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Holger Kraft
Eduardo S. Schwartz
Farina Weiss

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ABSTRACT

This paper studies the relation between firm value and a firm's growth options. We find strong empirical evidence that (average) Tobin's Q increases with firm-level volatility. However, the significance mainly comes from R&D firms, which have more growth options than non-R&D firms. By decomposing firm-level volatility into its systematic and unsystematic part, we also document that only idiosyncratic volatility has a significant effect on valuation. Second, we analyze the relation of stock returns to realized contemporaneous idiosyncratic volatility and R&D expenses. Single sorting on idiosyncratic volatility yields a significant negative relation between portfolio alphas and contemporaneous idiosyncratic volatility for non-R&D portfolios, whereas in a four-factor model the portfolio alphas of R&D portfolios are all positive. Double sorting on idiosyncratic volatility and R&D expenses also reveals these differences between R&D and non-R&D firms. To control for several explanatory variables simultaneously, we also run panel regressions of portfolio alphas which confirm the relative importance of idiosyncratic volatility that is amplified by R&D expenses.

Holger Kraft
Goethe University
Grueneburgplatz 1
65323 Frankfurt am Main
Germany
holgerkaft@finance.uni-frankfurt.de

Farina Weiss
Goethe University
Frankfurt, Germany
Farina.Weiss@hof.uni-frankfurt.de

Eduardo S. Schwartz
Anderson Graduate School of Management
UCLA
110 Westwood Plaza
Los Angeles, CA 90095
and NBER
eduardo.schwartz@anderson.ucla.edu

1 Introduction

The market value of a firm is the sum of the present value of the cash flows generated by the assets in place and its growth options.[1] Real option theory suggests that values of growth options are positively related to the volatility of firm value (or a firm's cash flows).[2] Everything else equal, we thus expect the market value of a firm to increase in volatility. Depending on whether a firm belongs to a growing or mature industry, this dependance is more or less strong. For instance, R&D as opposed to non-R&D firms are supposed to have more growth options and in turn should be more affected by volatility. In this paper, we first study the relation of firm value and volatility and find empirical evidence that Tobin's Q is positively related to a firm's stock volatility that serves as a proxy for the volatility of the underlying growth options.[3] As suggested by real options theory, we document that this relation is much stronger for R&D firms than for non-R&D firms.

Volatility however consists of a systematic and an unsystematic (idiosyncratic) part. By definition, the systematic part should be priced and thus expected returns should be affected by systematic volatility. In contrast standard capital-market theory suggests that idiosyncratic risk has no effect on expected returns.[4] Therefore, the effects of these two volatility components on firm value are different: Although both components increase the value of growth options, systematic volatility also increases discount rates that are used to discount future cash flows of a firm. Hence, the effect of systematic volatility on firm value is ambiguous. We thus decompose volatility into its systematic and unsystematic part. Our line of argument so far suggests that the effect of unsystematic volatility should be stronger than the effect of systematic volatility. Besides, the effect of unsystematic volatility should be the strongest for firms that have a lot of growth options (e.g. R&D firms). Our empirical results support these predictions: Whereas Tobin's Q is hardly affected by systematic volatility, there is a pronounced effect for unsystem-

[1] See, e.g., Berk, Green, and Naik (1999).

[2] Brennan and Schwartz (1985) and McDonald and Siegel (1986).

[3] See, e.g., Grullon, Lyandres, and Zhdanov (2012).

[4] There are however models where unsystematic risk is priced. For instance, Merton (1987) sets up a model where investors hold undiversified portfolios and thus demand a risk premium for unsystematic risk.

atic volatility. In particular, the effect for R&D firm observations is significantly stronger than for non-R&D firm observations.

Finally, we analyze the relation of realized stock returns to realized contemporaneous idiosyncratic volatility (ivol) and R&D expenses where we again split the whole sample into sub-samples of R&D and non-R&D observations. Single sorting on idiosyncratic volatility yields a significant negative relation between abnormal stock returns and contemporaneous ivol for non-R&D portfolios,[5] whereas in a four-factor model the portfolio alphas of R&D portfolios are all positive. This confirms the intuition that the values of growth options increase in (idiosyncratic) volatility and thus a larger ivol leads to higher contemporaneous returns. We also document that, although for R&D portfolios the average Tobin's Q and R&D expenses increase in average ivol, the relation is flat for non-R&D portfolios.[6] In other words, both sub-samples are very distinct with respect to the sizes and patterns of R&D expenses and Tobin's Q. On the contrary, the average ivols of the portfolios are similar. This finding is in line with our panel regression results that idiosyncratic volatility is particularly pricing relevant when it is interacted with an R&D dummy. Double sorting on idiosyncratic volatility and R&D expenses supports our findings for portfolio alphas: For high R&D observations all (three and four-factor) alphas are positive, whereas for low or zero R&D observations alphas in general are postive for low-ivol portfolios and negative for high-ivol portfolios. Besides, all difference portfolios (high minus low or zero R&D for given ivol level) have positive alphas where about half of them are individually significant.

