CONSERVATIVE ACCOUNTING AND RISK: THE CASE OF RESEARCH & DEVELOPMENT[*]

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Abstract

We investigate the role of conservative accounting in conveying information on cash flow uncertainty and systematic risk by considering the case of research and development (R&D) expenditures. By expensing R&D, conservative accounting aims to convey the long term-structure of uncertain expected earnings of firms that invest in R&D. We consider the link among R&D activity, equity duration and discount rate risk within an Intertemporal Capital Asset Pricing (ICAPM) framework. Consistent with our predictions, we find that equity duration increases with R&D intensity, discount rate betas are higher for R&D intensive firms, while cash flow betas do not depend on R&D intensity. Our results suggest that the well documented in the literature positive relation between current R&D activity and future returns is a result of higher risk exposure of R&D intensive firms. A hedge portfolio analysis shows that the mispricing explanation of the positive R&D-returns relation is not economically significant under the ICAPM.

JEL Classification: G12, G14, M40, M41, N22.

Keywords: R&D, Conservative Accounting, Duration, ICAPM, Discount Rate Beta, Cash Flow Beta.

[*]This version: January 2017. We are grateful to Vasiliki Athanasakou, Jose Carabias Palmeiro, Mark Clatworthy (dissertation committee), Victoria Dickinson, Bjorn Jorgensen, Gikas A. Hardouvelis, Richard D. F. Harris (dissertation committee), Panos N. Patatoukas, Li Qu (discussant), Andy Stark, Martin Walker and participants at the 2015 American Accounting Association Annual Meeting and the 2016 Macquarie Quantamental Research Seminar Series for their valuable comments and suggestions. Dimos gratefully acknowledges financial support from the Xfi Center for Finance & Investment, University of Exeter Business School. Any remaining errors are our responsibility alone.

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1 Introduction

Accounting standard setters have not attempted to formally incorporate notions of uncertainty and risk into the financial reporting framework, albeit financial reporting is intended to inform investors and creditors about these.[1] Nevertheless, unconditional conservative accounting can be interpreted as a form of accounting for "risk adjustment" conveying useful information to financial statement users (Barker and Penman 2016).[2] However, this "uncertainty accounting" (Penman 2016; Penman and Zhang 2016) is not necessarily fully informative about a firm's exposure to priced risk factors. Transactions that are expensed because of conservative accounting [e.g., the United States General Accepted Accounting Principles (US GAAP) treatment of research and development (R&D) expenditure] do not necessarily command a higher risk premium than transactions resulting in the recognition of assets on the balance sheet. In this paper we report empirical results on the cash flow uncertainty and risks associated with R&D expenditure. Our analysis serves to emphasize the importance of uncertainty-driven conservative accounting and the ability of financial statements to inform users about a firm's exposures to priced risk factors.

There is extensive evidence that, on average, R&D is priced by the market as an asset leading to future economic benefits. For example, R&D expenditure increases equity value on average and is incrementally useful in predicting future cash flows (e.g., Sougiannis 1994; Lev and Sougiannis 1996). However, R&D expenditure is expensed under US GAAP. The expensing of R&D is justified not because there are no future economic benefits expected from R&D, but because the economic benefits that are anticipated are insufficiently probable (too uncertain) to qualify R&D expenditure as the cost of an asset.[3] This treatment supports

[1] Accounting standard setters appeal to notions of uncertainty in future cash flows in reaching conceptual definitions of assets and liabilities. For example, paragraph 25 of the FASB Statement of Financial Accounting Concepts (SFAS) No. 6 (1985, pg. 16) defines assets as "...probable future economic benefits obtained or controlled by a particular entity as a result of past transactions or events". Consequently, transactions generating insufficiently probable future benefits are expensed, while those deemed to create sufficiently probable future benefits are capitalized.

[2] Historical cost accounting deals with uncertainty by deferring the recognition of earnings until uncertainty concerning future cash flows has been sufficiently resolved (Penman 2016; Barker and Penman 2016; Penman and Reggiani 2013). Unconditional conservative accounting occurs when future cash flows are insufficiently probable. The role of cash flow uncertainty in asset recognition has led Penman and Reggiani (2013), Penman (2016) and others to view unconditional accounting conservatism as a form of accounting for risk adjustment. Unconditional accounting conservatism violates the matching principle, but this serves to communicate risk to financial statement users, especially if the presentation of the income statement is designed accordingly (Penman 2016; Barker and Penman 2016)

[3] US GAAP requires the immediate expensing of R&D investment (SFAS No. 2 1974), with some exceptions in special cases (software development costs – SFAS No. 86 1985; acquired-in-progress R&D – SFAS No. 141-R 2007). On the other hand, International Financial Reporting Standards (IFRS) require develop-

the view that income statement items resulting from accounting conservatism embedded in the conceptual definition of an asset are informative about a firm's cash flow uncertainty.

However, it is unlikely that accounting conservatism loads all the information relevant to understanding a firm's cash flow uncertainty into the income statement. It is even less likely that the income statement is fully informative about risk that is relevant in security pricing. A firm's cost of capital depends also on properties of cash flows generated by assets and liabilities on the balance sheet. The balance sheet values could be more informative about risk factor exposures and risk premia than income statement items resulting from conservative accounting for uncertainty. Furthermore, the sources and nature of risk exposures might be different for income statement items. Our empirical analysis shows this to be the case for research and development expense.

Our empirical analysis proceeds as follows. We first consider the role of R&D in cash flow timing as a contributing factor to equity risk. The duration measure commonly used to capture discount rate risk exposure in fixed income securities can also be applied to equities. Equity duration is a summary measure of the term structure of expected earnings, and it is relevant because systematic risk depends on duration (Dechow et al. 2004). Earnings deferral by expensing R&D expenditure reduces short-term earnings and induces longer-run earnings growth when revenues or cost savings from successful R&D projects are realized. Furthermore, the time horizon over which the economic benefits from successful R&D projects are derived can be long, relative to the economic benefits derived from operating assets in place. Hence, Cornell (1999) argues that equity duration increases with R&D intensity. We use R&D intensity as a measure of the importance of R&D to a firm. We define R&D intensity as the ratio of capitalized and amortized R&D to market value of equity. We document that equity duration increases with R&D intensity, most prominently for small firms. This suggests that R&D intensity should capture information about discount rate risk in equities; the valuation of firms with cash flows weighted more into the future is sensitive to systematic changes in the discount rate factor (Dechow et al. 2004).

We then use well-established empirical tools from the asset pricing literature in finance to identify two components in unexpected stock returns and we test whether these components are priced by investors. The return decomposition proposed by Campbell (1991) isolates two components of returns: cash flow news and discount rate news. The covariance of a firm's

ment costs to be capitalized because future cash flows are deemed to become sufficiently probable once development commences.

returns with market cash flow news captures exposure to permanent systematic cash flow shocks, while the covariance of a firm's returns to market discount rate news captures the exposure to transitory intertemporal systematic risk. Campbell (1993, 1996) and Campbell and Vuolteenaho (2004) suggest that investors demand a higher risk premium for exposure to systematic cash flow risk (bad beta) than for exposure to discount rate risk (good beta). We test the extent to which R&D intensity contributes towards cash flow risk and discount rate risk, after controlling for other risk factors identified in the finance literature and known to contribute to priced risk.

Having documented that R&D intensive firms have higher cash flow duration, we predict that R&D intensive firms are exposed to more discount rate risk. However, to the extent that the cash flow benefits arising from R&D result from technological innovation specific to the firm, the covariance of cash flows with market cash flows should not depend on R&D intensity. In other words, we predict that R&D intensity does not affect cash flow risk. Consistent with our predictions, we document that discount rate betas are higher for R&D intensive firms, while cash flow betas do not depend on R&D intensity. Taken together, our findings suggest that systematic risk increases with R&D intensity and the channel through which systematic risk depends on R&D, is discount rate risk. Our research design confirms that our results are not a manifestation of the value/growth "anomaly" (e.g., Donelson and Resutek 2012).

Our results on equity duration and discount rate risk are consistent with a risk-based explanation of the relation between R&D intensity and future returns, but they do not on their own confirm that R&D activity generates a risk premium. To test whether the predictability of future returns by R&D reflects a risk premium or mispricing we conduct a battery of asset pricing tests. We compare the results for our base Intertemporal Capital Asset Pricing Model (ICAPM) to those obtained for a set of popular benchmarks: the single-factor Capital Asset Pricing Model (CAPM), the two-news factor model (two-factor)[4] and the Fama and French (1993) three-factor model (FF) in our main analysis; and the Carhart (1997) four-factor FF model (FF4), the Khan (2008) four-factor model (Khan-F4) and the Hou et al. (2015) Q-factor model (Q-FM) in our robustness analysis. The asset pricing metrics/tests yield mixed results; we cannot dismiss the mispricing explanation for the cross-section. Nevertheless, the R&D-related mispricing explanation is economically

[4]The two-factor model is a generalization of Campbell (1993)'s discrete time ICAPM which does not restrict the price of risk of cash flow and discount rate shocks.

insignificant. A hedging strategy that goes long on portfolios of R&D intensive firms and short on portfolios of firms with no R&D yields statistical insignificant abnormal returns based on the ICAPM model.

Our paper is relevant to an extensive literature documenting a positive association between R&D and future stock returns. This literature offers competing explanations for the predictability of returns by R&D. While many studies suggest that R&D is mispriced (e.g., Penman and Zhang 2002; Lev et al. 2005; Ali et al. 2012) or is a transformation of the value/growth "anomaly" (Donelson and Resutek 2012), others report evidence consistent with the R&D premium being compensation for risk (e.g., Chambers et al. 2002; Li 2011). Our paper challenges the mispricing interpretation of the R&D effect and it shows that the R&D effect is not a transformation of the value-growth anomaly. In fact, our paper complements the risk-based explanation.

Our study develops the risk-based explanation in prior research by identifying an economic channel –equity duration– through which the risk inherent in R&D arises using asset pricing tests. The key insight from our analysis is that R&D-related risk contributes to the component of systematic risk arising from exposure to stochastic discount rates.

Our results also contribute to the recent literature seeking links between financial statement numbers, the accounting principles on which they depend on and relevant dimensions of risk. In particular, Penman and Reggiani (2013) suggest that deferral of earnings recognition due to conservative accounting causes accounting information to reflect risk. Penman (2016) elaborates on this point: accounting bears on the discount for risk, as the risk adjustment in (stochastic) discount rates depends on the sequence of expected earnings. Our results directly build on this emerging line of research. In our context, the accounting information about the timing of cash flows is reflected by the impact of R&D intensity on equity duration. In turn, we find that this information leads to a positive relation between R&D intensity and systematically priced discount rate risk. Our choice of asset pricing model permits this inference because it accommodates stochastic discount rates and investors' intertemporal preferences.[5]

Finally, our approach is relevant to recent developments in the accounting research which obviate the need for time-varying discount rates (or expected returns) in the investigation

[5]Investors' intertemporal preferences map the hedging demands against shocks to future wealth. In our case, investors require compensation to hold the stocks of R&D intensive firms which generate high duration cash flows. The valuations of high duration R&D active firms are sensitive to systematic changes in the discount rates, the denominators.

of the relation between accounting numbers and returns (e.g., Callen 2009; Lyle and Wang 2015; Penman 2016). Lyle and Wang (2015) acknowledge that the time-variation in expected returns is important in investment decisions;[6] assets pricing models should, at least, implicitly assume time-varying expected returns to minimize the magnitude of pricing errors. Our hedging strategy analysis corroborates this argument. The ICAPM, which assumes time-varying expected returns, minimizes the magnitude of pricing errors of high R&D stocks to an extent that they cannot be exploited by a simple trading strategy.

The rest of the paper is organized as follows: Section 2 describes the data; Section 3 describes the research design, including the ICAPM, the estimation of cash flow and discount rate betas and the asset pricing tests; Section 4 reports the results; Section 5 contains robustness checks and sensitivity analyses; finally, Section 6 concludes.

2 Data

2.1 The Test Portfolios

To identify the risk in R&D, we base our analysis on test portfolios independently sorted on three variables: (a) size, (b) book-to-market ratio (BE/ME) and (c) R&D intensity. The asset pricing literature shows that portfolios formed on size and book-to-market have sufficient variation in expected returns to yield powerful tests of asset pricing models. Adding the third sorting dimension using R&D intensity enables us to establish the contribution of R&D to equity risk. We construct the R&D intensity measure for firm i at time t as follows: $R\&D\,intensity_{i,t} = \frac{R\&DC_{i,t}}{ME_{i,t}}$, where $R\&DC_{i,t}$ denotes R&D capital (i.e., the capitalized and amortized current and past R&D expenditures) and $ME_{i,t}$ is the market value of equity of the firm i in December of calendar year $t-1$.[7] We follow Lev and Sougiannis (1996) to estimate $R\&DC_{i,t}$ (see Appendix A).[8] $R\&DC_{i,t}$ corresponds to the value that would have

[6] See also Ang and Liu 2004.

[7] Scaling R&D capital with market value of equity raises concerns of a spurious relation in the association of R&D activity with returns (e.g., Chan et al. 2001; Chambers et al. 2002). We have two (at least) reasons to advice against caution. The focus of our study is the intuition for the R&D-returns relation provided by the Campbell and Vuolteenaho (2004) ICAPM. Following Chan et al. (2001), we put the base pricing model into the most difficult test, namely, with an R&D intensity measure that has been associated with the strongest evidence of abnormal performance. Moreover, we avoid data-snooping biases in the asset pricing tests, because the ICAPM risk factors are not derived from or in similar way to the test assets (portfolios) they try explain (for an extended discussion of data-snooping biases see Lo and MacKinlay 1990 and White 2000).

[8] This R&D asset measure does not exclude firms that can capitalize software development costs under SFAS No. 86 (1985). Instead, it already capitalizes software development costs. This needs no to be an issue,

been on the balance sheet in calendar year t, if this accounting treatment had been allowed in GAAP.

We obtain accounting data from COMPUSTAT and stock market data from CRSP. Our sample spans the fiscal period from 1975 to 2012. The beginning of the sample period is the effective date of SFAS No. 2 (1974), prescribing the expensing of R&D expenditure. Following existing studies, we apply several filters prior to constructing the test portfolios. First, we retain stocks with positive and non-missing $t-1$ sales and book value of equity. Second, we consider stocks with non-negative R&D;[9] we assign the value zero to R&D expense, if the COMPUSTAT value is missing. Third, we require stocks to have been covered in COMPUSTAT records for at least two years. This mitigates the backfill bias inherent in the procedure COMPUSTAT uses to add new firms to its files (see Kothari et al. 1995). Finally, to filter out data errors and potential mismatches, we disregard firms with December market value of equity less than \$10 million (e.g., Vuolteenaho 2002). After applying these filters, the sample comprises 105,890 NYSE, AMEX and NASDAQ firm-year observations for the fiscal period from 1975 to 2012. We estimate book value of equity following the procedure in Daniel and Titman (2006) (see Appendix B).

We construct test portfolios at the end of June of calendar year t using accounting data that refer to the preceding fiscal year (i.e., $t-1$); the (minimum) six-month lag ensures that accounting information is observable to all market participants at the portfolio formation date (e.g., Fama and French 1993).[10] First, we sort stocks on size. We use the median NYSE market value of equity (ME) at the end of June at year t as the size breakpoint. This yields two size portfolios: Small and Big. Second, we sort stocks on BE/ME, where

since according to Aboody and Lev (1998) the "real" capitalizers are few. Indeed, most software firms choose to always expense, despite having some profitable software products (Mohd 2005). Mohd (2005) lists a number of reasons software firms do not capitalize software development costs. Overall, these firms choose secrecy over more disclosure and also want to signal high earnings quality.

[9] As explained by COMPUSTAT, the cases of negative R&D expenditures are very rare. Indeed, in our sample there are only nine firm-years with negative R&D expenditures. However, these are not data errors. According to COMPUSTAT's internal investigation, negative R&D expenses likely reflect prior year adjustments.

[10] Following Beaver et al. (2007), with both monthly and delisting returns available, the delisting return is: $DLR_{t,t+k} = [(1 + R_{t,t+j-1})(1 + DLR_{t,t+j})] - 1$. With missing delisting returns, we do the following. If a firm was listed on NYSE or AMEX and has been dropped by the exchange or the Security Exchange Commission (SEC; delisting codes ranging from 500 to 591, but not 501 and 502), we assume -30% delisting return (Shumway 1997). If a firm was listed on NASDAQ and has been dropped by the exchange or the SEC (delisting codes ranging from 500 to 591, but not 501 and 502), we assume -55% delisting return (Shumway and Warther 1999). If a firm was listed on any of the three exchanges and has been or will be liquidated (delisting codes ranging from 400 to 490), we assume -100% delisting return (Prakash and Sinha 2012).

