4.511]	-0.39%	[-1.287]	-0.67%	[-2.547]	0.541	[5.326]
B/L	-0.03%	[-0.093]	-0.17%	[-0.801]	0.441	[4.361]	0.09%	[0.282]	-0.14%	[-0.571]	0.524	[6.742]
B/M	-0.15%	[-0.474]	-0.33%	[-1.574]	0.563	[6.316]	0.06%	[0.160]	-0.21%	[-0.909]	0.509	[6.149]
B/H	0.02%	[0.043]	-0.30%	[-0.930]	0.625	[3.735]	0.18%	[0.401]	-0.35%	[-0.831]	0.560	[3.377]
Combined	-0.03%	[-0.100]	-0.17%	[-0.890]	0.422	[4.800]	-0.10%	[-0.380]	-0.33%	[-2.270]	0.443	[6.431]

TABLE 7
Covariance vs. Characteristics: Multivariate Tests

This table presents multivariate tests examining the relative importance between covariance and characteristics in explaining the R&D anomaly. Panels A and B report results at the portfolio and firm levels, respectively. In Panel A, we use 3×3×3=27 portfolios sorted by size, *RD-MV*, and the estimated preformation R&D factor loadings as test assets. To estimate the postformation loadings for *MKT*, *SMB*, *HML*, *UMD*, *RMW*, *CMA*, and *RD-HML*, we regress the average returns of each portfolio univariately on each of the pricing factors on a 60-month rolling window and use these estimated postformation factor loadings to explain the cross section of portfolio returns in Fama and MacBeth (1973) cross-sectional regressions. *Avg. RD-MV* is the equal or value-weighted average portfolio *RD-MV*. We report in parentheses the Newey and West (1987) robust *t*-statistics, the average R-squared, and number of months for the estimation. Panel B reports firm-level Fama and MacBeth (1973) cross-sectional regressions. To reduce measurement errors, we assign the postformation factor loadings estimated at the portfolio level used in Panel A to their constituent stocks. The detailed definition of the firm characteristic controls can be found in Appendix A.1. We report Newey and West (1987) robust *t*-statistics (in squared brackets), average R-squared, and number of observations for each model. Symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A. Portfolio-Level Analysis

	RET							
	Equal weighted portfolio returns				*Value weighted portfolio returns*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{MKT}	-0.014*	-0.007	-0.006	-0.006	-0.013**	-0.010*	-0.009	-0.017***
	[-1.742]	[-1.015]	[-0.838]	[-0.677]	[-2.168]	[-1.704]	[-1.605]	[-2.676]
β_{SMB}	-0.005	-0.001	0.003	0.003	-0.005	-0.000	-0.000	-0.002
	[-1.107]	[-0.303]	[0.651]	[0.704]	[-1.359]	[-0.051]	[-0.048]	[-0.396]
β_{HML}	0.004	0.000	0.002	-0.004	-0.000	-0.004	-0.002	0.007
	[0.870]	[0.023]	[0.409]	[-0.632]	[-0.007]	[-1.202]	[-0.407]	[1.225]
β_{UMD}	-0.001	-0.007	-0.005		-0.003	-0.004	-0.004	
	[-0.198]	[-1.305]	[-0.827]		[-0.668]	[-1.016]	[-0.987]	
β_{RMW}				0.004				-0.003
				[0.809]				[-0.716]
β_{CMA}				0.004				-0.006**
				[0.934]				[-2.164]
$\beta_{RD\text{-}HML}$	0.014**		-0.006	-0.000	0.014**		0.002	0.003
	[2.280]		[-0.892]	[-0.066]	[2.397]		[0.405]	[0.428]
Avg. RD-MV		0.042***	0.048***	0.044***		0.043***	0.040***	0.044***
		[4.829]	[4.860]	[4.828]		[3.819]	[3.300]	[3.534]
Intercept	0.016***	0.011**	0.011**	0.014***	0.011***	0.010**	0.010***	0.012***
	[3.286]	[2.420]	[2.287]	[3.027]	[2.996]	[2.488]	[2.673]	[3.191]
Average R^2	0.472	0.475	0.515	0.547	0.466	0.464	0.511	0.544
Number of months	342	342	342	342	342	342	342	342