Since a single-sort on ivol simultaneously leads to orderings with respect to other variables (e.g. size, leverage, firm-level volatility, skewness), we also run panel regressions of portfolio alphas where we can simultaneously control for several explanatory variables. Our results suggest that

[5] Notice that we consider a contemporaneous relation between the two. This should not be confused with the so-called "ivol anomaly" which refers to the empirical finding that stocks with high (low) idiosyncratic volatility have abnormally low and negative (high and positive) expected average returns. See, e.g., Ang, Hodrick, Xing, and Zhang (2006).

[6] By definition, R&D expenses are zero for non-R&D portfolios so that these portfolios have trivially a flat relation for R&D expenses.

portfolio alphas depend on firm-level volatility, but predominately via its idiosyncratic part. If interacted with R&D expenses, all components of volatility matters.

Our paper is related to an increasing literature on the cross-sectional relation between returns and volatility or idiosyncratic volatility. Duffee (1995) documents a positive relation between stock returns and volatility at the firm level. Concerning idiosyncratic volatility, several empirical studies find evidence that expected returns vary systematically with idiosyncratic risk. This is in contrast to standard capital-market models such as the CAPM and the Fama-French model, which predict no relation between expected returns and idiosyncratic volatility. Ang, Hodrick, Xing, and Zhang (2006, 2009) measure idiosyncratic volatility relative to the Fama-French model and find a negative relation between expected returns and idiosyncratic risk (ivol anomaly). By measuring volatility in a different way, Fu (2009) and Fink, Fink, and He (2012) find that expected returns and idiosyncratic volatility are positively related. Our paper adds to this extensive literature. Motivated by the work from Cochrane (2011), we study the cross-sectional price variation and first concentrate on firm value. In contrast to the existing literature, we then study the *contemporaneous* relation between (abnormal) returns and idiosyncratic volatility, which complements our analysis for values. Similar to our results, Fink, Fink, and He (2012) find empirical evidence for a positive contemporaneous ivol-return relation.

Our paper is also related to the real option pricing literature that started with the papers by Brennan and Schwartz (1985) and McDonald and Siegel (1986). Option values increase in volatility (both systematic and idiosyncratic), which indicates why idiosyncratic volatility might be priced if a firm has growth options.

Several papers have examined the effect of volatility on returns (but not the effect of volatility on prices) and use real option theory to explain their observations. Grullon, Lyandres, and Zhdanov (2012) find evidence that expected returns increase in (firm-level) volatility. This relation is much stronger for firms with more real options. An important difference with our paper is however that they consider expected returns and do not decompose volatility into a systematic and an idiosyncratic part. Chen and Petkova (2012) consider idiosyncratic volatility and focus on the ivol anomaly. They suggest that their observed negative relation between idiosyncratic volatility and return in the Fama-French model arises from a missing factor. By introducing a new factor (a component of aggregated market variance), they can explain the ivol anomaly and relate this factor to a firm's growth options. In our paper, we also examine the effect of contemporaneous volatility on firm values and propose a growth option explanation for cross-sectional differences in firm values. We find clear evidence that firm value increases in firm-level volatility and this effect is stronger for firms with higher R&D expenses. These results are in line with the findings of Connolly and Hirschey (2005) and Czarnitzki, Hall, and Oriani (2006), who show that the amount of R&D expenses is a significant determinant of firm value.

Cao, Simin, and Zhao (2008) provide a link between growth options and the value-weighted average of idiosyncratic firm-level volatility. They show that average aggregated idiosyncratic volatility is positively related to growth options and that these options can explain the increasing aggregate idiosyncratic volatility over the last decades. Bekaert, Hodrick, and Zhang (2013) study aggregate idiosyncratic volatility in 23 countries and document that it is highly correlated across countries. They find that idiosyncratic volatility can be explained by growth opportunities and a business cycle sensitive risk indicator. These findings are in line with our results that firm values increase in (idiosyncratic) volatility due to growth options.