BE/ME at time t is the book value of equity for the last fiscal year end, divided by ME at December of calendar year $t-1$. We use the 30^{th} and 70^{th} NYSE percentiles as BE/ME cut-off points. This results in three BE/ME portfolios: Growth (G), Medium (M) and the Value (V) BE/ME portfolios. Finally, we sort the stocks on R&D intensity. The first portfolio includes all firm-year observations with no records on R&D expenses. Firms with R&D expenses are sorted in two portfolios using the median NYSE R&D intensities as a cut-off points.[11] This yields three R&D intensity portfolios (i.e., No-R&D, Low-R&D and High-R&D) and the R&D intensive firms are represented by the High-R&D portfolios (henceforth, we use the terms "High-R&D" and "R&D intensive" interchangeably). After aggregation into the 18 portfolios each test asset has 450 monthly value-weighted returns from July 1976 to December 2013.

Panel A of Table 1 reports the annualized average excess returns for the 18 test portfolios. To calculate the excess portfolio returns, we subtract the one-month Treasury bill rate, obtained from CRSP. The results confirm the relation between R&D activity and future returns, especially among small size stocks. In the case of the small stocks subset, we observe increasing returns along the R&D intensity dimension within each BE/ME bucket. This is a preliminary indication that the relation between R&D activity and future returns is a distinct phenomenon from the value-growth anomaly.

Panel B of Table 1 displays the average number of firms in each portfolio. Diversification is preserved since there are enough observations in each portfolio. Note that observations in the big/value portfolios are considerable low. We advice against caution since our partition approach ensures that at least nine firms exist at each point in time for each portfolio.

[Insert Table 1 here.]

2.2 Duration and R&D Intensity: A Preliminary Analysis

We first examine the relation between equity duration and R&D intensity. If equity duration depends on R&D intensity, this would point to discount rate risk being a relevant distinguishing risk dimension of R&D. We follow Dechow et al. (2004) and estimate the

[11] Our choice of R&D intensity breakpoint has no theoretical justification. However, we choose the median NYSE percentile as R&D intensity cut-off point because this ensures that the test portfolios are reasonable diversified, especially in the early years of our sample. In robustness checks we use alternative R&D intensity breakpoints –and, in turn, portfolio definitions– with qualitatively similar results (see Sub-Section 5.2).

implied equity duration as the weighted average time to maturity of cash flows. The weighted components are a finite 15-year duration and a terminal period duration. We use Dechow et al. (2004)'s financial variables and forecasting parameters in the estimation. Details are provided in Appendix C.

Table 2 reports the implied equity duration for the 18 test portfolios sorted on size, BE/ME and R&D intensity. Panel A shows the average (median) equity duration of the firms within each portfolio. Panel B treats the 18 test portfolios as if they were individual firms, and it reports their implied equity duration characteristics. Specifically, it shows the sample mean (median) of the 38 annual values, where an annual value is the weighted average of the implied equity duration of the firms in each portfolio, using the portfolio weights.

[Insert Table 2 here.]

Overall, the R&D-duration link is consistent with the R&D-returns relation in Table 1; it is positive and large among small-sized classifications. Panel A indicates that for small firms and within any given BE/ME partition, the average equity duration is higher as we move from the No-R&D to the High-R&D stocks. For example, an investor holding the stock of a Small/Growth and High-R&D firm has to wait on average 2.29 years more to realize future cash flows. Panel B displays exactly the same pattern, although differences are smaller due to diversification effects. For example, a diversified investor holding the Small/Growth and High-R&D portfolio has to wait on average 1.23 years more to realize future cash flows. The duration patterns in Panels A and B are similar based on medians, indicating that results are not attributable to extreme observations.

Evidence in this sub-section is in-line with existing studies that associate R&D activity with higher equity duration (e.g., Cornell 1999). The results in Table 2 predict that, after controlling for the BE/ME effect, small R&D intensive stocks will be more exposed to discount rate risk. In the next sub-section we examine this prediction in depth using an ICAPM framework. Our ICAPM specification directly identifies the component of systematic risk attributable to discount rate news.

2.3 Risk Factors

In our main analysis, we consider the ICAPM and a set of alternative benchmark pricing models including the CAPM, the two-factor and FF three-factor model as benchmarks [also the FF4 four-factor, Khan-F4 and Q-FM in our robustness analysis (Sub-Section 5.3)]. To estimate these models, we construct the following risk factors: cash flow news (NCF) and discount rate news (NDR); and we obtain the following factor returns: excess market return ($r^e_{M,t}$), small minus big (SMB), and high minus low book-to-market (HML). All factors are measured on a monthly basis over the period from July 1976 to December 2013 (450 observations). $r^e_{M,t}$ is the difference between the log value-weighted return stock index and the log one-month Treasury bill rate (r_f), both of which are obtained from CRSP. SMB is the return spread between the portfolios of small and big firms. HML is the return spread between the portfolios of high book-to-market firms and low book-to-market firms. We obtain both SMB and HML factor returns from Professor Kenneth R. French's website.[12]

Following Campbell and Vuolteenaho (2004), we use the Vector Auto-Regression (VAR) methodology to extract the two market-wide news components – cash flow news (NCF) and discount rate news (NDR) – for the ICAPM model using state variables that predict the aggregate stock market (see Sub-Section 3.1). The state variables are: the excess log market return ($r^e_{M,t}$), the smoothed price-to-earnings ratio (PE), the term yield (TY), the small stocks value spread (VS) and the default spread (DEF).

The state variables span the months from January 1929 to December 2013 yielding 1020 time series observations. $r^e_{M,t}$ is defined as above. PE is the ratio of the S&P 500 price over the ten-year moving average of the S&P 500 earnings and is taken from Professor Robert J. Shiller webpage.[13] TY is the difference between the log-yields of ten-year Treasury bonds, from Professor Robert J. Shiller's webpage, and three-month Treasury bills, from CRSP. VS is the difference between the log-BE/ME of the small value portfolio and the log-BE/ME of the small growth portfolio at the end of June of any given year t. For the remaining months, the VS spread is constructed by adding the cumulative log returns of the small growth portfolio and subtracting the cumulative log returns of the small value portfolio realized over the last year (see Campbell and Vuolteenaho 2004). The data used to construct VS are obtained from Professor Kenneth R. French's webpage. Finally, DEF is constructed as the difference between the log-yields of Moody's BAA and AAA corporate bonds. The data on corporate bonds are obtained from the Federal Reserve Bank of St. Louis (FRED).

[12] SMB and HML factor returns are from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[13] PE and the ten-year Treasury bond rate are from: http://www.econ.yale.edu/~shiller/data.htm.

3 Methodology

3.1 The ICAPM Model

According to the Merton (1973) ICAPM, multi-period investors hedge against shocks to total wealth (market) and to unfavorable shifts in the investment opportunity set. Investors face two sources of risk: (1) covariation of asset returns with the return on the total wealth (as in the CAPM) and (2) covariation of asset returns with the state variables that describe the investment opportunity set and affect current consumption. The CAPM is a special case of ICAPM when the investment opportunity set is not stochastic (i.e., only shocks to total wealth are hedged).

Campbell (1993) derives a two-factor discrete-time version of Merton (1973)'s ICAPM. This is based on Epstein and Zin (1989, 1991) preferences and the Campbell (1991) return decomposition. The Campbell (1991) return decomposition is:

$$r_{t+1} - E_t[r_{t+1}] = NCF_{t+1} - NDR_{t+1} \tag{1}$$

where $r_{t+1} - E_t[r_{t+1}]$ is the unexpected market return, $NCF_{t+1} = \Delta E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$ is cash flow news and $NDR_{t+1} = \Delta E_{t+1} \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ is discount rate news, and ρ is the log-linearization discount factor. A risk-averse investor should be more concerned about NCF than NDR. NCF has only a wealth effect, while NDR has both a wealth effect and an offsetting investment opportunities effect. More specifically, negative (positive) NDR decreases (increases) the value of wealth today. However, negative (positive) NDR also signals better (worse) investment opportunities since less (more) needs to be saved today to earn a dollar in the future. In contrast, negative (positive) NCF decreases (increases) the value of wealth permanently, since there is no change in the investment opportunity set to offset the loss (gain).

Campbell (1993) expresses the expected return of any test asset i as a function of the NCF and NDR:

$$E_t[r_{i,t+1}] - r_{f,t+1} + \sigma_{i,t}^2/2 = \gamma cov_t(r_{i,t+1}, NCF_{t+1}) + cov_t(r_{i,t+1}, -NDR_{t+1}) \tag{2}$$

where γ is the coefficient of relative risk aversion; $\sigma_{i,t}^2$ is the return variance; and $\sigma_{i,t}^2/2$ adjusts for Jensen's Inequality.

Campbell and Vuolteenaho (2004) re-formulate the model in equation (2) in a beta representation form:

$$E_t[r_{i,t+1}] - r_{f,t+1} + \sigma^2_{i,t}/2 = \gamma\sigma^2_{M,t}\beta_{i,NCF_M,t} + \sigma^2_{M,t}\beta_{i,NDR_M,t} \tag{3}$$

where $\beta_{i,NCF,t} \equiv \frac{Cov_t(r_{i,t+1},NCF_{t+1})}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])}$ is the CF beta and $\beta_{i,NDR,t} \equiv \frac{Cov_t(r_{i,t+1},-NDR_{t+1})}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])}$ is the DR beta.[14] Equation (3) states that the risk price of the CF beta is γ times greater than the risk price of the DR beta. Moreover, the DR beta premium is restricted to equal the variance of the market portfolio.[15]

3.2 Estimating Cash Flow and the Discount Rate News

To estimate the NCF and NDR, we follow Campbell (1991) and assume that the data generating process of the state variables is a first-order VAR:

$$z_{t+1} = c + \Gamma z_t + u_{t+1} \tag{4}$$

where z_t is the $(k \times 1)$ vector of the k state variables with the excess market return as its first element, c is the $(k \times 1)$ vector of intercepts, Γ is the $(k \times k)$ matrix of coefficients, and u_{t+1} is the $(k \times 1)$ vector of the i.i.d. disturbance terms. Based on equation (4), NCF and NDR can be expressed as a linear function of the disturbance terms:

$$NDR_{t+1} = e1'\lambda u_{t+1} \tag{5}$$

$$NCF_{t+1} = (e1' + e1'\lambda)u_{t+1} \tag{6}$$

[14]Not all firms have stocks that trade frequently and/or synchronously, especially in the beginning of our sample period. The inclusion of stocks with stale prices, might affect our empirical analysis. The relation between portfolio returns and market return news might be spurious even in relatively low-frequency sampled data (such as monthly), thus, contaminating the beta estimates (e.g., Dimson 1979). Moreover, transaction prices partly react with a one-month lag to market-wide news, and this delay is more evident the smaller the firm (e.g., Lo and MacKinlay 1990). To alleviate these issues, we follow prior research and estimate each beta by adding a lag (e.g., Dimson 1979; Fowler and Rorke 1983; Lo and MacKinlay 1990; Kothari et al. 1995; Campbell and Vuolteenaho 2004). Specifically, we include one lag of each market return news component in the beta numerators $\Big\{$i.e., $\beta_{i,NCF,t} \equiv \frac{Cov_t(r_{i,t+1},NCF_{t+1})}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])} + \frac{Cov_t(r_{i,t+1},NCF_t)}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])}$ and $\beta_{i,NDR,t} \equiv \frac{Cov_t(r_{i,t+1},-NDR_{t+1})}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])} + \frac{Cov_t(r_{i,t+1},-NDR_t)}{Var_t(r^e_{M,t+1}-E_t[r^e_{M,t+1}])}\Big\}$.

[15]The $\beta_{i,NCF,t}$ and $\beta_{i,NDR,t}$ sum-up to the CAPM beta, approximately. The two beta definitions ensure that the ICAPM is an extension of the CAPM (see Merton 1973; Campbell 1993). The ICAPM collapses to the CAPM with same risk prices for both the CF and the DR betas (Campbell and Vuolteenaho 2004).

where $e1$ is a vector with first element one and the remaining elements zero, $\lambda \equiv \rho\Gamma(I-\rho\Gamma)^{-1}$ maps the state variables shocks into the two market-wide news components, and ρ is the log-linearization discount factor [see also equation (1)]. We follow standard practice in the related asset pricing literature and set $\rho = 0.95$, implying a constant 5% annual average consumption-to-wealth ratio (see for instance, Campbell 1993).

We estimate equation (4) using the following state variables: excess log market return (r^e_M), smoothed price-to-earnings ratio (PE), term yield (TY), small stocks value spread (VS) and default spread (DEF). We choose these variables because prior studies suggest that they explain the long-term time variation in market returns (e.g., Campbell and Vuolteenaho 2004; Campbell et al. 2013, and references therein). For brevity, the VAR(1) results are reported and discussed in Appendix D.

Using the residuals of the estimated VAR(1), we construct the NDR and NCF time series [see equations (5) and (6), respectively]. Figure 1 shows the evolution of NCF and NDR across time. The gray shaded areas correspond to the recessions as defined by the National Bureau of Economic Research (NBER).

[Insert Figure 1 here.]

Estimates are in-line with the findings documented by Campbell (1991) and Campbell and Vuolteenaho (2004). Specifically, the NDR series is more volatile than NCF, suggesting that, overall, NDR dominates the time variation of returns. Also the two news series do not move together – hence they capture separate sources of risk (correlation coefficient: 0.006).

3.3 Estimating the Pricing Models

Our base model is the unconditional version of the discrete time ICAPM:

$$E[R_i - R_f] = \gamma\sigma^2_M\beta_{i,NCF} + \sigma^2_M\beta_{i,NDR} \tag{7}$$

which restricts the NDR premium to equal the variance of the market portfolio [see equation (3)]. As is standard in the asset pricing literature, $R_i - R_f$ denotes simple excess returns of a test asset i.

In our main analysis, we evaluate the performance of the base model against three benchmarks. The *first* benchmark is the CAPM:

$$E[R_i - R_f] = \lambda_M \beta_{i,M} \tag{8}$$

where λ_M is the market price risk and $\beta_{i,M}$ is the CAPM beta.

The *second* benchmark is a generalization of Campbell (1993)'s discrete time ICAPM with no restrictions on the NCF and NDR risk prices. We refer to this model as the two-factor model:

$$E[R_i - R_f] = \lambda_{NCF} \beta_{i,NCF} + \lambda_{NDR} \beta_{i,NDR} \tag{9}$$

The *third* benchmark is the three-factor Fama and French (1993) (FF) model:

$$E[R_i - R_f] = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML} \tag{10}$$

for consistency with prior research that seeks to explain the R&D-returns relation (e.g., Lev and Sougiannis 1996).

We estimate all pricing models with a two-step Fama-MacBeth (1973) approach. First, we estimate the betas for any given test portfolio ($i = 1, 2, ..., 18$): for models in (7) and (9), we follow the beta definitions given in Sub-section 3.1; and for models in (8) and (10), we run time-series regressions.[16] Second, we estimate the risk prices with one cross-sectional regression for each time period, with the first-step betas serving as independent variables. This is:

$$R_{i,t} - R_{f,t} = g_t + \sum_j \lambda_{j,t} \beta_{i,j} + \alpha_{i,t} \quad i = 1, 2, ..., 18 \; for \; each \; t \tag{11}$$

where g_t is the constant, $\lambda_{j,t}$ is the risk price of the j^{th} factor ($j = 1, 2$ for the ICAPM, $j = 1$ for the CAPM, $j = 1, 2$ for the two-factor model and $j = 1, 2, 3$ for the FF model), $\beta_{i,j}$ is the beta of the i^{th} portfolio on the j^{th} factor and $\alpha_{i,t}$ is the residual term which captures the pricing error for each portfolio i.