Panel B. Firm-Level Analysis

	RET								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\beta_{RD\text{-}HML}$	0.005*		0.002	0.001	0.001	0.002	0.002	0.007*	0.007*
	[1.730]		[0.886]	[0.316]	[0.284]	[1.401]	[1.423]	[1.951]	[1.805]
RD-MV		0.023***	0.019***	0.015***	0.014**	0.034***	0.034***	0.033***	0.034***
		[3.536]	[3.888]	[2.783]	[2.464]	[3.837]	[3.904]	[3.577]	[3.749]
ln(ME)				-0.001	-0.001	-0.001**	-0.001**	-0.001**	-0.001**
				[-1.353]	[-1.167]	[-2.214]	[-2.024]	[-2.316]	[-2.343]
ln(BM)				0.003***	0.003***	0.003***	0.003***	0.002***	0.004***
				[2.828]	[2.851]	[2.901]	[2.845]	[2.666]	[4.251]
RET(2,12)				-0.000	-0.001	0.001	0.001	0.001	0.000
				[-0.117]	[-0.285]	[0.436]	[0.524]	[0.475]	[0.222]
OP					0.000	0.001	0.001	0.001	0.001
					[0.557]	[0.927]	[0.966]	[0.842]	[1.205]
INV					-0.004***	-0.004***	-0.005***	-0.005***	-0.004***
					[-5.031]	[-3.611]	[-3.880]	[-3.772]	[-3.443]
REV						-0.048***	-0.052***	-0.050***	-0.054***
						[-6.680]	[-6.691]	[-6.746]	[-7.653]
ln(TURN)						0.001	0.001	0.001	0.001
						[0.801]	[0.699]	[0.782]	[0.907]
ILLIQ						0.003	0.003	0.003	-0.003
						[0.242]	[0.187]	[0.182]	[-0.147]
LIQU						0.017	0.018	0.021	0.019
						[0.894]	[1.019]	[1.121]	[0.975]
ln(IVOL)						-0.001	-0.001	-0.001	-0.002
						[-0.532]	[-0.871]	[-0.799]	[-1.158]
MAX						0.005	0.010	0.011	0.011
						[0.299]	[0.567]	[0.643]	[0.641]
O-A						0.002**	0.002**	0.002**	0.003**
						[2.169]	[2.196]	[2.013]	[2.361]
ln(DISP)						-0.003***	-0.003***	-0.003***	-0.003***
						[-6.107]	[-6.360]	[-6.283]	[-7.471]
KZ index						-0.000	-0.000	-0.000	-0.000
						[-1.114]	[-1.088]	[-1.241]	[-0.934]
PPE-A						0.002	0.002	0.003	0.002
						[0.574]	[0.626]	[0.817]	[0.629]
Z-score						-0.000	-0.000	-0.000	-0.000*
						[-1.398]	[-1.090]	[-1.275]	[-1.835]
β_{MKT}							0.003*	0.002	0.002
							[1.771]	[1.435]	[1.573]
β_{SMB}							0.000	0.000	0.000
							[0.671]	[0.631]	[0.623]
β_{HML}							0.000	-0.000	-0.000
							[0.131]	[-0.109]	[-0.419]
β_{UMD}							-0.001		
							[-0.622]		
β_{RMW}								0.001	0.001
								[0.334]	[0.434]

β_{CMA}								0.001	0.001
								[0.995]	[0.711]
Intercept	0.005**	0.008**	0.006**	0.013***	0.013***	-0.010	-0.016*	-0.012	-0.019**
	[2.017]	[2.329]	[2.392]	[2.925]	[2.960]	[-1.001]	[-1.738]	[-1.224]	[-2.068]
Industry FE									Yes
Average R^2	0.011	0.005	0.014	0.033	0.038	0.121	0.139	0.139	0.209
Obs.	548,203	622,793	548,203	545,715	493,034	200,122	200,122	200,122	200,122

TABLE 8
Investor Sentiment and the R&D Anomaly

This table reports the results of our analysis of size-adjusted R&D quintile portfolios conditional on investor sentiment states. Sentiment state is defined as high (low) if the beginning-of-period value of the Baker and Wurgler (2006) sentiment index is higher (lower) than the sample median. We divide the R&D stocks independently into 2×5 size and *RD-MV* portfolios and calculate the equal and value-weighted average monthly portfolio returns within each state. We adjust for the size effect by equal averaging the average returns of the two size portfolios within each R&D rank. Panel A reports the portfolio average excess returns of the quintile and zero-cost spread (Portfolio 5-1) portfolios. Panels B and C report the estimated alpha from the *C-4* and *FF-5* models.