Pastor and Veronesi (2003) develop a framework for valuing stocks whose average future profitability is unknown. They find that uncertainty about a firm's average profitability increases its idiosyncratic return volatility. This uncertainty is especially large for the newly listed firms. Kogan and Papanikolaou (2012) develop a theoretical model in which a firm's sensitivity to technological shocks is a function of the ratio between growth opportunities and firm value. Firms with more growth options benefit more from positive technological shocks than firms with limited investment opportunities. Hence, differences in the ratio between growth opportunities and firm value lead to difference in returns, and technological shocks lead to differences in stock returns across firms.

Finally, our paper is related to the q-theory of investment that studies the relation between investment decisions and firm value. Belo and Zhang (2010) combine q-theory and asset pricing literature. They develop a neoclassical model to study the determinants of firm value and focus on the investment-to-capital ratio to explain cross-sectional differences in firm value.[7]

The remainder of the paper is structured as follows: Section 2 discusses the economic hypotheses. Section 3 describes the data set and introduces definitions of variables. Section 4 presents results of benchmark panel regressions. Section 5 studies how these results change when we decompose volatility into a systematic and an idiosyncratic part. Section 6 analyzes the relation of R&D expenses and realized idiosyncratic volatility with contemporaneous stock returns. Section 7 concludes.

2 Economic Hypotheses

Following Berk, Green, and Naik (1999), we posit that firm value is the sum of the present value of cash flows of assets in place and the value of a firm's growth options (call options). Tobin's Q is then defined as the ratio of firm value and book value.

Our first analysis consists in panel regressions of Tobin's Q on the variables that affect the value of the growth options, controlling for other factors that may have an impact on firm valuation. Our regressions involve long-term interest rates that affect discount rates and call option prices, but in different directions. Present values decrease in discount rates, whereas call option prices increase. Additionally, interest rates also vary with the business cycle. Therefore, the overall effect of interest rates on firm value is not obvious.

Motivated by the findings of Ang, Hodrick, Xing, and Zhang (2006) that aggregate volatility risk is priced, we add the volatility of the S&P 500 index to our regressions. Since market volatility is a measure of global risk, we expect Tobin's Q to be negatively related to market volatility.

On the contrary, individual stock volatility is directly related to the volatility of firm value. On

[7]For further literature that studies the effect of real investment decisions on asset prices and returns see, e.g., Chan, Lakonishok, and Sougiannis (2001), Desai, Wright, Chuang, and Charoenwong (2003), Aguerrevere (2009), Carlson, Fisher, and Giammarino (2010), and Hackbarth and Johnson (2012).

the one hand, discount rates increase in systematic volatility, which in turn has a negative effect on firm value. On the other hand, growth options increase in both systematic and idiosyncratic volatility. We thus expect that for firms with a lot of growth options (e.g. R&D firms) firm value and firm-level volatility are positively related. The effect should be particularly strong for idiosyncratic volatility, which should not affect discount rates. Furthermore, firm-level skewness and Tobin's Q should be positively related, since a larger skewness leads to larger values of growth options.

Roll, Schwartz, and Subrahmanyam (2009) proxy for investment opportunities by including capital expenditures, but disregard R&D expenses. On the other hand, Connolly and Hirschey (2005) and Czarnitzki, Hall, and Oriani (2006) find that R&D expenses affect firm values positively. We thus include both variables. Whereas R&D expenses create growth options, capital expenditures are a direct measure of investment opportunities actually undertaken, i.e. exercised growth options. Therefore, we expect Tobin's Q to increase with R&D expenses. This is also inline with Kogan and Papanikolaou (2012) who theoretically show that Tobin's Q is positively related to growth opportunities. The effect of capital expenditures is however not obvious, since capital expenditures destroy growth options, but can also create new ones.[8]

Following Roll, Schwartz, and Subrahmanyam (2009), among others, our regressions involve several control variables. We use turnover of a firm's shares as a liquidity proxy. Since investors are willing to pay a premium for liquid assets, the market value of a firm and thus Tobin's Q should increase in stock turnover. Besides, we include market capitalization as a size measure and expect Tobin's Q to increase with market capitalization due to the size effect. We also control for leverage. Depending on whether leverage is a proxy for default risk or whether debt might make managers more careful about investments (see Jensen and Meckling (1976)) the effect can be positive or negative. Besides, return on assets is used a profitability measure. The relation to Tobin's Q could be positive since profitable firms might have more growth options. On the other hand, the relation could be negative if mature firms with few growth options are more profitable. Finally, we include a dividend dummy that proxies for capital constraints.