We estimate the Fama-MacBeth (1973) constant (g), risk premia (λ_j) and pricing errors (α_i) as the time-series averages of the fitted and residuals values of the cross-sectional

[16] This is the approach in Campbell and Vuolteenaho (2004). Recall that the cash flow and discount rate beta estimations include one lag of the respective market-wide news components in their numerators. Those estimates deviate from the fitted values of the commonly used first-step time-series estimation.

regressions in (11):

$$\hat{g} = \frac{1}{T}\sum_{t=1}^{T}\widehat{g}_t \tag{12}$$

$$\hat{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T}\widehat{\lambda}_{j,t} \tag{13}$$

$$\hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}\widehat{\alpha}_{i,t} \tag{14}$$

Since a primary objective in the paper is to examine whether the ICAPM and the benchmark models are able to explain the returns of all test portfolios, the two step approach offers advantages over available alternatives.[17] [18]

3.4 Evaluating the Pricing Models

We first test whether an asset pricing models implies a reasonable risk free rate (zero-beta rate, R_{zb}) and, hence, fits the equity premium adequately. R_{zb} is the return on a test portfolio with zero sensitivity to a pricing model's risk factors. A model fits the equity premium, if it implies a R_{zb} that is no different from the prevailing risk free rate observed in the market (Black 1972). The difference between the implied R_{zb} and the observed risk free rate is given by the fitted constant in the second-step cross-sectional regression (i.e., $\hat{g} = R_{zb} - R_f$). The test requires the estimation of two versions for each model. Version one sets the cross-sectional constant to zero, restricting the zero-beta rate to be equal to the observed risk-free rate. Version two has unrestricted constant, and the zero-beta rate is not equal to the observed risk-free rate.[19] A pricing model adequately fits the equity premium, if its unrestricted constant is statistically insignificant (i.e., $\hat{g} = R_{zb} - R_f \equiv 0$; e.g., Jagannathan and Wang 1996; Cochrane 2005).

[17] Alternatives include the one-step time-series regression approach, and the one-step generalized method of moments discount factor (GMM/DF) approach. However one-step approaches are not appropriate because cash flow news and discount rate news are not tradeable portfolios. Hence, their prices of risk need not to be equal to the sample means of cash flow and discount rate news, as theory requires (see Brennan et al. 2004, for example).

[18] Asset pricing models used by prior research have failed to explain the returns of small and R&D intensive portfolios (e.g., Chan et al. 2001). That is, small and R&D intensive stocks have realized higher returns than predicted by a version of the FF model. Additionally, the returns of these portfolios also exhibit high variance. Therefore, the one-step GMM/DF that uses the Hansen (1982) optimal weighting matrix would allow models to place low weights on the high return variance small and R&D intensive portfolios. However, this would likely eliminate the R&D effect that is our primary interest.

[19] Note the following implications. The restricted version implies that the investor allocates her wealth between Treasuries and equities. The unrestricted version implies that the investor allocates her wealth only in equities.

We also consider five alternative metrics to evaluate the asset pricing models under consideration. The first metric is the R^2, defined as follows:

$$R^2 = 1 - \frac{\hat{\alpha}'\hat{\alpha}}{[(\overline{R}_i^e) - \sum_i (\overline{R}_i^e)]'[(\overline{R}_i^e) - \sum_i (\overline{R}_i^e)]} \tag{15}$$

where $\hat{\alpha}$ is the vector of the pricing errors estimated from the cross-sectional regression; and $\overline{R}_i^e$ is the vector of average return over the risk-free rate for portfolio i. The R^2 can take negative values for poorly performing models under the restricted zero-beta rate versions.

The R^2 metric weights all test portfolios equally, even though some are less volatile than others (Campbell and Vuolteenaho 2004; Khan 2008). To address this concern we consider two further metrics, both of which test the null hypothesis of zero pricing errors (in the second-step Fama-MacBeth 1973 cross-sectional regression; $H_0 : \hat{\alpha} = 0$). With respect to the first metric, we estimate the covariance matrix of the cross-sectional regression pricing errors:

$$cov(\hat{\alpha}) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\alpha}_{i,t} - \hat{\alpha}_i)(\hat{\alpha}_{i,t} - \hat{\alpha}_i)' \tag{16}$$

and compute the test statistic as follows:

$$alpha = \hat{\alpha}' cov(\hat{\alpha})^{-1}\hat{\alpha} \;\sim\; \chi^2_{n-j} \tag{17}$$

where n is the number of test portfolios; j is the number of factors for any given asset pricing model.[20] If $alpha$ exceeds the χ^2_{n-j} 5% critical value we reject the null hypothesis of zero pricing errors.

We also report the Composite Pricing Error (CPE) used by Campbell and Vuolteenaho (2004):

$$CPE = \hat{\alpha}\Omega^{-1}\hat{\alpha} \;\sim\; \chi^2_{n-j} \tag{18}$$

where Ω is a diagonal matrix with the portfolio return variances on the main diagonal. We do not consider the off-diagonal elements of the variance-covariance matrix to avoid the dimensionality issue (e.g., Campbell and Vuolteenaho 2004; Ledoit and Wolf 2004). If CPE exceeds the 5% critical value, we reject the null hypothesis of zero pricing errors. The

[20]The Shanken (1992) correction for the sampling error in the first-step beta estimations cannot be applied in the case of the ICAPM and the two-factor model. This is because we do not obtain the corresponding betas from time-series regressions. To be consistent, we do not estimate the Shanken (1992) correction for the remaining models too.

critical value for each pricing model's CPE is obtained from a bootstrap distribution (see Appendix E).

We supplement the analysis by considering the magnitude of the pricing errors across models (Hansen and Jagannathan 1997). To this end, we report two measures of pricing errors magnitudes. The first is the square root of the CPE, defined as:

$$PEM = [\hat{\alpha}\Omega^{-1}\hat{\alpha}]^{1/2} \tag{19}$$

The second statistic is the Hansen and Jagannathan (1997) distance measure:

$$HJ = [\hat{\alpha}'(\overline{R}_i^{e\prime}\overline{R}_i^{e})^{-1}\hat{\alpha}]^{1/2} \tag{20}$$

This statistic uses the moment matrix of expected portfolio excess returns for weighting matrix. Effectively, HJ is the maximum pricing error per unit of payoff norm (Hansen and Jagannathan 1997).

4 Results

4.1 Cash Flow and Discount Rate Betas

Table 3 reports the estimated betas for the 18 size, BE/ME and R&D intensity portfolios, as well as the differences in betas between Value minus Growth partitions (V-G) and High-R&D minus No-R&D (H-N) partitions. Panels A and B show the results for the CF and the DR betas, respectively. The t-statistics, shown in parentheses, are based on bootstrap standard errors. With the bootstrap simulation we take into account the uncertainty both in the estimation of the news terms with the VAR methodology, and the uncertainty in the computation of the respective betas. Details about the bootstrap simulation are available in Appendix E.

[Insert Table 3 here.]

Four main of observations follow from Table 3. First, the DR betas increase with R&D intensity within any given size and BE/ME partition. Within each size and BE/ME subset, the differences between the DR betas of High-R&D and No-R&D portfolios are positive and statistically significant. In other words, Table 3 supports the view that the R&D effect on systematic risk is distinct from –and not subsumed by– the growth/value effect (see for instance, Donelson and Resutek 2012). The higher betas for High-R&D firms suggest that these stocks are exposed to more systematic DR risk than No-R&D stocks. Hence, they are expected to earn higher returns. Second, the magnitude of CF betas increases along the R&D intensity dimension within any given size and BE/ME partition, but differences in cash flow betas are insignificant. The lack of significance comes as no surprise given that NCF are well diversified at the market level (e.g., Hecht and Vuolteenaho 2006). Third, both CF and DR betas decrease as size increases for any given BE/ME and R&D intensity subset. Finally, value stocks have higher CF betas and lower DR betas than growth stocks. The last two findings are in-line with those of Campbell and Vuolteenaho (2004) and Campbell et al. (2010, 2013).

Overall, our findings provide new insights to the risk channels capable of explaining of the relation between R&D activity and future returns proposed in the literature (e.g., Chan et al. 2001; Chambers et al. 2002; Kothari et al. 2002). In particular, our results show that R&D intensive stocks are exposed to higher discount rate risk than No-R&D firms. This finding is predicted by our earlier results showing that R&D intensity is associated with higher equity duration (e.g., Cornell 1999; Campbell and Vuolteenaho 2004).

4.2 The Prices of Cash Flow Risk and Discount Rate Risk

Table 4 presents the results of the Fama-MacBeth (1973) cross-sectional regressions for the ICAPM and the three main benchmark models. For any given asset pricing model, the first (second) column reports results in the case where the zero-beta rate is (is not) constrained to equal the risk-free rate. Panel A reports the estimated prices of risk, the Fama-MacBeth (1973) Newey-West adjusted t-statistics in parentheses and the annualized risk premia in square brackets. Panel B reports the R^2, $alpha$, CPE, PEM and HJ for each model-version.

[Insert Table 4 here.]

Panel A reveals that the ICAPM handles the equity premium adequately; the excess return on the zero-beta portfolio is insignificant (i.e., $\hat{g} = R_{zb} - R_f \equiv 0$). In addition, the price of risk for NCF is higher (between 38% and 29%) than for NDR (around 3%). The positive and large difference in the two risk premia is also confirmed by the two-factor model.

Panel B shows that the ICAPM performs relatively well, even though the number of free parameters is low. In particular, the ICAPM explains a reasonable proportion of cross-sectional variation in test portfolio returns (around 27%). The PEM and HJ statistics are similar to the corresponding statistics for the best performing benchmarks, namely, the FF model and the two-factor model. Turning to the zero pricing errors t-statistics, the null hypothesis and, therefore, the underlying model, is rejected if $alpha$ and CPE exceed the 5% critical values obtained from the normal and a bootstrap distribution, respectively (reported below each statistic). As is the case for all benchmark models, we reject the null hypothesis of zero pricing errors ($H_0 : \hat{\alpha} = 0$) based on the $alpha$ statistics. In contrast, based on the CPE statistics we cannot reject the null hypothesis of zero pricing errors ($H_0 : \hat{\alpha} = 0$) for the ICAPM with constrained zero-beta portfolio and both versions of the news-factor model (generalized ICAPM). In sum, based on these mixed results, we cannot dismiss a mispricing explanation of the cross-section (that includes the R&D-returns relation too).

Figures 2 and 3 plot the expected versus the realized mean excess returns for the constrained and unconstrained zero-beta rate models, respectively. Panels (a), (b), (c) and (d) correspond to the ICAPM, the CAPM, the two-new factor and the FF models, respectively. The red asterisks correspond to the High-R&D test portfolios. The 45° line depicts where the test portfolios would lie in the case of a perfect fit model. Co-ordinates below (above) the 45° line correspond to negative (positive) pricing errors, $\hat{\alpha}_i$, for a given test portfolio.

[Insert Figure 2 here.]

[Insert Figure 3 here.]

The figures provide graphical illustrations of the findings in Table 4. The CAPM fits the data poorly. The performance of the ICAPM is comparable to the performances of the FF and the two-factor models. Notably, red stars, denoting High-R&D portfolios, are on average closer to the 45° line under the ICAPM than under the FF model. The extreme outliers below the 45° line confirm prior literature and show that small/growth stock returns are difficult to predict. The extreme outliers above the 45° line show that the excess returns of some High-R&D stocks are understated by all pricing models considered by this study. We further examine the magnitude of mispricing for High-R&D stocks in the next sub-section.

The results described in this sub-section indicate that the FF model performs well in terms of R^2. However, this result should be viewed with caution for at least four reasons.

First, the FF model is an empirical model and lacks theoretical motivation. Second, the high explanatory power of the FF model may just reflect the additional degrees of freedom; the FF model has three parameters that are freely estimated (Campbell and Vuolteenaho 2004). Third, the FF model handles the equity premium inadequately, since the excess return on the zero-beta portfolio is significant and large in magnitude (i.e., $\hat{g} = R_{zb} - R_f \neq 0$). Fourth, similar to the other models, the FF model yields significant pricing errors.

In sum, our findings are mixed and suggest that none of the asset pricing models used explains the cross-section of realized returns perfectly. However, the ICAPM combines adequate empirical power with theoretical-economic support. In the following sub-section, we explicitly examine the mispricing explanation of the relation between R&D activity and future returns by means of a trading strategy.

4.3 Risk Premia versus Mispricing

This section investigates the relative pricing ability of the ICAPM with respect to the R&D-returns relation only. The mispricing literature suggests that investors underprice R&D intensive stocks. To quantify this potential mispricing, we form portfolios by going long on High-R&D stocks and short on No-R&D stocks within each size and BE/ME bucket. This zero investment trading strategy enables us to hedge against the (size- and BE/ME-adjusted) R&D intensity effect on returns that is not captured by our pricing models. Thus, we now examine the mispricing explanation of the R&D-returns relation from a different angle. Here, we consider pricing errors for individual test portfolios and not for the cross-sectional average as in Sub-Section 4.2. A pricing model is unable to explain the R&D-returns relation, if it generates R&D-mispricing that is exploitable with our trading strategy.

We form six hedge portfolios long on High-R&D stocks and short on No-R&D stocks for each size and BE/ME bucket. For any given pricing model, the average abnormal return of a hedge portfolio is the average pricing error on the long portfolio minus the average pricing error on the short portfolio. Recall, the average pricing error of a (long or short) portfolio is the mean of the residuals, ($\hat{\alpha}_i$, where i=1 to 18) from the second-step cross-sectional regression [see (11) and (14)]. In Table 5, we illustrate the procedure with which we form the six hedge portfolios (HP_s, where s=1 to 6).

[Insert Table 5 here.]

Table 6 shows the annualized abnormal returns and their Fama-MacBeth (1973) Newey-West t-statistics in parentheses of the hedge portfolios for any given asset pricing model.

[Insert Table 6 here.]

Overall, the ICAPM results indicate that the R&D-related mispricing is economically and statistically insignificant. Specifically, we observe that the ICAPM model yields insignificant hedge portfolio abnormal returns and explains the R&D-returns relation in all but one case.

After controlling for discount rate and cash flow risk, R&D cannot be profitably exploited. The only exception occurs for large value stocks. Note that in this case the hedge portfolio, HP_6, earns a negative abnormal return. This is inconsistent with the suggestion that investors underprice High-R&D stocks.

In contrast, the CAPM is unable to capture the R&D effect on returns. The CAPM effectively generates similar pricing errors for the test portfolios (see Figures 2 and 3). Table 6 reflects that the CAPM's pricing errors for No-R&D and High-R&D portfolios cancel each other out in our long-short trading strategy within each size and BE/ME subset.

Interestingly, the FF model also fails to explain the R&D-returns relation, since hedge portfolio returns for small firms are statistical significant (i.e., HP_1, HP_2 and HP_3). The hedge portfolio tests confirm that the most serious problem with the FF model is in relation to the pricing of small stocks (e.g., Fama and French 2015). Our results suggest that a dimension of this problem is related with R&D intensity.

The results from the hedge portfolio tests underscore the importance of pinning the risk explanation for the R&D-returns relation to the characteristics of R&D activity. We have argued that R&D activity channels risk through increased equity duration. The hedge portfolio tests further support this explanation empirically. The risk-duration link, as reflected by the ICAPM, suggests that R&D is appropriately priced to reflect the discount risk effects of R&D on equity duration.

5 Robustness Checks

We perform a number of additional exercises to provide reassurance on the robustness of our results. Full details of the robustness checks are reported in Appendix F, but we summarize the results here.

5.1 Quarterly Observations

We sample data with monthly frequency, but even with this low frequency stale prices might contaminate our betas. To alleviate this issue, we estimated betas by adding one lag of each market news terms in their numerators. Here we move the sample frequency one notch down, and we sample quarterly data. By using an even lower frequency, we avoid the "curse" of stale prices and the ambiguous use of lags in the beta estimations. We run all our empirical analyses with quarterly-sampled data and assess the robustness of our main findings. Specifically, we have estimated the betas, the prices of risk, the evaluation metrics and the hedge portfolio annualized abnormal returns for any given model with quarterly-sampled data. All the results are analogous to those obtained with monthly-sampled data.

5.2 Alternative Breakpoints and Portfolio Definitions

Portfolio construction based on accounting-based effects is an empirical issue. We construct our portfolios with arbitrarily chosen R&D intensity breakpoints. To examine the robustness of this choice, we use alternative R&D intensity breakpoints. Instead of annually splitting R&D active firms using the NYSE median value, here we annually separate them using the 30^{th} and the 70^{th} as well as the 40^{th} and the 60^{th} NYSE percentiles. We repeat our analyses for the expanded set of test portfolios (size and BE/ME specifications are the same). Our checks demonstrate that our main results are robust to reasonable changes in R&D intensity breakpoints. The choice of R&D intensity breakpoints makes little difference to: the R&D-returns relation; the R&D-duration relation; the CF and DR betas; and the prices of risk and hedge portfolio abnormal returns for all models/versions. We advocate the NYSE median R&D intensity specification, because it ensures in any given month each portfolio consists of at least nine firms. Under the alternatives, there are a few portfolio-months with no allocated firms.