Panel A. Size-Adjusted Excess Returns

		EW						*VW*					
Portfolio	Sentiment	1 (L)	2	3	4	5 (H)	5-1	1 (L)	2	3	4	5 (H)	5-1
RET	High	-0.32%	0.00%	0.25%	0.51%	0.93%	1.25%	-0.26%	-0.10%	0.18%	0.31%	0.51%	0.78%
t-stat		[-0.646]	[0.005]	[0.499]	[0.927]	[1.489]	[4.637]	[-0.663]	[-0.240]	[0.425]	[0.658]	[1.001]	[3.089]
RET	Low	1.08%	1.42%	1.71%	2.00%	2.38%	1.29%	0.94%	1.12%	1.26%	1.59%	1.76%	0.82%
t-stat		[3.027]	[3.783]	[4.212]	[4.394]	[4.317]	[4.208]	[3.010]	[3.226]	[3.376]	[3.820]	[3.388]	[2.538]
RET	H-L	-1.40%	-1.42%	-1.46%	-1.49%	-1.44%	-0.04%	-1.20%	-1.22%	-1.08%	-1.27%	-1.25%	-0.05%
p-value		0.027	0.031	0.031	0.046	0.096	0.914	0.017	0.024	0.055	0.044	0.087	0.912

Panel B. C-4 Alpha

Portfolio	Sentiment	1 (L)	2	3	4	5 (H)	5-1	1 (L)	2	3	4	5 (H)	5-1
α	High	-0.30%	0.03%	0.23%	0.55%	0.99%	1.29%	-0.44%	-0.28%	0.01%	0.18%	0.30%	0.74%
t-stat		[-1.504]	[0.134]	[1.511]	[2.683]	[3.237]	[4.374]	[-3.422]	[-2.153]	[0.110]	[1.107]	[1.355]	[2.785]
α	Low	-0.04%	0.22%	0.49%	0.57%	0.75%	0.80%	-0.16%	0.00%	0.10%	0.22%	0.13%	0.29%
t-stat		[-0.338]	[2.011]	[3.929]	[3.480]	[3.273]	[3.442]	[-1.426]	[0.043]	[0.958]	[1.627]	[0.601]	[1.199]
α	H-L	-0.26%	-0.19%	-0.26%	-0.03%	0.23%	0.49%	-0.28%	-0.28%	-0.09%	-0.05%	0.17%	0.45%
p-value		0.375	0.532	0.286	0.945	0.461	0.186	0.155	0.144	0.780	0.993	0.495	0.202

Panel C. FF-5 Alpha

Portfolio	Sentiment	1 (L)	2	3	4	5 (H)	5-1	1 (L)	2	3	4	5 (H)	5-1
α	High	-0.08%	0.25%	0.45%	0.80%	1.23%	1.31%	-0.28%	-0.10%	0.13%	0.41%	0.45%	0.73%

t-stat		[-0.320]	[0.935]	[2.384]	[3.195]	[3.358]	[4.385]	[-2.122]	[-0.737]	[1.217]	[2.609]	[2.063]	[2.820]
α	Low	-0.18%	0.12%	0.40%	0.60%	0.91%	1.09%	-0.01%	0.03%	0.16%	0.38%	0.40%	0.41%
t-stat		[-1.438]	[1.118]	[3.343]	[3.926]	[4.221]	[5.099]	[-0.073]	[0.306]	[1.508]	[2.741]	[1.976]	[1.770]
α	H-L	0.10%	0.13%	0.05%	0.19%	0.32%	0.22%	-0.27%	-0.13%	-0.03%	0.03%	0.05%	0.32%
p-value		0.580	0.538	0.658	0.402	0.379	0.550	0.194	0.635	0.879	0.707	0.738	0.350