[8]Notice that capital expenditure increase not only the physical capital, but also the option to invest further and can thus create new growth options. See, e.g., Carlson, Fisher, and Giammarino (2010).

Firms that pay dividends may have more free cash flow, which may potentially be used to overinvest in marginal projects. This would lead to a negative relation to Tobin's Q. This could also be due to a tax effect, since taxes on dividends are higher than on capital gains.

3 Data

Since we are interested in analyzing the effect of volatility on Tobin's Q and stock returns, we distinguish firms with more growth options (R&D firms) from firms with less growth options (non-R&D firms). Therefore, our sample period starts in 1975 (ranging until 2009). Before 1975 firms were allowed, but not required to capitalize R&D expenses. Since 1975 there are stricter rules and it is required that all R&D expenses are expensed in the period incurred (with a few exceptions). Consequently, the year 1975 is the natural starting point of the sample. Notice that it is not straightforward to distinguish between R&D and non-R&D firms.[9] For this reason, we are going to split the observations into firm-year observations in which R&D expenses are reported and into firm-year observations where this is not the case (missing or zero). We have also tried alternative ways to identify R&D vs. non-R&D firms (e.g. more than 90% firm-year observations in the past with R&D) and the results were very similar to the results reported below.

The data comes from several sources. Firstly, we use two macro variables, the 10y Treasury yield and the historical volatility of the S&P 500 index. The Treasury yield comes from the database of the FED St. Louis. The S&P 500 index data is reported by CRSP. At the end of every month of the sample period we calculate the historical index volatility by computing the daily standard deviation of the returns over the year up to that month.[10] The volatility is then annualized by multiplying by $\sqrt{250}$. Table 1 reports summary statistics of both macro variables. The average treasury yield is about 7.4% and the average historical volatility of the

[9] For instance, there are firms that initially do not report R&D expenses and then start to do so or vice versa. In particular, one has to be careful not to use any forward-looking criteria.

[10] We use the returns excluding distributions, but our results do not change if we use returns including distributions.

S&P 500 index is 15.8%.[11]

[INSERT TABLE 1 ABOUT HERE]

The firm data comes from Compustat and CRSP. The sample is selected by deleting any firm-year observations with missing accounting data. Financial firms and utilities are excluded from the sample as well. Our benchmark results presented in Section 4 are based on 106,219 observations coming from 12,935 firms over 35 years. There are 49,244 observations including R&D expenses and 56,975 observations not including R&D expenses. Figure 1 depicts the percentage of observations with R&D expenses per Fama-French industry, both for the whole sample and after cleaning the data (referred to as 'benchmark'). It can be seen that the frequencies are similar in the 'benchmark' sample and in the whole sample. The industries in which close to 90% or more of the observations involve R&D expenses are Measuring and Control Equipment, Pharmaceutical Products, Computers, Medical Equipment, and Electronic Equipment.

[INSERT FIGURE 1 ABOUT HERE]

The relevant data includes the following items derived from Compustat: Tobin's Q is defined as the ratio between (i) the sum of book value of assets plus the difference between market value and book value of equity minus deferred taxes (Compustat: at + prcc_f × csho - ceq - txdb), where we set deferred taxes equal to zero if they are missing,[12] and (ii) book value of assets (Compustat: at). Invest denotes the investments of a firm defined as capital expenditures (Compustat: capx) over sales (Compustat: sale).[13] Size is defined as the logarithm of real market capitalization that is obtained by dividing nominal market capitalization (Compustat: prcc_f × csho) by the Consumer Price Index from the Bureau of Labor Statistics. The return on assets, ROA, is given as the ratio between income before extraordinary items plus total

[11] VIX data is not available for the whole time period and thus we decided to use historical volatility.

[12] Our results are robust to this assumption.