5.3 Additional Benchmark Models

We confirm that considering additional benchmark models does not add incremental information to our main analysis. We also consider: the Carhart (1997) four-factor FF model; the Khan (2008) four-factor model; and the Hou et al. (2015) Q-factor model. Using the initial set of test portfolios, we estimate the risk prices, the evaluation metrics and the hedge portfolio abnormal returns for the three additional benchmark models. Qualitatively, the results of this exercise are already documented with the main set of benchmarks. These empirically-motivated models also: (1) have higher R^2s than the ICAPM but with more degrees of freedom too; (2) some risk factors are not priced or get theoretically invalid prices; (3) generate unreasonably high excess zero-beta rates, hence, do not fit the equity premium; (4) violate the null hypothesis of zero pricing errors, thus, generate large pricing errors for the cross-section; and (5) result to statistical significant abnormal hedge portfolio returns for small firms, hence, generate profitable R&D-related mispricing.

We do not include these models in the main body, because our objective is not to identify the best performing model. Rather we seek to assess the relative pricing ability of the ICAPM with respect to the R&D effect on returns. The expanded set of benchmark models re-affirms the conclusion that the ICAPM performs relatively well. The ICAPM combines theoretical underpinnings with empirical power. Hence, it supports the duration risk channel as an explanation of the positive R&D-returns relation. The details on the pricing ability of the additional benchmark models are provided in Appendix F.

5.4 Financial Constraints and R&D Intensity: An Alternative Risk Channel?

Li (2011) advocates a positive interplay between financial constraints and R&D. The author observes that R&D is typically irreversible, since it requires constant cash injections to be viable. As such, financially constrained R&D intensive firms are more likely to mothbal/discontinue R&D projects, which makes these projects risky. In support, Li (2011) demonstrates that the positive R&D-return relation prevails only among financially constrained firms, and the positive constraints-return relation exists only among R&D-active firms. Financial constraints is a reasonable alternative explanation for the risk in our R&D intensive portfolios. The higher risk of High-R&D portfolios, established by means of DR betas, may just as well reflect the risk inherent in financially constrained R&D intensive firms rather than the risk inherent in the equity duration.

To rule out this possibility, we measure the financial constraints characteristics of our test portfolios with the Hadlock and Pierce (2010) index (HPI).[21] We look at the sam-

[21] We also use the Lamont et al. (2001) version of the Kaplan-Zingales (1997) financial constraints index (KZ). We obtain qualitatively similar results, which are available upon request. We discuss the caveats of the KZ in Appendix F.

ple means/medians of the annual HPI portfolio-level values, which are the value-weighted averages of the HPI values of the firms in each portfolio. We also check the percentage proportions of firm-years within each test portfolio that have top tercile HPI values, and they can be classified as constrained. To the extent that financial constraints are the source of priced risk, we expect High-R&D portfolios to exhibit higher HPI values *and* to proportionally consist of more financially constrained firms than No-R&D portfolios.

Overall, our robustness checks produce mixed results. High-R&D test portfolios are subject to similar financial constraints as the No-R&D test portfolios, but they, proportionally, have more individual High-R&D firms classified as constrained. Specifically, we observe negligible variation across the HPI estimates across our test portfolios. Mean/median HPI values do not change from No-R&D to High-R&D test portfolios. However, the percentage of firm-years classified as constrained is slightly increased in small and High-R&D test portfolios. Collectively, we view these results as evidence that R&D-related financial constraints appear to diversify in aggregate portfolios. Given the focus on aggregate portfolios and priced risk, we believe that the R&D-duration risk channel, established by the paper, is not directly affected by financial constraints.

Note that we do not rule out Li (2011)'s R&D-constraints hypothesis. However, we provide evidence suggesting that financial constraints is not the channel through which systematic risk depends on R&D. Also, note that our setting is not directly comparable to Li (2011). More importantly, both analyses are subject to the well-documented measurement error in the existing financial constraint metrics.[22]

6 Summary and Conclusion

Some argue for a change in the conservative R&D accounting in favor of recognizing part of R&D expenditure as asset in the balance sheet. Others argue that such a change will downplay some firm-level risk-bearing characteristics related to R&D activity. We complement the risk view by connecting conservative R&D accounting with the economic channel through which systematic risk in R&D intensive firms arises. We provide evidence that highlight the ability of conservative R&D accounting to inform users about the R&D-

[22]The financial constraints proxy employed by Li (2011) and ourselves have been heavily criticised by Farre-Mensa and Ljungqvist (2016), who argue that it captures the life cycle stage of a firm rather than financial constraints *per se*.

induced exposure to priced risk. Conservative R&D accounting informs users about the long-time-ahead expected earnings that may result from current R&D expenditures. The accounting information about the long-lasting time sequence of R&D-related cash flows is reflected by the positive effect of R&D activity on equity duration. In turn, this effect leads to a positive relation between R&D activity and systematic discount rate risk. We validate this process by employing an asset pricing model –ICAPM– that directly measures the dimension of systematic risk –discount rate– relevant to the equity duration characteristics of R&D activity and the corresponding conservative R&D accounting.

Our empirical analysis has three main findings. First, R&D activity indeed results to increased equity duration. Second, R&D activity is associated with systematic risk through the sensitivity to the market portfolio's discount rate news. Three, extensive asset pricing tests suggest that the evidence on mispricing cannot be exploited in the market. We, thus, argue that R&D expensing does not appear to lead to economically significant mispricing and conveys information about risk and equity duration. However, the investigation is far from over. Whether and why R&D is misvalued is part of a broader investigation on whether and why innovation is misvalued by the capital markets (e.g., Cohen et al. 2013; Hirshleifer et al. 2013). We leave that investigation for future research.

We acknowledge that our results may be subject to a number of limitations. First, Chen and Zhao (2009) express concerns that the return decomposition into cash flow and discount rate news is sensitive to the VAR's specification. These concerns have been allayed by Campbell et al. (2010) and Engsted et al. (2012) to a large extent. Second, Koh and Reeb (2015) show that some firms may choose not to report their R&D expenses despite their active involvement with R&D. This finding should have implications mostly for our classification of No-R&D and Low-R&D firms. However, the occurrence of No-R&D firms incurring but not reporting material research expenses would have worked against, rather than in favour of, finding differences in returns, equity durations and DR betas between High-R&D and No-R&D test portfolios. We, nonetheless, acknowledge that a more detailed investigation taking into account patent filings would possibly yield stronger results. Finally, we follow prior research in estimating our proxy for R&D intensity by capitalising and then, amortizing current and past R&D expenditures using the amortization rates presented in Lev and Sougiannis (1996). Arguably, the estimation approach we follow involves assumptions which may bias our R&D intensity variable. However, it is difficult to predict the direction of this bias.

Our study responds to calls for considering alternative asset pricing models in assessing the mispricing explanation of the relation between R&D activity and future returns (Chambers et al. 2002; Skinner 2008). Donelson and Resutek (2012) also comment that popular empirical asset pricing models are not well-specified, especially with respect to certain subsets of firms. The ICAPM shows potential as it accommodates investors' exposure to stochastic discount rates. This feature is important in evaluating the returns of R&D intensive firms, given their increased equity duration. However, we acknowledge that the empirical application of ICAPM has shortcomings. We hope that future developments in asset pricing will offer improvements in that respect.

Appendices

Appendix A: Off-balance sheet R&D capital ($R\&DC_{i,t}$)

The estimation of the "off-balance sheet" R&D asset $R\&DC_{i,t}$ follows the procedure outlined in Lev and Sougiannis (1996). We measure $R\&DC_{i,t}$ for firm i at time t, as the proportion of current and past R&D expenditure (COMPUSTAT mnemonic XRD) that is still productive in June of a given calendar year t. Prior research lacks a consensus over the useful life and the amortization rates of R&D assets. Lev et al. (2005) argue that an industry-specific schedule is more reliable than a uniform amortization schedule. An industry-specific schedule is able to reflect the variation in the useful lives across industries (Shi 2003). Therefore, we adopt the amortization rates and useful lives that correspond to the two-digit SIC industry classification of firm i as estimated by Lev and Sougiannis (1996). Evidence suggest that these amortization rates have not dramatically changed over time. Amir et al. (2007) repeat the Lev and Sougiannis (1996) procedure on an updated sample, and their results are identical.

We compute $R\&DC_{i,t}$ as follows:

$$R\&DC_{i,t} = \sum_{k=0}^{N-1} R\&D_{i,t-k}(1 - \sum_{j=0}^{k} \delta_j) \tag{A.1}$$

where k takes the value of a given year of the industry-specific useful life of the R&D expenditures and δ_j corresponds to the amortization rates in Lev and Sougiannis (1996, pg. 121)'s Table 3.

Appendix B: Book Value of Equity

The book value of equity is estimated following Daniel and Titman (2006). The starting block is the shareholder's equity (COMPUSTAT mnemonic SEQ). If missing, we substitute its value with the sum of total common equity (COMPUSTAT mnemonic CEQ) and preferred stockholder's equity, at par value (COMPUSTAT mnemonic PSTK). When the last two variables are missing, we use total assets (COMPUSTAT mnemonic AT) minus total liabilities (COMPUSTAT mnemonic LT). If none of the above yields a valid figure for shareholder's equity, we treat shareholder's equity as missing for this year.

To estimate book value of equity, we subtract from the shareholder's equity the value of the preferred stock. The latter is estimated with the redemption value (COMPUSTAT mnemonic PSTKRV), liquidating value (COMPUSTAT mnemonic PSTKL) or carrying value (COMPUSTAT mnemonic PSTK), in that order, as available. If all of the PSTKRV, PSTKL or PSTK are missing, we treat book value of equity as missing for that year.

Finally, if book value of equity is not missing, we add balance sheet deferred taxes (COMPUSTAT mnemonic TXDITC) and subtract the post retirement benefit asset (COMPUSTAT mnemonic PRBA).

Appendix C: Implied Equity Duration Measurement Procedure

To estimate the implied equity duration (DUR) of the 18 test portfolios (Sub-Section 2.2), we use the Dechow et al. (2004) measure. We forecast cash flows for a 15-year finite period as well as for a terminal period. Similar to the Macaulay bond duration, DUR captures the weighted average time to maturity of the finite and terminal cash flows. On any given firm i and (calendar) year t, DUR is:

$$DUR_{i,t} = \underbrace{\frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{ME_{i,t}}}_{\text{Finite-period part}} + \overbrace{\left(T + \frac{1+r}{r}\right) \times \frac{ME_{i,t} - \sum_{s=1}^{T} CF_{i,t+s}/(1+r)^s}{ME_{i,t}}}^{\text{Terminal-period part}} \tag{C.1}$$

where $s = 1$ to 15; $T = 15$; CF is the forecasted cash flows; ME is the market value of equity.

To forecast CFs, we employ Dechow et al. (2004)'s set of financial variables/ratios and forecasting parameters. Recall, calendar year t uses accounting data that refer to the preceding fiscal year (i.e., $t-1$). The financial variables are: (1) earnings before extraordinary items in $t-1$ over one-year-lagged book value of equity (ROE); (2) book value of equity in fiscal year ending in $t-1$ (BE); (3) sales growth in fiscal year ending in $t-1$ (g); and (4) ME as of December $t-1$. The fixed across firms and time forecasting parameters are: (1) autocorrelation coefficient for ROE (α_{ROE}) – 0.57; (2) cost of equity capital (r) – 0.12; (3) autocorrelation coefficient for g (α_g) – 0.24; and (4) long-term g (μ_g) – 0.06. With these inputs, we estimate equation (C.1) following Dechow et al. (2004)'s steps. For the finite period part:

1. Revert g to the mean, μ_g, using the autocorrelation coefficient α_g. Apply the forecasted gs to estimate BEs [i.e., $BE_{i,t+s} = BE_{i,t+s-1}(1 + g_{t+s})$].

2. Revert ROE to the mean, r, using the autocorrelation coefficient α_{ROE}. Apply the forecasted ROEs to estimate earnings (Es) [i.e., $E_{i,t+s} = BE_{i,t+s-1}(ROE_{i,t+s})$].

3. The forecasted Es and BEs are used to extract CF forecasts [i.e., $CF_{i,t+s} = E_{i,t+s} - (BV_{i,t+s} - BV_{i,t+s-1})$].

4. Using r to discount, estimate the sum of the present values of the forecasted CFs [i.e., $\sum_{s=1}^{T} PV(CF_{i,t+s})$]. Multiply the discounted CFs with the time subscripts, s,

and sum the products [i.e., $\sum_{s=1}^{T} sPV(CF_{i,t+s})$].

5. Obtain the 15-year duration as: $DUR_{i,fin,t} = \sum_{s=1}^{T} sPV(CF_{i,t+s}) / \sum_{s=1}^{T} PV(CF_{i,t+s})$.

6. The weight for the 15-year duration is: $w_{fin,i,t} = \sum_{s=1}^{T} PV(CF_{i,t+s}) / ME_{i,t}$. Effectively, $W_{fin,i,t}$ is the part of the value reflected in the current ME, expected to be realized during the detailed forecasting period (Dechow et al. 2004).

For the terminal period part:

1. The terminal period duration is the same for all firm-years [i.e., $DUR_{ter} = T + (1 + r)/r \approx 15 + 1.12/0.12 \approx 24.33$].

2. The weight for the DUR_{ter} is the part of the value reflected in the current ME, expected to be realized after T=15 years (i.e., $w_{ter,i,t} = 1 - w_{fin,i,t}$)

Then for any firm-year, the implied equity duration is the weighted sum of the finite and terminal durations: $DUR_{i,t} = w_{fin,i,t} DUR_{fin,i,t} + w_{ter,i,t} DUR_{ter}$.

Appendix D: Estimation of *NCF* and *NDR* and VAR(1)

We estimate the VAR(1) of equation (4). Recall:

$$z_{t+1} = c + \Gamma z_t + u_{t+1}$$

where z_t is the $(k \times 1)$ vector of the k state variables at time t ($k = 1$ for $r^e_{M,t}$, 2 for PE_t 3 for TY_t, 4 for VS_t and 5 for DEF_t). The estimated NCF and NDR are obtained from equations (6) and (5), respectively.

[Insert Table D1 here.]

Table D1 shows the estimated coefficients, Newey-West t-statistics in parentheses, adjusted R^2 and F-statistics. We can see that the PE is a significant predictor; increases in PE forecast a lower excess market return. TY is positive and significant return predictor. However, VS (negative coefficient) and DEF (negative coefficient) are not significant. We acknowledge the possibility that those findings might be affected by the multicollinearity among the persistent state variables (e.g., VS–DEF correlation: 0.62). Nevertheless, in the return-prediction regression all five state variables are jointly significant, which suffices for the estimation of the NCF and the NDR (Campbell et al. 2010, 2013).

Appendix E: The Bootstrap Simulation

The CF and the DR betas are not time-series regression coefficients. To obtain standard errors, also accounting for the errors-in-variables from the NCF–NDR estimation, we use a bootstrap simulation.[23] We employ Runkle (1987)'s approach as follows.

1. Estimate the VAR(1) of equation (4) and save the coefficient matrix, Γ, and the residuals matrix, υ_{t+1}; where t takes values from 1 to 1020.

2. Draw with replacement a sample, ${\upsilon_{t+1}}^{\star}$, from the estimated residuals in step 1. The new and the original samples have the same size. We partition ${\upsilon_{t+1}}^{\star}$ with the test portfolios returns in two groups; January 1929 to June 1976; and July 1976 to December 2013. This ensures that the simulated data are observable during our sample period (see Campbell and Vuolteenaho 2004).

3. Recursively estimate the new state variables series, ${z_{t+1}}^{\star}$, by adding the product ${z_t}^{\star} \times \Gamma$ with ${\upsilon_{t+1}}^{\star}$ from step 2. To initialise the process we use the December 1928 values.

4. Steps 1 to 3 are repeated $2,500$ times.

We use the $2,500$ samples in obtaining new NCF and NDR, as described in Appendix D. Then, we compute $2,500$ CF and DR betas for the ICAPM along with the $V - G$ and $H - N$ differences. The standard deviation of the series of betas and beta differences are the standard errors, used in the t-statistics of Table 3. Finally, we estimate the pricing models (see Subsection 3.3) and, in turn, the corresponding CPE metrics [see equation (18)].[24] As in Campbell and Vuolteenaho (2004), for each model in consideration, the 5^{th} percentile value of the $2,500$ CPE realizations is the critical value to reject the zero pricing errors hypothesis. The 5% critical values are reported in Panel B of Table 4 (and robustness Tables F1 and F4).