TABLE 9
Limits To Arbitrage and the R&D Anomaly

This table reports the results of the difference-in-differences analysis that exploits the exogenous variation in limits to arbitrage, specifically the restriction to short selling, provided by the pilot program under Regulation SHO between June 2005 and July 2007. The sample includes all of our R&D stocks that are constituents of the Russell 3000 index. Panel A compares the average firm characteristics of the pilot and non-pilot R&D stocks at the end of 2003 (prior to the announcement of Regulation SHO). We also report the mean firm characteristics for both pilot and non-pilot R&D stocks that are in the long and short legs, respectively. The difference-in-means test results are reported for the full Russell R&D sample, and the long and short legs. Panels B and C report the difference-in-differences estimates of the effect of reducing the short-sale restriction on the equal and value-weighted average returns of the high (long), low (short) and high-minus-low (long-minus-short spread) R&D quintile portfolios, respectively. The R&D quintile portfolios are formed using the full-sample breakpoints as in Table 1. We report results based on excess returns, and risk-adjusted returns by the *C-4* and *FF-5* models (computed by adding the estimated intercepts to the *C-4* and *FF-5* regression residuals). *Pilot* is a treatment dummy equal to one for pilot stocks under Regulation SHO, and zero otherwise. *During* is a dummy that equals one for the period June 2005 to July 2007 and zero otherwise. *Post* is a dummy equal to one after July 2007 and zero otherwise. *T*-statistics based on Newey and West (1987) robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Panel A. Summary Statistics (Mean values at 2003m12)

	Sample: R&D stocks in the Russell 3000 index								
	Treatment			Control			Treatment minus Control		
	Full	Short	Long	Full	Short	Long	Full	Short	Long
RD-MV	0.086	0.012	0.364	0.107	0.011	0.447	-0.021**	0.000	-0.082
Ln(ME)	6.684	7.327	5.610	6.613	7.307	5.499	0.071	0.020	0.112
Ln(BM)	-0.802	-1.113	-0.407	-0.710	-0.926	-0.109	-0.092*	-0.186*	-0.297**
RET(2,12)	0.697	0.484	1.403	0.690	0.352	1.778	0.007	0.132	-0.376
OP	0.163	0.523	-0.519	0.091	0.310	-0.430	0.073	0.214	-0.089
Inv	0.074	0.211	-0.236	0.071	0.207	-0.163	0.003	0.005	-0.073
REV	0.045	0.050	0.022	0.039	0.041	0.057	0.006	0.008	-0.035
Ln(TURN)	0.542	0.227	0.797	0.576	0.260	0.928	-0.034	-0.034	-0.131
ILLIQ	0.002	0.003	0.004	0.003	0.002	0.004	0.000	0.001	0.000
LIQU	0.012	0.005	0.033	0.011	0.001	0.045	0.001	0.004	-0.012
Ln(IVol)	-4.041	-4.331	-3.529	-4.049	-4.352	-3.601	0.008	0.021	0.072
MAX	0.059	0.044	0.082	0.061	0.045	0.091	-0.002	-0.001	-0.009
O-A	1.041	0.900	1.359	1.145	0.929	1.297	-0.104	-0.029	0.061
Ln(Disp)	-6.040	-7.129	-3.981	-5.952	-6.891	-3.850	-0.088	-0.238	-0.131
KZ index	-4.838	-4.193	-5.169	-5.078	-4.009	-3.903	0.240	-0.183	-1.266
PPE-A	0.182	0.211	0.147	0.189	0.268	0.155	-0.007	-0.057***	-0.008
Z-score	22.699	20.890	14.850	22.586	19.682	16.494	0.113	1.208	-1.644

Panel B. Equal weighted portfolio returns

	RET			*C-4 adjusted returns*			*FF-5 adjusted returns*		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pilot×During	0.0019	-0.0005	0.0024	0.0024	-0.0006	0.0030	0.0017	-0.0005	0.0021
	(0.3160)	(-0.2377)	(0.3960)	(0.4122)	(-0.2994)	(0.5160)	(0.2848)	(-0.2172)	(0.3598)
Pilot×Post	-0.0004	0.0001	-0.0006	-0.0003	0.0002	-0.0005	-0.0014	0.0001	-0.0015
	(-0.0848)	(0.0487)	(-0.0937)	(-0.0536)	(0.0834)	(-0.0790)	(-0.2697)	(0.0479)	(-0.2600)
Pilot	0.0020	0.0010	0.0010	0.0022	0.0008	0.0015	0.0036	0.0003	0.0033