[23]The assumption is that the VAR is not misspecified (see Berkowitz and Kilian 2000).
[24]For the FF model, we partition its risk factors with ${\upsilon_{t+1}}^{\star}$ as in step 2.

Appendix F: Details of the Robustness Checks

F.1 Quarterly Observations

By sampling data with monthly frequency we still run the risk of stale prices contaminating our beta estimates. Following Campbell and Vuolteenaho (2004), we include one-month lags of market news on the numerators of our betas. An alternative is to use even lower frequency observations (e.g., Kothari et al. 1995, and references therein). Under this alternative, we no longer need to add lags of market-wide news to estimate the betas.

[Insert Table F1 here.]

[Insert Table F2 here.]

Table F1 shows the prices of risk and the evaluation metrics for any given model, when quarterly-sampled observations are used. Table F2 shows the corresponding hedge portfolio annualized abnormal returns. All point estimates are analogous to those reported in our main analysis. Sampling frequency does not appear to affect our main inferences.

F.2 Alternative II breakpoints

We consider alternative R&D intensity breakpoints to form our test portfolios. Specifically, we use the 30^{th} and the 70^{th} as well as the 40^{th} and the 60^{th} NYSE percentiles as cut-off points. Below, we discuss results for the portfolio definitions with the 30^{th}–70^{th} R&D intensity cut-offs. Using the definitions with the 40^{th}–60^{th} R&D intensity cut-offs produces identical results.

We define 24 value-weighted test portfolios, constructed as the intersection of two size, three BE/ME and four R&D intensity portfolios. The size and BE/ME classifications are those used in our main empirical analysis (see Sub-Section 2.1). We then assign firm-years with missing R&D expenditures to the No-R&D portfolio. Firm-years with R&D intensity below the 30^{th} NYSE percentile are assigned to the Low-R&D portfolio; firm-years with R&D intensity between the 30^{th} and 70^{th} NYSE percentiles are assigned to the Medium-R&D portfolio; and the remaining firm-years are assigned to the High-R&D portfolio.

[Insert Table F3 here.]

Table F3 presents the annual excess returns on the 24 portfolios (Panel A); and the differences in CF and DR betas between the High-R&D and the No-R&D portfolios within each size and BE/ME subset (Panel B). The findings are qualitatively similar to those discussed in our main empirical analysis. Panel A confirms the positive relation between R&D activity and future returns, especially among small size stocks. In the case of the small stocks subset, we observe statistically significant increasing returns along the R&D intensity dimension within each BE/ME subset. Panel B re-affirms the lack of an R&D effect on CF sensitivity. More importantly, it also confirms that R&D intensive stocks are exposed to higher DR risk than No-R&D stocks. Reassuringly, the differences on CF and DR betas are similar in magnitude and statistical significance with those reported in Table 3.

It must be noted that under the alternative R&D intensity breakpoints there are some months where no firms are allocated in portfolios. In these instances, we substitute missing returns with those of portfolios in the same size and BE/ME classification and with the closest R&D intensity. To maintain the diversification of idiosyncratic noise, we maintain the portfolio definitions obtained with the NYSE median R&D intensity cut-offs for our main empirical analysis. This setting ensures that in any given month, each portfolio consists of at least nine firms.

F.3 Additional Benchmark Models

We also consider: the Carhart (1997) four-factor FF model (FF4); the Khan (2008) four-factor model (Kahn-F4); and the Hou et al. (2015) Q-factor model (Q-FM). Table F4 presents the risk prices and the evaluation metrics for the additional benchmark models and, for comparison reasons, the main analysis models too. In turn, Table F5 presents the hedge portfolio abnormal returns. Below, we discuss their evaluation and trading strategy results.

[Insert Table F4 here.]

[Insert Table F5 here.]

The Carhart (1997) four-factor model augments the FF model with a return momentum factor. Table F4's results suggest that the addition of the momentum factor improves the goodness of fit marginally. The momentum price of risk is statistically insignificant, and the model violates the null hypothesis of zero pricing errors. The FF4 model also implies statistical significant excess zero-beta rate and, hence, fails to fit the equity premium. The trading strategy in Table F5 implies statistical significant abnormal returns within the small subset of firms.

The Khan (2008) four-factor model replaces the market factor in the FF model with the cash flow and discount rate news factors. Table F4 suggests that the Khan (2008) four-factor model is rejected under both the *alpha* and the CPE statistics, and it fails in the estimation of the equity premium. Particularly, Khan (2008)'s model implies an unreasonable high excess zero-beta rate (22% annually). The trading strategy in Table F5 also reveals that the model does not explain the R&D-return relation adequately, since it implies profitable R&D-related mispricing in small firms.

The Hou et al. (2015) Q-Factor model expresses expected returns as a function of assets' betas to the market portfolio, a size factor, a profitability factor and an investment factor.[25] The Q-FM performs well. However, Tables F4 and F5 suggest that it has four shortcomings. The Q-FM does not explain the equity premium, since it implies a statistical significant excess zero-beta rate. One of Q-FM's risk factors, namely profitability, is not relevant to the cross-section of our 18 test portfolios. Its price of risk is statistically insignificant under both zero-beta rate versions of the model. The Q-FM is rejected, because it violates the zero pricing errors hypothesis under both the *alpha* and the CPE statistics. Finally, the trading strategy in Table F5 implies statistical significant abnormal returns –thus exploitable R&D-related mispricing– within the small subset of firms.

We conclude with a clarification. This study does not seek for the best performing model, but it assesses the performance of the ICAPM in explaining the R&D effect on returns. In that respect, the ICAPM needs to perform relatively well in order to support our risk-duration hypothesis for the positive R&D-returns relation. Our overall comparative analysis suggests that the ICAPM has the relative pricing ability and, hence, supports our explanation.

[25] Each quarter, the profitability factor is defined as the return on a portfolio of firms that have high return on (one-quarter-lagged) book value of equity over the return of a portfolio of firms that have low return on (one-quarter-lagged) book value of equity. The investment factor is defined as the return on a portfolio of low investment firms (small change in assets, scaled by one-year-lagged assets) over the return of a portfolio of high investment firms (large change in assets, scaled by one-year-lagged assets). Unlike the FF factors, Q-FM's size, profitability and investment factors are rebalanced monthly.

F.4 Financial Constraints and R&D Intensity: An Alternative Risk Channel?

Li (2011) advocates a positive interplay between financial constraints and R&D. The author observes that R&D is typically irreversible, since it requires constant cash injections to be viable. As such, financially constrained R&D intensive firms are more likely to mothbal/discontinue R&D projects, which makes these projects risky. In support, Li (2011) demonstrates that the positive R&D-return relation prevails only among financially constrained firms, and the positive constraints-return relation exists only among R&D-active firms. Financial constraints is a reasonable alternative explanation for the risk in our R&D intensive portfolios. The higher risk of High-R&D portfolios, established by means of DR betas, may just as well reflect the risk inherent in financially constrained R&D intensive firms rather than the risk inherent in the equity duration.

To rule out this possibility, we measure the financial constraints characteristics of our test portfolios. In addition, we also check the percentage proportions of firm-years within each test portfolio that can be classified as constrained. To the extent that financial constraints are the source of priced risk, we expect High-R&D portfolios to have higher financial constraint characteristics and to proportionally consist of more financially constrained firms than No-R&D portfolios.

We measure financial constraints with the Hadlock and Pierce (2010) index (HPI). HPI reflects financial constraints as a function of size and age, only; financial constraints sharply decrease as small and young firms start to grow and mature. We calculate HPI as: $HPI = -(0.737{\times}Size) + (0.043{\times}Size^2) - (0.040{\times}Age)$; where $Size$ is the log inflation-adjusted total assets;[26] and Age is the number of years the firm is listed with a non-missing stock price on COMPUSTAT.[27] We follow Hadlock and Pierce (2010) and winsorize (the log of) $Size$ at \$4.5 billion and Age at 37 years.

Table F6 Panel A shows the financial constraints characteristics of our 18 test portfolios.[28] We first estimate HPI for each firm-year. Then, we estimate the annual weighted averages of the HPIs for the firms in each portfolio, using the portfolio weights (i.e., value-weighted HPIs). Panel A reports the sample means (medians) of the 38 annual HPI values of each test portfolio. The larger the HPI value, the more financially constrained a test portfolio. Table F6 Panel B shows the percentage proportion of firm-years in each test

[26] Assets are inflation-adjusted in 2004 dollars with Consumer Price Index (CPI) data from FRED.
[27] Less than 1% of the initial firm-years is excluded due to missing price figures on COMPUSTAT.
[28] This estimation is also done by Lamont et al. (2001). We follow their approach and terminology.

portfolio that are classified as constrained. Every June of year t, we classify firms using their $t-1$ HPI values. Following convention, firms above the 70^{th} percentile are constrained (see Farre-Mensa and Ljungqvist 2016, and references therein).

[Insert Table F6 here.]

Albeit the results are mixed, Table F6 largely confirms the robustness of our results to financial constraint effects. High-R&D test portfolios are subject to similar financial constraints as the No-R&D test portfolios, but, proportionally, they have more individual High-R&D firms classified as constrained. Specifically, Panel A suggests HPI values do not critically change from No-R&D to High-R&D test portfolios. Small High-R&D test portfolios have slightly higher HPI values than small No-R&D test portfolios. Big High-R&D test portfolios have slightly lower HPIs than big No-R&D ones. BE/ME does not affect the HPI-R&D relation in this intersection. In all cases, HPI changes are small and even smaller with median figures, in parentheses. Panel B suggests that the proportion of firm-years classified as constrained is slightly larger in High-R&D test portfolios. Taken together, Table F6 suggests financial constraints appear in the firm-level but, to a large extent, diversify in aggregation. As such, we argue that financial constraints do not manifest themselves in our test portfolios. Our High-R&D test portfolios are, on average, subject to similar financial constraints as the No-R&D ones.

Note that we do not dismiss Li (2011)'s R&D-constraints hypothesis. We, however, provide evidence suggesting that financial constraints is not the channel through which systematic risk depends on R&D. Also, note that our setting is not directly comparable to Li (2011)'s. More importantly, both analyses are subject to extensive measurement error in the financial constraint metrics they employ. As such, we cannot yet conclusively answer whether the pricing of R&D intensive stocks is associated with financial constraints.

Li (2011) uses firm-level data on R&D active firms with positive real sales growth (High/Low R&D specifications from our setting only), and she runs Fama-MacBeth (1973) regressions of returns on measures of R&D intensity and financial constraints and their interaction terms. Li (2011) documents that R&D intensity is associated with financial constraints. She then establishes that financial constraints is a risk-bearing characteristic; the involved test portfolios, indeed, load on "popular" risk factors. However, this is not necessarily priced risk, since it is not clear whether the returns on these portfolios is explained by the employed asset pricing models. We, focus on the US cross-section, only employ test portfolios and run a battery of asset pricing tests. With this approach we avoid firm-level noise and aim to priced risk only. Although we confirm that financial constraints are indeed more present in High-R&D firms, they appear to diversify in aggregate portfolios. The lack of risk premium for financial constraints is plausible; most R&D firms hold excess cash to remedy the effect of financial constraints.[29] Therefore, investors need not to particularly concern for financial constraints in aggregated R&D portfolios.

We also emphasize that, both ours and Li (2011)'s results have considerable measurement error. The ability of measures of financial constraints to identify actually constrained firms has been questioned. A recent study by Farre-Mensa and Ljungqvist (2016) suggests that, mainstream financial constraints measures classify as constrained firms that, although with a specific set of characteristics, are not constrained in their ability to externally finance themselves. This is because these measures pick-up endogenous firm characteristics, irrelevant to financial constraints. Since we both use recently criticized financial constraints measures, our empirical tests are contaminated by errors-in-variables.[30]

[29]This is due to Bates et al. (2009) and Brown and Petersen (2011). An increasing number of firms become R&D active; and their management is aware of R&D's sensitivity to financial constraints. They hold excess cash to "smooth" the cash inflows required by R&D projects. R&D active firms build-up cash reserves during "booms" to buffer potential shocks in future "busts" (Bates et al. 2009; Brown and Petersen 2011). Collectively, an R&D intensive firm with excess cash holdings is less likely to mothbal/discontinue R&D projects due to financial constraints. Untabulated results suggest our High-R&D firms indeed hoard, on average, more cash than the No-R&D firms.

[30]As Li (2011), we also estimate the Lamont et al. (2001) version of the Kaplan-Zingales (1997) financial constraints index (KZ). It is not our principal choice, because we want to avoid selection bias and ensure the representativeness of our test portfolios, i.e., estimate the financial constraint characteristics with all, or at least most, underlying firms. With the KZ we lose many firm-years; KZ requires non-missing figures for all annual COMPUSTAT items used in the calculation. Overall, the KZ estimation suggests R&D intensity is associated with lower financial constraints. Within each size and BE/ME subset, High-R&D test portfolios have lower KZ characteristics than No-R&D portfolios. These results are inconsistent with Li (2011), however, they are consistent with Farre-Mensa and Ljungqvist (2016). Farre-Mensa and Ljungqvist (2016, pg. 279) document that KZ-coded constrained firms "...spend considerably less on R&D". Moreover, KZ "...stands out as an outlier" (Farre-Mensa and Ljungqvist 2016, pg. 277); its association with firm characteristics, such as R&D activity, is different than other financial constraints measures. Recall, we do not dismiss the financial constraints story; we highlight that our robustness checks and Li (2011)'s conclusions come from less than perfect measures of financial constraints.

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Figure 1: Evolution of cash flow and negative of discount rate news

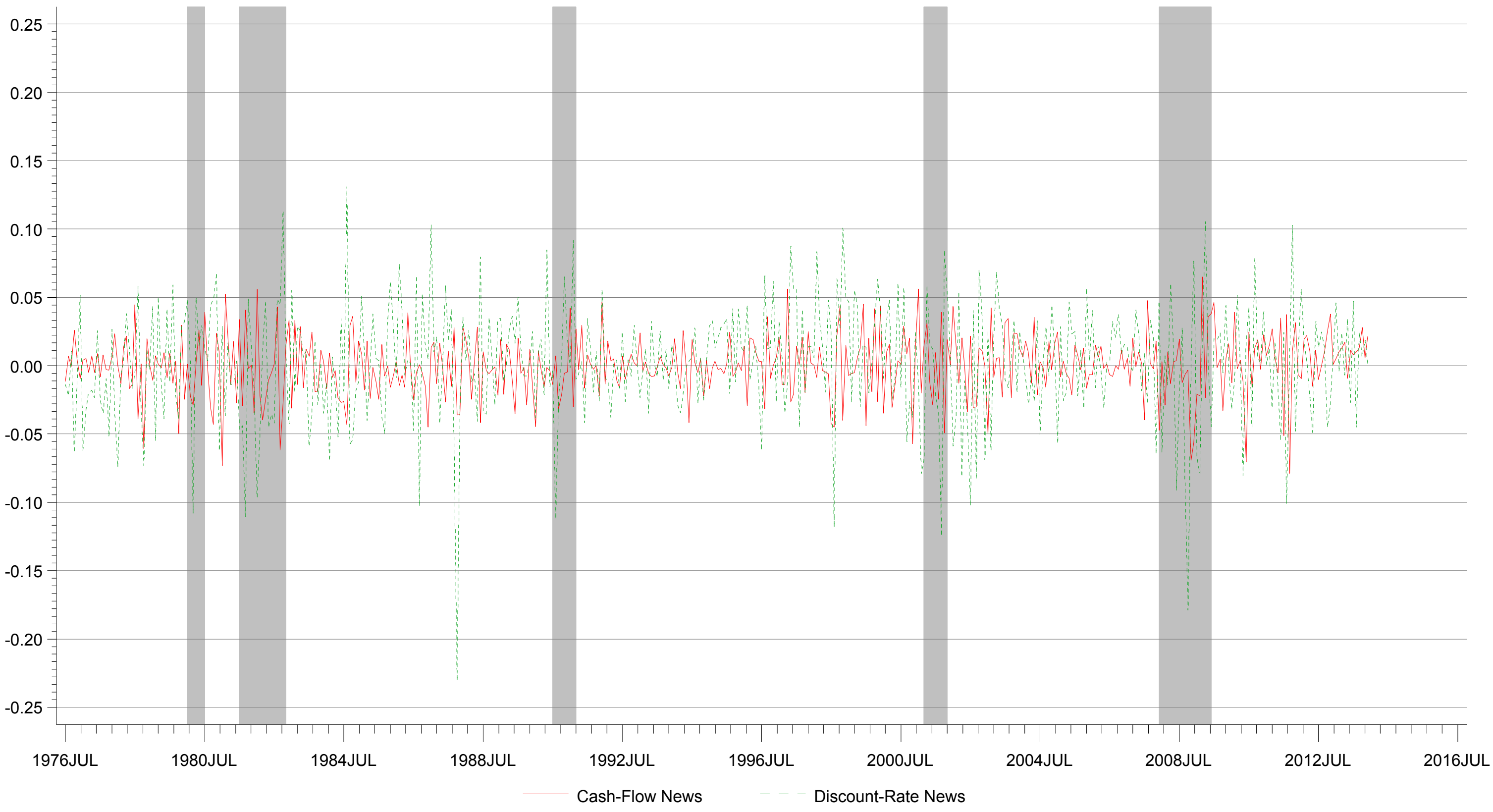
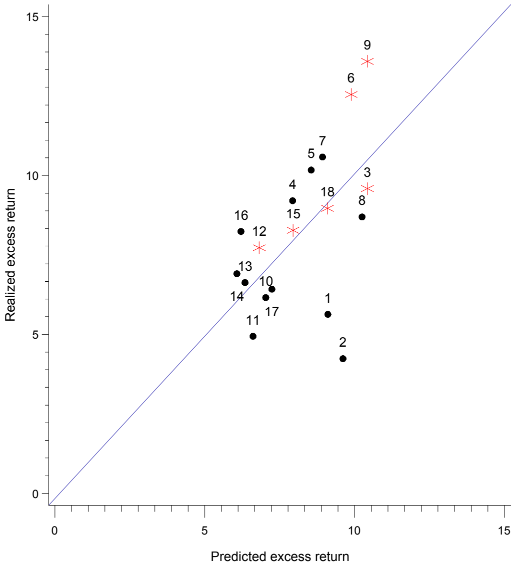
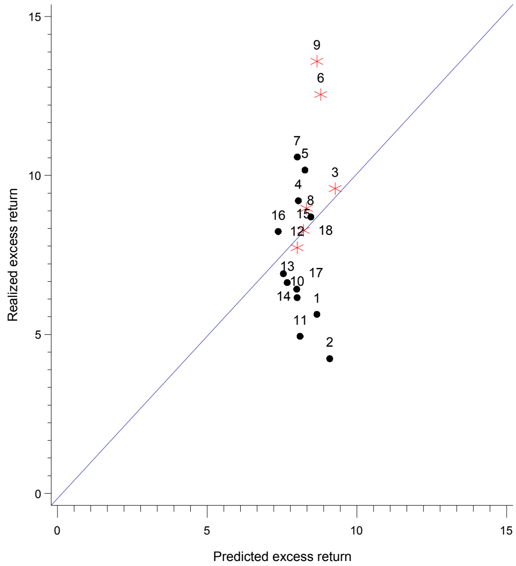


Figure 1 shows the evolution of NCF (red line) and negative of NDR (green line) across time. The grey shaded area corresponds to NBER recessions. The sample spans the period from July 1976 to December 2013.

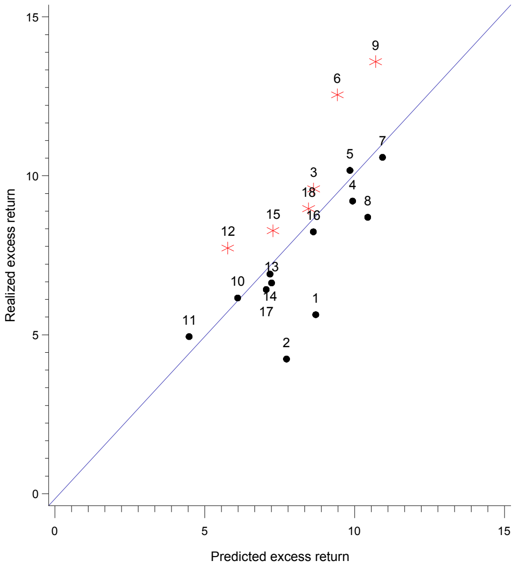
Figure 2: Predicted Vs Realized returns (constrained zero-beta rate)



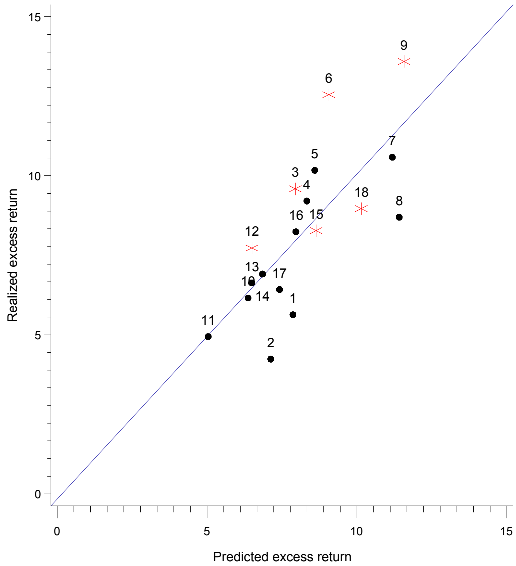
(a) ICAPM with constrained zero-beta rate



(b) CAPM with constrained zero-beta rate



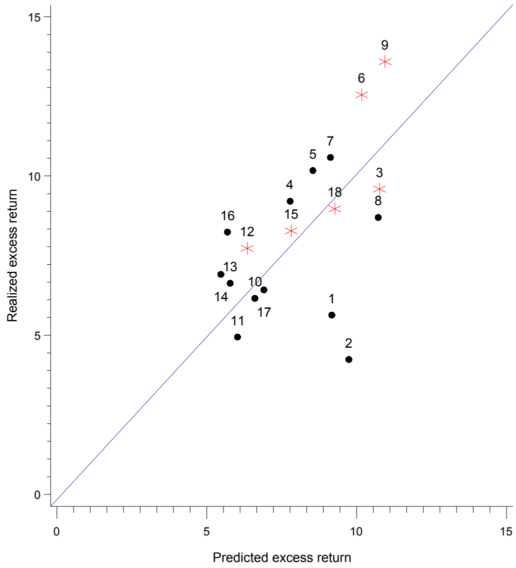
(d) FF with constrained zero-beta rate



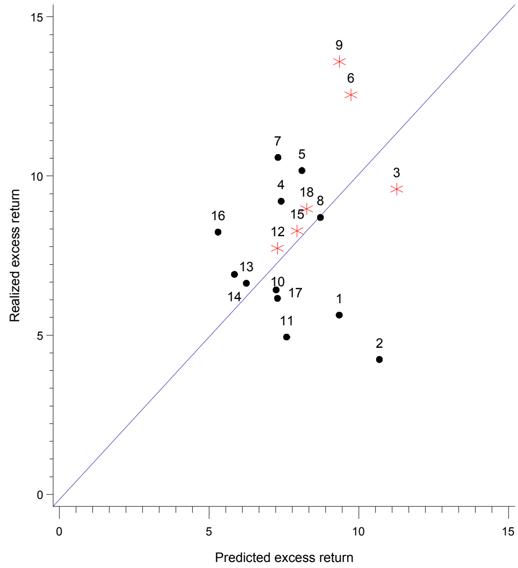
(c) Two-factor with constrained zero-beta rate

Clockwise from top left, the figures correspond to the ICAPM (a), the CAPM (b), the two-factor model (c) and the Fama-French (1993) model (d), all with constrained zero-beta rates. The horizontal axis denotes the predicted excess returns, obtained from the regressions of Table 4. The vertical axis denotes the realized excess returns. Black dots represent the No-R&D and Low-R&D size and BE/ME portfolios, while red stars represent the High-R&D size and BE/ME portfolios. The numbering of the portfolios follows our partitions and starts from 1, for the No-R&D and Small/Growth portfolio, goes to 3 for the High-R&D and Small/Growth portfolio, 4 for the No-R&D and Small/Medium portfolio and so on, until 18 which stands for the High-R&D and Large/Value portfolio.

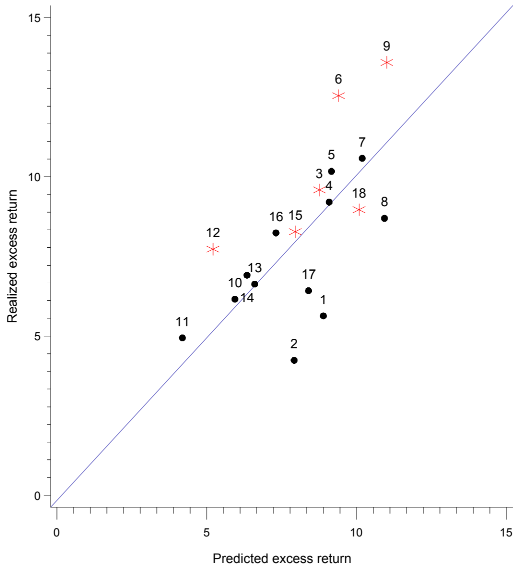
Figure 3: Predicted Vs Realized returns (free zero-beta rate)



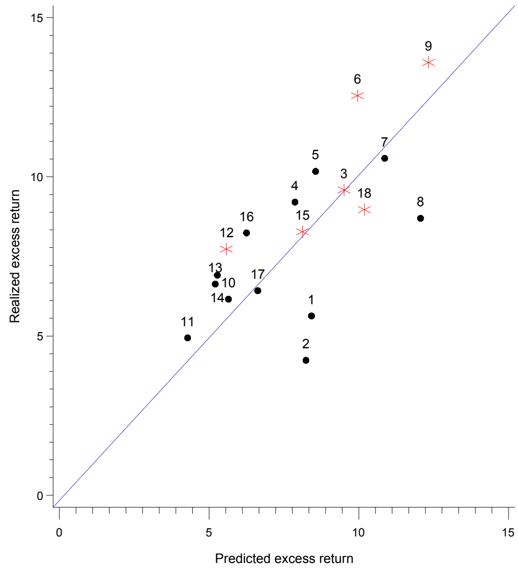
(a) ICAPM with free zero-beta rate



(b) CAPM with free zero-beta rate



(d) FF with free zero-beta rate



(c) Two-factor with free zero-beta rate

Clockwise from top left, the figures correspond to the ICAPM (a), the CAPM (b), the two-factor model (c) and the Fama-French (1993) model (d), all with freely estimated zero-beta rates. The horizontal axis denotes the predicted excess returns, obtained from the regressions of Table 4. The vertical axis denotes the realized excess returns. Black dots represent the No-R&D and Low-R&D size and BE/ME portfolios, while red stars represent the High-R&D size and BE/ME portfolios. The numbering of the portfolios follows our partitions and starts from 1, for the No-R&D and Small/Growth portfolio, goes to 3 for the High-R&D and Small/Growth portfolio, 4 for the No-R&D and Small/Medium portfolio and so on, until 18 which stands for the High-R&D and Large/Value portfolio.

Table 1: Characteristics of the 18 size, BE/ME and R&D intensity portfolios

	Size=Small			Size=Big		
	BE/ME			BE/ME		
	G *(Growth)*	M	V *(Value)*	G *(Growth)*	M	V *(Value)*
R&D intensity						
Panel A: Annualized average excess returns on the test portfolios						
N *(No-R&D)*	**6.97%***	**11.63%*****	**13.47%*****	**7.65%*****	**8.26%*****	**10.35%*****
L	5.21	**12.92%*****	**10.95%*****	**6.10%****	**8.62%****	**7.99%****
H *(High-R&D)*	**12.14%****	**16.15%*****	**17.59%*****	**9.68%*****	**10.40%*****	**11.31%*****
H - N	**5.16%****	**4.52%*****	**4.13%*****	2.03%	2.14%	0.96%
Panel B: Average number of firms in each portfolio						
N *(No-R&D)*	301.30	360.10	378.70	121.75	109.06	62.34
L	238.71	120.84	66.06	109.46	48.57	15.90
H *(High-R&D)*	210.32	217.84	188.54	66.48	57.00	19.69

Entries on Panel A show the annualized average excess returns of the 18 test portfolios, in percentages, over the 450 months from July 1976 to December 2013. Panel B displays the average number of firms in each portfolio. The portfolios, which are constructed at the end of June, are the intersections of 2 portfolios formed on size, 3 portfolios formed on the ratio of book value of equity to market value of equity (BE/ME) and 3 portfolios formed on R&D intensity (the ratio of capitalized and amortized R&D to market value of equity). The size breakpoint for year t is the median NYSE market value of equity at the end of June of year t. The BE/ME for June of year t is the book value of equity for the last fiscal year end in $t-1$ calendar year, divided by the ME for December of $t-1$ calendar year. The BE/ME breakpoints are the 30^{th} and 70^{th} NYSE percentiles. R&D intensity for June of calendar year t is the capitalized and amortized R&D expenses for the last fiscal year end in $t-1$ calendar year, divided by ME for December of $t-1$ calendar year. The No-R&D portfolios include all firm-year observations with no records for R&D expenses. For firm-year observations with R&D records the breakpoint for year t is the median NYSE R&D intensity (Low-R&D, High-R&D). "$H-N$" is the difference between High-R&D and No-R&D portfolios within each size and BE/ME subset. [*], [**] and [***] indicate significance levels of 10%, 5% and 1%, respectively.

Table 2: Implied equity duration for the test portfolios

	Size=Small			Size=Big		
	BE/ME			BE/ME		
	G	**M**	**V**	**G**	**M**	**V**
	(Growth)		***(Value)***	***(Growth)***		***(Value)***
R&D intensity						
Panel A: Average (median) equity duration of the firms within each portfolio						
N *(No-R&D)*	21.60	18.62	14.06	21.19	18.30	14.76
	(21.41)	(18.64)	(14.70)	(21.30)	(18.59)	(15.33)
L	22.25	18.64	14.64	21.58	18.22	15.93
	(22.00)	(18.68)	(14.84)	(21.61)	(18.73)	(15.80)
H *(High-R&D)*	23.89	20.63	17.43	21.47	18.70	14.67
	(23.56)	(19.87)	(16.26)	(21.48)	(18.96)	(15.21)
H - N	2.29	2.00	3.37	0.28	0.40	-0.10
	(2.16)	(1.22)	(1.56)	(0.19)	(0.37)	(-0.12)
Panel B: Implied equity duration characteristics of the 18 portfolios						
N *(No-R&D)*	20.94	17.88	13.83	21.11	18.14	14.75
	(21.29)	(18.84)	(15.11)	(21.71)	(18.99)	(15.35)
L	21.52	18.07	15.38	21.45	19.81	17.12
	(21.96)	(18.91)	(16.20)	(21.85)	(20.17)	(17.08)
H *(High-R&D)*	22.17	18.85	14.86	21.14	18.80	15.38
	(22.87)	(19.65)	(15.76)	(21.64)	(19.71)	(16.01)
H - N	1.23	0.97	1.03	0.03	0.66	0.63
	(1.58)	(0.81)	(0.65)	(-0.08)	(0.71)	(0.66)

The table reports the implied equity duration for the 18 size, BE/ME and R&D intensity portfolios. To estimate the equity duration, we employ Dechow et al. (2004)'s measure. The estimation has a detailed period of 15 years and a terminal period, and it uses Dechow et al. (2004)'s forecasting parameters: (1) autocorrelation coefficient for return on equity – 0.57; (2) cost of equity capital – 0.12; (3) autocorrelation coefficient for growth in sales/book value of equity – 0.24; (4) long-term growth in sales/book value of equity – 0.06. Panel A shows the average (median) equity duration of the firms within each portfolio. Panel B reports the implied equity duration characteristics of the 18 portfolios. Panel B shows the sample mean (median) of the 38 annual values, where an annual value is the weighted average of the implied equity duration of the firms in each portfolio, using the portfolio weights.