	(0.7666)	(0.7579)	(0.3508)	(0.8745)	(0.6234)	(0.5017)	(1.3805)	(0.2247)	(1.1282)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	912	912	912	912	912	912	912	912	912
R^2	0.9450	0.9696	0.8536	0.7925	0.7107	0.7911	0.7692	0.7524	0.7656

Panel C. Value-weighted portfolio returns

	RET			*C-4 adjusted returns*			*FF-5 adjusted returns*		
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pilot×During	0.0062	-0.0011	0.0074	0.0061	-0.0007	0.0068	0.0061	-0.0007	0.0068
	(0.6799)	(-0.3426)	(0.8433)	(0.7250)	(-0.2298)	(0.8048)	(0.7333)	(-0.2245)	(0.8008)
Pilot×Post	-0.0174**	0.0012	-0.0186**	-0.0209***	0.0012	-0.0221***	-0.0208***	0.0010	-0.0218***
	(-2.4485)	(0.3674)	(-2.4148)	(-3.0514)	(0.3893)	(-2.9144)	(-3.0168)	(0.3143)	(-2.8594)
Pilot	0.0083**	-0.0008	0.0091**	0.0094***	-0.0017	0.0111***	0.0096***	-0.0015	0.0111***
	(2.1119)	(-0.4363)	(2.1175)	(2.7332)	(-0.8995)	(2.8029)	(2.7895)	(-0.7955)	(2.8027)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	912	912	912	912	912	912	912	912	912
R^2	0.8442	0.9119	0.7371	0.6739	0.6394	0.6883	0.6548	0.6331	0.6770

APPENDIX A.1
Detailed Variable Definitions

Accounting variables are from Compustat with fiscal year end in calendar year *t*-1 are matched with monthly CRSP returns from July of year *t* to June of year *t+1*.

Variable	Definition	Source
RD-MV	Total R&D expenditure in fiscal year ending in year *t-1* divided by total market capitalization as at the end of December year *t-1*.	Compustat and CRSP
ln(BM)	Log of the book-to-market equity ratio. Following Fama and French (1993), book equity is total assets for year *t-1*, minus liabilities, plus balance sheet deferred taxes and investment tax credit if available, minus preferred stock liquidating value if available, or redemption value if available, or carrying value. Market equity is shares outstanding at the end of December of year *t-1* times share price.	Compustat and CRSP
ln(ME)	Log of the market capitalization (shares outstanding times share price) at the end of June of year *t*.	CRSP
RET(-12,-2)	Momentum is calculated as the cumulated compounded stock return from month *j-12* to month *j-2*, which is updated monthly.	CRSP
OP	Operating profitability, computed as revenue minus costs of goods sold, minus selling, general and administrative expenses, minus interest expenses, all divided by book equity.	Compustat
INV	Investment, computed as the change in total assets from fiscal year ending in year *t-2* to the fiscal year ending in year *t-1*, divided by *t-2* total assets.	Compustat
REV	Short-term reversal is the stock return in the previous month following Jegadeesh (1990).	CRSP
ln(TURN)	Following Chordia et al. (2001), a stock's turnover ratio is share trading volume divided by the number of shares outstanding. We use the log turnover ratio of month *j-2* to explain returns in month *j*.	CRSP

ILLIQ	Following Amihud (2002), a stock's market illiquidity in month *j* is measured as the average of the daily ratio of absolute stock return to trading volume: $$ILLIQ_{i,j}=Avg[(\lvert R_{i,d}\rvert)/VOLD_{i,d}]$$ where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and trading volume of stock *i* on day *d* in month *j*. Following Gao and Ritter (2010), institutional features are taken into account by dividing the NASDAQ volume by 2.0, 1.8, 1.6 and 1 for the periods prior to Feb 2001, between Feb 2001 and Dec 2001, between January 2002 and Dec 2003 and Jan 2004 and later years, respectively. Similar to Bali et al. (2014), we require a stock to have at least 15 daily return observations within month *j* to compute this illiquidity measure and scale this variable by 10^6.	CRSP
LIQU	Following Bali et al. (2014), a stock's illiquidity shock is computed as: $$LIQU_{i,j} = ILLIQ_{i,j} - AVGILLIQ_{i,j-12,j-1}$$ where $ILLIQ_{i,t}$ is the monthly stock illiquidity measure of Amihud (2002) of stock *i* in month *j* and $AVGILLIQ_{i,j\text{-}12,j\text{-}1}$ is the mean $ILLIQ_{i,t}$ over the past 12 months (from month *j-12* to *j-1*).	CRSP
ln(IVOL)	Following Ang et al. (2006), a stock's monthly idiosyncratic volatility (*IVol*) is defined as the log of one plus the standard deviation of residuals from the Fama and French (1993) three factor model, estimated using daily returns within that month. We require a stock to have at least 15 daily stock return observations for the estimation.	CRSP
MAX	The maximum daily return in the previous month following Bali et al. (2011).	CRSP