Table 3: Cash flow and discount rate beta for the test portfolios

Panel A: Cash Flow Beta

	Size = Small			Size = Big			BE/ME V-G ($Value - Growth$)	
	BE/ME			BE/ME			Size = Small	Size = Big
	G *(Growth)*	M	V *(Value)*	G *(Growth)*	M	V *(Value)*		
R&D intensity								
N *(No-R&D)*	**0.207****	**0.181****	**0.223*****	**0.146***	**0.130***	**0.136****	0.016	-0.011
	(2.03)	*(2.13)*	*(2.55)*	*(1.85)*	*(1.80)*	*(2.00)*	*(0.42)*	*(-0.30)*
L	**0.215***	**0.198****	**0.257*****	0.127	**0.125***	**0.158***	0.042	0.031
	(1.81)	*(2.20)*	*(2.55)*	*(1.55)*	*(1.78)*	*(1.75)*	*(0.80)*	*(0.64)*
H *(High-R&D)*	**0.240***	**0.234****	**0.263****	**0.141***	**0.183****	**0.221****	0.023	**0.079****
	(1.92)	*(2.19)*	*(2.50)*	*(1.75)*	*(2.06)*	*(2.27)*	*(0.47)*	*(2.08)*
H-N	0.033	0.053	0.040	-0.005	**0.053***	**0.085***		
	(0.79)	*(1.49)*	*(1.24)*	*(-0.19)*	*(1.70)*	*(1.90)*		

Panel B: Discount Rate Beta

	Size = Small			Size = Big			BE/ME V-G ($Value - Growth$)	
	BE/ME			BE/ME			Size = Small	Size = Big
	G *(Growth)*	M	V *(Value)*	G *(Growth)*	M	V *(Value)*		
R&D intensity								
N *(No-R&D)*	**1.244*****	**0.978*****	**0.974*****	**0.940*****	**0.795*****	**0.663*****	**-0.270*****	**-0.277*****
	(10.18)	*(9.47)*	*(8.92)*	*(10.33)*	*(9.20)*	*(7.93)*	*(-5.10)*	*(-4.97)*
L	**1.396*****	**1.083*****	**1.219*****	**0.951*****	**0.715*****	**0.907*****	**-0.178****	-0.044
	(10.08)	*(9.85)*	*(9.71)*	*(9.77)*	*(8.40)*	*(7.71)*	*(-2.23)*	*(-0.49)*
H *(High-R&D)*	**1.500*****	**1.313*****	**1.242*****	**0.888*****	**0.960*****	**1.080*****	**-0.257*****	**0.192*****
	(10.13)	*(10.27)*	*(9.63)*	*(9.76)*	*(9.29)*	*(8.91)*	*(-3.53)*	*(2.57)*
H-N	**0.256*****	**0.335*****	**0.268*****	-0.052	**0.165*****	**0.417*****		
	(3.77)	*(5.96)*	*(5.84)*	*(-1.14)*	*(3.09)*	*(6.04)*		

Entries show the estimated cash flow (*CF*, Panel A) and discount rate (*DR*, Panel B) betas and their t-statistics in parentheses for the 18 test portfolios. The t-statistics are based on bootstrap standard errors. The last two columns in each panel report the difference in betas between the value and the growth portfolios. The last row in each panel reports the difference in betas between R&D intensive and No-R&D stocks. [*], [**] and [***] asterisks denote rejection of the null hypothesis of a zero beta (or a zerobeta difference) at a 10%, 5% and 1% significance level, respectively. The sample spans the period from July 1976 to December 2013.

Table 4: The prices of cash flow risk and discount rate risk

	ICAPM		CAPM		Two-Factor		FF	
	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$
Panel A: Prices of risk								
$R_{zb} - R_{rf}$	0	0.002	0	**0.006***	0	0.005	0	**0.009*****
	-	*(0.69)*	-	*(1.60)*	-	*(1.48)*	-	*(2.57)*
	[0.0%]	*[1.9%]*	*[0.0%]*	*[6.8%]*	*[0.0%]*	*[5.4%]*	*[0.0%]*	*[10.7%]*
NCF	**0.032****	**0.024***			**0.070*****	**0.066*****		
	(2.36)	*(1.68)*			*(2.96)*	*(2.85)*		
	[38.2%]	*[28.4%]*			*[83.8%]*	*[79.3%]*		
NDR	0.002	0.002			-0.005	-0.008		
	-	-			*(-1.09)*	*(-1.48)*		
	[2.5%]	*[2.5%]*			*[-5.8%]*	*[-9.9%]*		
R^e_M			**0.007*****	0.002			**0.006*****	-0.002
			(3.14)	*(0.55)*			*(2.93)*	*(-0.53)*
			[8.9%]	*[2.8%]*			*[7.7%]*	*[-2.7%]*
SMB							0.002	**0.003***
							(1.24)	*(1.88)*
							[2.4%]	*[3.7%]*
HML							**0.003***	0.003
							(1.70)	*(1.54)*
							[3.3%]	*[3.1%]*
Panel B: Evaluation metrics								
R^2	23.6%	26.1%	-15.3%	4.1%	40.1%	55.2%	42.3%	52.1%
alpha	**58.12****	**47.32****	**65.26****	**46.22****	**57.68****	**39.98****	**51.05****	**35.36****
	> 27.59	> 26.30	> 27.59	> 26.30	> 26.30	> 25.00	> 25.00	> 23.69
CPE	0.021	**0.019****	**0.032****	**0.025****	0.018	0.011	**0.015****	**0.012****
	< 0.022	> 0.016	> 0.021	> 0.016	< 0.018	< 0.014	> 0.011	> 0.008
PEM	0.144	0.138	0.178	0.159	0.133	0.103	0.122	0.108
HJ	0.057	0.054	0.092	0.076	0.048	0.036	0.046	0.038

Entries show the results from the second step of the Fama and MacBeth (1973) framework for the asset pricing models under consideration. The first column for any given model restricts the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). In Panel A we can see the price of risk; the Newey-West t-statistics, in parenthesis; and the annualized prices of risk, in square brackets. In Panel B we can see the R^2, *alpha*, *CPE*, *PEM* and *HJ* for any given asset pricing model. [*], [**] and [***] asterisks denote rejection of the null hypothesis at a 10%, 5% and 1% level, respectively. In the case of the t-statistic the null hypothesis is that the price of risk is equal to zero, while in the cases of *alpha* and CPE the null hypothesis is that the pricing errors are, on average, equal to zero. For *alpha* and CPE [**] asterisks denote rejection of the zero-pricing errors hypothesis since the statistic exceeds the 5% critical value shown below each statistic. The 5% critical value, for *alpha*, is obtained from the normal distribution, while for CPE is obtained from a bootstrap distribution. The asset pricing models are estimated using monthly observations over the period from July 1976 to December 2013.

Table 5: Formation of hedge portfolios

Size	BE/ME	R&D intensity	HP_1	HP_2	HP_3	HP_4	HP_5	HP_6
Small	G	No-R&D	$-\hat{\alpha}_1$					
		Low-R&D						
		High-R&D	$+\hat{\alpha}_3$					
	M	No-R&D		$-\hat{\alpha}_4$				
		Low-R&D						
		High-R&D		$+\hat{\alpha}_6$				
	V	No-R&D			$-\hat{\alpha}_7$			
		Low-R&D						
		High-R&D			$+\hat{\alpha}_9$			
Big	G	No-R&D				$-\hat{\alpha}_{10}$		
		Low-R&D						
		High-R&D				$+\hat{\alpha}_{12}$		
	M	No-R&D					$-\hat{\alpha}_{13}$	
		Low-R&D						
		High-R&D					$+\hat{\alpha}_{15}$	
	V	No-R&D						$-\hat{\alpha}_{16}$
		Low-R&D						
		High-R&D						$+\hat{\alpha}_{18}$

The table illustrates how hedge portfolios are formed from the 18 size, BE/ME and R&D intensity portfolios. HP_1, HP_2, HP_3, HP_4, HP_5 and HP_6) are formed by going long \$1 on the R&D intensive portfolio and short \$1 on the No-R&D portfolio within each size and BE/ME subset. The abnormal return for each hedge portfolios is the pricing error for the long portfolio minus the pricing error for the short portfolio. The pricing error of a portfolio (i=1 to 18) is the mean of the residuals, ($\hat{\alpha}_i$) from the second-step Fama-MacBeth cross-sectional regression.

Table 6: Hedge portfolios

Size	BE/ME	Hedge Portfolios	ICAPM $R_{rf} = R_{zb}$	ICAPM $R_{rf} \neq R_{zb}$	CAPM $R_{rf} = R_{zb}$	CAPM $R_{rf} \neq R_{zb}$	Two-Factor $R_{rf} = R_{zb}$	Two-Factor $R_{rf} \neq R_{zb}$	FF $R_{rf} = R_{zb}$	FF $R_{rf} \neq R_{zb}$
Small	G	HP_1	2.9%	3.2%	2.5%	**4.1%***	3.5%	**4.8%****	**5.0%****	**4.9%****
			(1.02)	*(1.21)*	*(0.89)*	*(1.83)*	*(1.31)*	*(2.12)*	*(2.43)*	*(2.39)*
	M	HP_2	1.2%	1.7%	1.2%	**3.2%****	1.5%	**3.2%****	**3.7%*****	**4.7%*****
			(0.59)	*(0.95)*	*(0.63)*	*(2.32)*	*(0.82)*	*(2.26)*	*(2.71)*	*(3.68)*
	V	HP_3	1.4%	1.8%	1.2%	**2.9%****	1.9%	**3.2%****	**2.7%****	**4.0%*****
			(0.88)	*(1.21)*	*(0.72)*	*(2.25)*	*(1.20)*	*(2.44)*	*(2.00)*	*(3.11)*
Big	G	HP_4	2.2%	2.2%	1.9%	1.9%	2.0%	1.7%	**2.8%***	2.3%
			(1.43)	*(1.39)*	*(1.23)*	*(1.23)*	*(1.27)*	*(1.09)*	*(1.86)*	*(1.50)*
	M	HP_5	-0.5%	0.0%	-0.1%	1.3%	-1.5%	-0.6%	0.3%	1.9%
			(-0.28)	*(0.03)*	*(-0.03)*	*(0.81)*	*(-0.86)*	*(-0.37)*	*(0.21)*	*(1.29)*
	V	HP_6	**-3.4%***	-2.6%	-2.6%	-0.3%	**-3.8%***	-1.7%	-2.4%	1.1%
			(-1.65)	*(-1.10)*	*(-1.20)*	*(-0.10)*	*(-1.76)*	*(-0.71)*	*(-1.09)*	*(0.67)*

Entries show annualized average abnormal returns, in percentages, and their Newey-West t-statistics, in parentheses, of the hedge portfolios under consideration. The risk-adjustment is from the model identified at the top of each column. We form six hedge portfolios (HP_1, HP_2, HP_3, HP_4, HP_5 and HP_6) by going long on the R&D intensive stocks and short on the No-R&D stocks within each size and BE/ME bucket. Table 5 contains the details of hedge portfolio formation. The sample spans the period from July 1976 to December 2013 (450 monthly observations).

Table D1: State variables' VAR(1) model

	$R^e_{M,t+1}$	PE_{t+1}	TY_{t+1}	VS_{t+1}	DEF_{t+1}
c	**0.056*** **	0.015	-0.025	0.027	0.050
	(3.07)	*(1.46)*	*(-0.18)*	*(0.72)*	*(1.14)*
$R^e_{M,t}$	**0.104***	**0.515*** **	-0.212	-0.019	**-1.085*** **
	(1.88)	*(13.50)*	*(-0.77)*	*(-0.46)*	*(-4.92)*
PE_t	**-0.015*** **	**0.995*** **	0.011	0.005	**-0.022***
	(-2.76)	*(323.98)*	*(0.32)*	*(0.440)*	*(-1.66)*
TY_t	**0.003***	0.001	**0.937*** **	-0.001	0.000
	(1.62)	*(1.04)*	*(60.25)*	*(-0.58)*	*(-0.09)*
VS_t	-0.006	-0.004	0.016	**0.968*** **	**0.045** **
	(-0.75)	*(-0.81)*	*(0.48)*	*(89.93)*	*(2.05)*
DEF_t	-0.003	0.002	**0.059*** **	**0.013***	**0.950*** **
	(-0.31)	*(0.46)*	*(2.50)*	*(1.76)*	*(39.42)*
Adj.R^2	1.90%	99.07%	90.70%	95.97%	96.03%
F	**4.94** **	**21,813.80*** **	**1,988.64*** **	**4,850.77*** **	**4,934.70*** **

The entries report results from the state variables' VAR(1) of equation (4). This is, $z_{t+1} = c + \Gamma z_t + \upsilon_{t+1}$ where z_t is the $k \times 1$ vector of state variables at time $t(k = 1, 2, 3, 4, 5)$, c is the $k \times 1$ vector of constants, Γ is the $k \times k$ matrix of slope coefficients and υ_{t+1} is the $k \times 1$ vector of residuals. Estimated coefficients, Newey-West t-statistics in parentheses, adjusted R^2 and F-statistic are reported. The t-statistic tests the null hypothesis of a zero coefficient and the F-statistic tests the null hypothesis that the coefficients for any given equation within the VAR(1) are jointly equal to zero. [*], [**] and [***] asterisks denote rejection of the null hypothesis at a 10%, 5% and 1% level, respectively. The sample spans the period from January 1929 to December 2013 (1020 monthly observations).

Table F1: Prices of risk using quarterly data

	ICAPM		CAPM		Two-Factor		FF	
	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$
Panel A: Prices of risk								
$R_{zb} - R_{rf}$	0	0.007	0	0.014	0	0.015	0	**0.018***
	-	*(0.89)*	-	*(1.43)*	-	*(1.49)*	-	*(1.66)*
	[0.0%]	*[2.7%]*	*[0.0%]*	*[5.7%]*	*[0.0%]*	*[6.0%]*	*[0.0%]*	*[7.4%]*
NCF	**0.162*****	**0.108***			**0.186*****	**0.185*****		
	(2.70)	*(1.68)*			*(2.95)*	*(2.92)*		
	[65.0%]	*[43.4%]*			*[74.5%]*	*[74.1%]*		
NDR	0.007	0.007			0.004	-0.011		
	-	-			*(0.41)*	*(-0.82)*		
	[2.9%]	*[2.9%]*			*[1.7%]*	*[-4.5%]*		
R^e_M			**0.023*****	0.011			**0.020*****	0.002
			(3.53)	*(0.96)*			*(3.06)*	*(0.12)*
			[9.1%]	*[4.2%]*			*[8.2%]*	*[0.7%]*
SMB							0.006	**0.009***
							(1.39)	*(1.78)*
							[2.5%]	*[3.5%]*
HML							0.009	0.008
							(1.53)	*(1.45)*
							[3.5%]	*[3.3%]*
Panel B: Evaluation metrics								
R^2	25.6%	32.2%	-5.0%	11.3%	26.2%	44.3%	50.3%	54.8%
alpha	**59.76****	**49.85****	**70.18****	**49.61****	**59.56****	**47.41****	**54.57****	**39.98****
	> 27.59	> 26.30	> 27.59	> 26.30	> 26.30	> 25.00	> 25.00	> 23.69
CPE	0.055	**0.046****	**0.082****	**0.066****	0.055	**0.037****	**0.036****	**0.032****
	< 0.079	> 0.036	> 0.075	> 0.041	< 0.056	> 0.030	> 0.034	> 0.022
PEM	0.234	0.215	0.286	0.258	0.235	0.194	0.190	0.179
HJ	0.061	0.053	0.088	0.075	0.062	0.047	0.042	0.038

Entries show the results from the second step of the Fama and MacBeth (1973) framework for the asset pricing models under consideration. The first column for any given model restricts the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). In Panel A we can see the price of risk; the Newey-West t-statistics, in parenthesis; and the annualized prices of risk, in square brackets. In Panel B we can see the R^2, *alpha*, *CPE*, *PEM* and *HJ* for any given asset pricing model. [*], [**] and [***] asterisks denote rejection of the null hypothesis at a 10%, 5% and 1% level, respectively. In the case of the t-statistic the null hypothesis is that the price of risk is equal to zero, while in the cases of *alpha* and CPE the null hypothesis is that the pricing errors are, on average, equal to zero. For *alpha* and CPE [**] asterisks denote rejection of the zero-pricing errors hypothesis since the statistic exceeds the 5% critical value shown below each statistic. The 5% critical value, for *alpha*, is obtained from the normal distribution, while for CPE is obtained from a bootstrap distribution. The asset pricing models are estimated using quarterly observations over the period from September 1976 to December 2013.

Table F2: Hedge portfolios at a quarterly frequency

Size	BE/ME	Hedge Portfolios	ICAPM $R_{rf} = R_{zb}$	ICAPM $R_{rf} \neq R_{zb}$	CAPM $R_{rf} = R_{zb}$	CAPM $R_{rf} \neq R_{zb}$	Two-Factor $R_{rf} = R_{zb}$	Two-Factor $R_{rf} \neq R_{zb}$	FF $R_{rf} = R_{zb}$	FF $R_{rf} \neq R_{zb}$
Small	**G**	HP_1	2.1%	2.8%	2.3%	3.9%	2.1%	4.1%	**5.1%****	**5.5%****
			(0.61)	*(0.91)*	*(0.68)*	*(1.41)*	*(0.63)*	*(1.58)*	*(1.97)*	*(2.15)*
	M	HP_2	1.7%	2.3%	1.1%	**2.9%***	1.8%	**4.0%*****	**3.8%****	**4.6%*****
			(0.72)	*(1.07)*	*(0.49)*	*(1.79)*	*(0.80)*	*(2.75)*	*(2.39)*	*(3.06)*
	V	HP_3	1.5%	2.1%	1.1%	**2.7%***	1.7%	**3.6%*****	**2.6%***	**3.7%*****
			(0.80)	*(1.16)*	*(0.58)*	*(1.81)*	*(0.89)*	*(2.52)*	*(1.70)*	*(2.49)*
Big	**G**	HP_4	1.0%	1.3%	2.2%	2.0%	0.9%	0.8%	**2.7%***	**2.6%***
			(0.65)	*(0.87)*	*(1.40)*	*(1.26)*	*(0.56)*	*(0.49)*	*(1.77)*	*(1.67)*
	M	HP_5	-1.7%	-0.7%	0.6%	1.2%	-2.1%	-1.6%	0.8%	0.9%
			(-0.93)	*(-0.38)*	*(0.35)*	*(0.77)*	*(-1.15)*	*(-0.89)*	*(0.47)*	*(0.55)*
	V	HP_6	0.7%	0.4%	-2.3%	-0.6%	1.2%	3.4%	-2.4%	0.1%
			(0.23)	*(0.15)*	*(-0.96)*	*(-0.21)*	*(0.47)*	*(1.14)*	*(-0.97)*	*(0.04)*

Entries show annualized average abnormal returns, in percentages, and their Newey-West t-statistics, in parentheses, of the hedge portfolios under consideration. The risk-adjustment is from the model identified at the top of each column. We form six hedge portfolios (HP_1, HP_2, HP_3, HP_4, HP_5 and HP_6) by going long on the R&D intensive stocks and short on the No-R&D stocks within each size and BE/ME bucket. Table 5 contains the details of hedge portfolio formation. The sample spans the period from September 1976 to December 2013 (150 quarterly observations).

Table F3: Alternative definitions – 24 size, BE/ME and R&D intensity portfolios

	Size=Small			Size=Big		
	BE/ME			BE/ME		
	G (*Growth*)	M	V (*Value*)	G (*Growth*)	M	V (*Value*)
R&D intensity						
Panel A: Annualized average excess returns on the test portfolios						
N *(No-R&D)*	**6.97%***	**11.63%*** **	**13.47%*** **	**7.65%*** **	**8.26%*** **	**10.35%*** **
L *(Low-R&D)*	2.99	**12.12%*** **	**8.84%** **	**5.90%***	**8.08%*** **	**8.01%** **
M *(Medium-R&D)*	**10.42%** **	**14.86%*** **	**14.74%*** **	**7.79%*** **	**10.08%*** **	**8.14%** **
H *(High-R&D)*	**13.88%*** **	**16.18%*** **	**17.71%*** **	**10.55%*** **	**10.94%*** **	**12.01%*** **
H - N	**6.91%** **	**4.56%** **	**4.25%** **	2.91%	2.69%	1.66%
Panel B: H - N differences in CF and DR betas						
CF Betas: H - N	0.034	0.064	0.043	0.004	**0.068***	**0.080***
DR Betas: H - N	**0.307*** **	**0.377*** **	**0.288*** **	0.049	**0.173*** **	**0.481*** **

Entries on Panel A show the annualized average excess returns of the 24 test portfolios, in percentages, over the 450 months from July 1976 to December 2013. Panel B displays the differences in CF and DR betas between High and No-R&D portfolios. The portfolios are constructed at the end of June as the intersections of 2 portfolios formed on size, 3 portfolios formed on the ratio of book value of equity to market value of equity (BE/ME) and 4 portfolios formed on R&D intensity (the ratio of capitalized and amortized R&D to market value of equity). The size breakpoint for year t is the median NYSE market value of equity at the end of June of year t. The BE/ME for June of year t is the book value of equity for the last fiscal year end in $t-1$ calendar year, divided by the ME for December of $t-1$ calendar year. The BE/ME breakpoints are the 30^{th} and 70^{th} NYSE percentiles. R&D intensity for June of calendar year t is the capitalized and amortized R&D expenses for the last fiscal year end in $t-1$ calendar year, divided by ME for December of $t-1$ calendar year. The No-R&D portfolios include all firm-year observations with no records for R&D expenses. For firm-year observations with R&D records the breakpoints for year t are the 30^{th} and 70^{th} NYSE percentiles. (Low-R&D, Medium-R&D, High-R&D). "$H-N$" is the difference between High-R&D and No-R&D portfolios within each size and BE/ME subset. [*], [**] and [***] indicate significance levels of 10%, 5% and 1%, respectively.

Table F4: Prices of risk with the main and the additional benchmark models

	ICAPM		CAPM		Two-Factor		FF		FF4		Khan-F4		Q-FM	
	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$	$R_{\mathrm{rf}} = R_{\mathrm{zb}}$	$R_{\mathrm{rf}} \neq R_{\mathrm{zb}}$
Panel A: Prices of risk														
$R_{zb} - R_{rf}$	0	0.002	0	**0.006***	0	0.005	0	**0.009*****	0	**0.008****	0	**0.018*****	0	**0.008****
	-	*(0.69)*	-	*(1.60)*	-	*(1.48)*	-	*(2.57)*	-	*(1.98)*	-	*(4.35)*	-	*(2.34)*
	[0.0%]	*[1.9%]*	*[0.0%]*	*[6.8%]*	*[0.0%]*	*[5.4%]*	*[0.0%]*	*[10.7%]*	*[0.0%]*	*[9.1%]*	*[0.0%]*	*[22.2%]*	*[0.0%]*	*[9.8%]*
NCF	**0.032****	**0.024***			**0.070*****	**0.066*****					0.021	**0.074*****		
	(2.36)	*(1.68)*			*(2.96)*	*(2.85)*					*(1.09)*	*(3.54)*		
	[38.2%]	*[28.4%]*			*[83.8%]*	*[79.3%]*					*[25.3%]*	*[89.3%]*		
NDR	0.002	0.002			-0.005	-0.008					0.002	**-0.033*****		
	-	-			*(-1.09)*	*(-1.48)*					*(0.28)*	*(-3.63)*		
	[2.5%]	*[2.5%]*			*[-5.8%]*	*[-9.9%]*					*[1.9%]*	*[-39.8%]*		
R_M^e			**0.007*****	0.002			**0.006*****	-0.002	**0.008*****	-0.000			**0.006*****	-0.002
			(3.14)	*(0.55)*			*(2.93)*	*(-0.53)*	*(3.34)*	*(-0.06)*			*(2.94)*	*(-0.40)*
			[8.9%]	*[2.8%]*			*[7.7%]*	*[-2.7%]*	*[9.1%]*	*[-0.3%]*			*[7.7%]*	*[-2.0%]*
SMB							0.002	**0.003***	**0.003***	0.002	0.002	**0.004*****		
							(1.24)	*(1.88)*	*(1.74)*	*(1.39)*	*(1.23)*	*(2.51)*		
							[2.4%]	*[3.7%]*	*[3.6%]*	*[2.8%]*	*[2.4%]*	*[5.2%]*		
HML							**0.003***	0.003	0.002	0.002	**0.003***	**0.003***		
							(1.70)	*(1.54)*	*(1.41)*	*(1.39)*	*(1.78)*	*(1.69)*		
							[3.4%]	*[3.1%]*	*[2.9%]*	*[2.8%]*	*[3.5%]*	*[3.4%]*		
UMD									0.010	0.006				
									(1.41)	*(0.77)*				
									[12.4%]	*[7.3%]*				
ME													**0.003****	**0.003****
													(1.93)	*(1.97)*
													[3.9%]	*[4.0%]*
I/A													**0.003****	**0.003****
													(2.29)	*(1.97)*
													[3.8%]	*[3.3%]*
ROE													0.003	-0.003
													(-0.19)	*(-1.03)*
													[-0.6%]	*[-3.0%]*

Table F4: Prices of risk with the main and the additional benchmark models (*Cont.*)

	ICAPM		CAPM		Two-Factor		FF		FF4		Khan-F4		Q-FM	
	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$	$R_{\text{rf}} = R_{\text{zb}}$	$R_{\text{rf}} \neq R_{\text{zb}}$
Panel B: Evaluation metrics														
R^2	23.6%	26.1%	-15.3%	4.1%	40.1%	55.2%	42.3%	52.1%	47.3%	53.3%	45.8%	66.9%	56.8%	63.8%
alpha	**58.12****	**47.32****	**65.26****	**46.22****	**57.68****	**39.98****	**51.05****	**35.36****	**44.57****	**32.94****	**48.85****	**29.75****	**37.18****	**28.40****
	> 27.59	> 26.30	> 27.59	> 26.30	> 26.30	> 25.00	> 25.00	> 23.69	> 23.69	> 22.36	> 23.69	> 22.36	> 23.69	> 22.36
CPE	0.021	**0.019****	**0.032****	**0.025****	0.018	0.011	**0.015****	**0.012****	**0.014****	**0.012****	**0.014****	**0.009****	**0.012****	**0.009****
	< 0.022	> 0.016	> 0.021	> 0.016	< 0.018	< 0.014	> 0.011	> 0.008	> 0.010	> 0.008	> 0.010	> 0.007	> 0.008	> 0.006
PEM	0.144	0.138	0.178	0.159	0.133	0.103	0.122	0.108	0.119	0.109	0.120	0.093	0.109	0.097
HJ	0.057	0.054	0.092	0.076	0.048	0.036	0.046	0.038	0.042	0.037	0.043	0.026	0.034	0.029

Entries show the results from the second step Fama and MacBeth (1973) estimation for the asset pricing models under consideration. The first column for any given model restricts the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). Panel A presents the prices of risk, the Newey-West t-statistics in parenthesis and the annualized prices of risk in square brackets. Panel B shows the R^2, *alpha*, *CPE*, *PEM* and *HJ* for any given asset pricing model. [*], [**] and [***] asterisks denote rejection of the null hypothesis at a 10%, 5% and 1% level, respectively. In the case of the t-statistic the null hypothesis is that the price of risk is equal to zero, while in the cases of *alpha* and CPE the null hypothesis is that the pricing errors are, on average, equal to zero. For *alpha* and CPE [**] asterisks denotes rejection of the zero-pricing errors hypothesis since the statistic exceeds the 5% critical value denoted below each statistic. The 5% critical value, for *alpha*, is obtained from the normal distribution, while for CPE is obtained from a bootstrap distribution. The asset pricing models are estimated using monthly observations over the period from July 1976 to December 2013. R_M^e is the excess value-weighted market return. SMB and HML are the small-minus-big and Fama-French (1993) factors. UMD is the Carhart (1997) momentum factor. I/A and ROE are the investment and profitability Hou et al. (2015) factors.

Table F5: Hedge portfolios with the main and the additional benchmark models

Size	BE/ME	Hedge Portfolios	ICAPM		CAPM		Two-Factor		FF		FF4		Khan-F4		Q-FM	
			$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$	$R_{rf} = R_{zb}$	$R_{rf} \neq R_{zb}$
Small	G	HP_1	2.9%	3.2%	2.5%	**4.1%***	3.5%	**4.8%****	**5.0%****	**4.9%****	**4.3%****	**4.5%****	**4.6%****	**3.9%****	**3.7%****	**3.3%***
			(1.02)	*(1.21)*	*(0.89)*	*(1.83)*	*(1.31)*	*(2.12)*	*(2.43)*	*(2.39)*	*(2.10)*	*(2.28)*	*(2.37)*	*(2.01)*	*(1.99)*	*(1.80)*
	M	HP_2	1.2%	1.7%	1.2%	**3.2%****	1.5%	**3.2%****	**3.7%*****	**4.7%*****	**3.7%*****	**4.6%*****	**3.2%*****	**3.3%*****	**3.5%*****	**4.0%*****
			(0.59)	*(0.95)*	*(0.63)*	*(2.32)*	*(0.82)*	*(2.26)*	*(2.71)*	*(3.68)*	*(2.73)*	*(3.59)*	*(2.89)*	*(2.96)*	*(3.22)*	*(3.70)*
	V	HP_3	1.4%	1.8%	1.2%	**2.9%****	1.9%	**3.2%****	**2.7%****	**4.0%*****	**3.0%****	**3.9%*****	**2.3%***	**4.0%*****	**2.7%****	**3.4%*****
			(0.88)	*(1.21)*	*(0.72)*	*(2.25)*	*(1.20)*	*(2.44)*	*(2.00)*	*(3.11)*	*(2.25)*	*(3.09)*	*(1.91)*	*(3.13)*	*(2.36)*	*(2.97)*
Big	G	HP_4	2.2%	2.2%	1.9%	1.9%	2.0%	1.7%	**2.8%***	2.3%	**3.0%****	**2.5%***	**2.6%***	1.5%	**2.4%****	1.4%
			(1.43)	*(1.39)*	*(1.23)*	*(1.23)*	*(1.27)*	*(1.09)*	*(1.86)*	*(1.50)*	*(1.97)*	*(1.61)*	*(1.74)*	*(1.05)*	*(2.06)*	*(1.25)*
	M	HP_5	-0.5%	0.0%	-0.1%	1.3%	-1.5%	-0.6%	0.3%	1.9%	1.7%	**2.4%***	-0.4%	0.4%	0.5%	1.7%
			(-0.28)	*(0.03)*	*(-0.03)*	*(0.81)*	*(-0.86)*	*(-0.37)*	*(0.21)*	*(1.29)*	*(1.11)*	*(1.67)*	*(-0.25)*	*(0.26)*	*(0.29)*	*(1.14)*
	V	HP_6	**-3.4%***	-2.6%	-2.6%	-0.3%	**-3.8%***	-1.7%	-2.4%	1.1%	-0.5%	1.6%	-2.9%	1.6%	-2.6%	0.4%
			(-1.65)	*(-1.10)*	*(-1.20)*	*(-0.10)*	*(-1.76)*	*(-0.71)*	*(-1.09)*	*(0.67)*	*(-0.32)*	*(1.31)*	*(-1.43)*	*(0.98)*	*(-1.20)*	*(0.24)*

Entries show annualized average abnormal returns, in percentages, and their Newey-West t-statistics, in parentheses, of the hedge portfolios under consideration. The risk-adjustment is from the model identified at the top of each column. We form six hedge portfolios (HP_1, HP_2, HP_3, HP_4, HP_5 and HP_6) by going long on the R&D intensive stocks and short on the No-R&D stocks within each size and BE/ME bucket. Table 5 contains the details of hedge portfolio formation. contains the details of hedge portfolio formations. The sample spans the period from July 1976 to December 2013 (450 monthly observations).

Table F6: Financial constraints for the test portfolios

	Size=Small			Size=Big		
	BE/ME			BE/ME		
	G *(Growth)*	M	V *(Value)*	G *(Growth)*	M	V *(Value)*
R&D intensity						
Panel A: Mean (Median) financial constraint characteristics						
N *(No-R&D)*	-3.16	-3.52	-3.60	-3.80	-3.84	-3.95
	(-3.04)	(-3.46)	(-3.53)	(-3.82)	(-3.87)	(-4.04)
L	-2.99	-3.50	-3.52	-3.87	-4.00	-3.94
	(-2.88)	(-3.43)	(-3.48)	(-3.90)	(-4.07)	(-3.95)
H *(High-R&D)*	-3.11	-3.45	-3.55	-3.98	-4.00	-3.98
	(-3.07)	(-3.40)	(-3.51)	(-4.07)	(-4.05)	(-4.00)
Panel B: Proportion of constrained firm-years in the portfolios						
N *(No-R&D)*	52.06%	25.09%	18.81%	4.42%	1.75%	1.71%
L	65.68%	32.41%	23.18%	8.05%	1.92%	1.98%
H *(High-R&D)*	60.64%	36.37%	28.94%	1.73%	1.35%	1.73%

Table F6 shows the financial constraint characteristics of each size, BE/ME and R&D intensity test portfolio. Financial constraints are estimated with the Handlock and Pierce (2010) index (HPI) as: $HPI = -(0.737 \times Size) + (0.043 \times Size^2) - (0.040 \times Age)$; where $Size$ is the log inflation-adjusted assets; and Age is the number of years the firm is listed with a non-missing stock price. $Size$ is capped at (the log of) \$4.5 billion, and Age is capped at 37 years. Panel A reports the sample means (medians) of the 38 annual values, where an annual value is the weighted average of the HPI values of the firms in each portfolio, using the portfolio weights. Panel B reports the percentage proportion of firm-years on each test portfolio classified as constrained. Every June of calendar year t firms are coded based on their HPI values in calendar year $t-1$. Firms in the top tercile are considered constrained.