O-A	The intensity of organization capital, computed as the ratio of the stock of organization capital to total assets. The stock of organization capital is computed as the capitalized SG&A expenses based on the perpetual inventory method. Specifically, a firm's stock of organization capital (*OC*) is computed by recursively cumulating its deflated value of SG&A expenses as follows: $$OC_{i,t} = (1 - \delta_o) \cdot O_{i,t-1} + (SG\&A_{it} / cpi_t),$$ where δ_o is the depreciation rate and cpi_t is the US consumer price index. For each firm, we start the recursive estimation of its stock of organizational capital since its first observation in the Compustat database. Following prior studies, we treat missing observations of the SG&A expenses as zero. The initial stock of organization capital is defined as: $$OC_0 = SG\&A_1 / (g + \delta_o).$$ Following prior studies (Eisfeldt and Papanikolaou, 2013), a depreciation rate of 15% is used. The growth rate *g* is assumed to be 10%.	Compustat
ln(DISP)	Analyst forecast dispersion is the log of the cross-sectional standard deviation of analysts' one-year ahead earning per share forecasts. Following Zhang (2006), we calculate the time series of monthly standard deviations in each fiscal year as analysts update their forecasts and then average these to obtain a measure for each firm's fiscal year. To reduce the problem of heteroskedasticity, this average is scaled by the fiscal year end market price before taking the log.	I/B/E/S

KZ index	Financial constraint index, computed according to Kaplan and Zingales (1997) as follows: $KZ\ Index = -1.002\times(Cash\ flow) + 0.283\times(Tobin's\ Q) + 3.139\times(Leverage) - 39.368\times(Dividends) - 1.315\times(Cash\ holdings)$, where *Cash flow* is the sum of income before extraordinary items and depreciation and amortization, divided by total net property, plant & equipment. *Tobin's Q* is computed as ((book value of assets + market equity (at fiscal year end))-book equity-Deferred Taxes)/book value of assets). *Leverage* is the sum of long-term debt and debt in current liabilities, divided by the sum of long-term debt, debt in current liabilities and total stockholders' equity. *Dividend* is the sum of common and preferred dividends, divided by total net property, plant & equipment. *Cash holdings* are the cash and short-term investments to total net property, plant & equipment. The total net property, plant & equipment used in computing this *KZ index* is lagged by one year.	Compustat and CRSP
PPE-A	Net property, plant & equipment to total book value of assets, as a measure of asset tangibility.	Compustat
Z-score	The Altman (1968) Z-score measure for bankruptcy prediction. Following Altman (1968), we estimate the *Z-score* as: $Z\text{-}score = 1.2\times(WC/TA) + 1.4\times(RE/TA) + 3.3\times(EBIT/TA) + 0.6\times(MVEQ/DEBT) + 0.999\times(SALE/TA)$, where *WC, TA, RE, EBIT, MVEQ, DEBT* and *SALE* are working capital, total assets, earnings before interest and taxes, market equity value, book value of debts and total sales. For easier interpretation of our regression coefficient we divide the *Z-score* by 1000.	Compustat
Pilot	A treatment dummy variable equal one when a R&D stock is designated as a pilot stock under Regulation SHO, and zero otherwise.	Fang et al. (2016), SEC (2004)
During	A dummy variable equal one between June 2005 and July 2007, and zero otherwise.	SEC (2004)
Post	A dummy variable equal one after July 2007, and zero otherwise.	SEC (2004)