[13] There are 20 observations with negative sales where we set sales to missing. Notice that our regression results are very similar if we divide by lagged sales. In order to make our results easier comparable to Roll, Schwartz, and Subrahmanyam (2009), we divide by sales.

interest and related expense (Compustat: ib plus xint) and lagged book value of total assets (Compustat: lag of at). Leverage is long-term debt over total assets (Compustat: dltt/at). RDexp is defined as the ratio between R&D expenses (Compustat: xrd) and sales. Missing R&D expenses are set to zero. A dummy variable for whether the firm pays a dividend is included in most regressions as well.

We also calculate the annualized historical volatility and skewness of a firm's stock returns using the CRSP daily stock file for every firm fiscal year (including distributions).[14] Firm-level volatility and skewness are denoted by Vol_firm and Skew_firm.[15] The turnover of a firm's share is given as the average daily turnover of shares divided by the number of outstanding shares. We use the information about volume as reported in CRSP with the following exceptions. If volume and return are missing, then volume is replace by zero. The same is true if volume is missing and return is zero. If volume is missing, but return is non-zero, then we keep the missing value of volume. However, our results hardly change if we disregard missing volume information altogether.

[INSERT TABLE 2 ABOUT HERE]

Table 2 reports summary statistics of the firm specific variables. It also provides these statistics for the sub-samples of firm-year observations involving R&D expenses and not-involving R&D expenses. It can be seen that R&D observations have higher Tobin's Q, higher firm-specific volatility, lower skewness and are related to more liquidity as measured by turnover. Furthermore, the relative capital expenditures are lower, size is bigger, and profitability and leverage are smaller. Besides, the probability of a dividend payment is smaller.

[14] We have calculated volatility and skewness using all available return observations. As a robustness check, however, we have tried several alternatives to account for missing observations. We have calculated the firm-level volatilities by disregarding days where return is missing. Then we have only used days where trading volume is positive and returns are not missing. Finally, we have set missing returns to zero. Besides, we have used daily returns including and excluding distributions. Our regression results only marginally change, though.

[15] In contrast to the firm-level volatility that is annualized the firm-level skewness is not annualized. This is because the annualized skewness equals the daily skewness multiplied by $250 \cdot \sqrt{250}$, which leads to inconveniently large number.

[INSERT TABLE 3 ABOUT HERE]

Table 3 summarizes the correlations between the variables involved in our analysis. First, note that – except for few correlations close to zero – all signs of the correlations are the same for the full sample and the two sub-samples. Furthermore, Tobin's Q is negatively related to the Treasury yield, so its role as discount rate seems to dominate in the data. The S&P volatility is also negatively related indicating that it proxies for global risk. On the contrary, firm-level volatility and skewness are positively related to Tobin's Q, which suggests that growth options are indeed relevant for pricing. Both capital expenditures and R&D expenses are positively related to Tobin's Q, where the latter relation is reported in Panel B of Table 3. The positive relation of capital expenditures is even true for R&D observations, which points in the direction that the effect of creating new growth options dominates the effect of destroying existing ones. As we will see later on, this relation reverses in multi-dimensional regressions where we control for both R&D expenses and capital expenditures at the same time. The control variables size and turnover have the expected positive relation to Tobin's Q. Profitability as measured by ROA is negatively correlated suggesting that mature firm's with less growth options are more profitable. Leverage is also negatively related indicating that leverage proxies for default risk. This is also true for the dividend dummy and the effect is more pronounced for R&D firms, i.e. for those firms dividend payments seem to particularly damaging.[16] To summarize, the relations between Tobin's Q and the volatility or skewness variables have the expected signs. Besides, the controls have the same signs as in Roll, Schwartz, and Subrahmanyam (2009). While these are one-dimensional results, in the following sections we will run panel regressions controlling simultaneously for several factors and distinguishing more clearly between the effects that are pricing relevant for R&D and non-R&D observations.

[16] This result is in line with Tobin and Brainard (1977) who suggest that firms with high market-to-book values (R&D firms) should undertake investments.

4 Benchmark Results

In this section we examine the relation of Tobin's Q to the joint explanatory variables discussed above. We run several panel regressions that use all the information contained in the cross-section of firms and in the time-series. The residuals of the cross-sectional regressions are likely to be serially correlated. Furthermore, there might be cross-sectional dependance as well. To overcome these potential problems, we correct our t-statistics using the approach outlined in Driscoll and Kraay (1998). They assume an error structure that is heteroscedastic, autocorrelated up to some lag, and possibly correlated between the units.[17] The resulting standard errors are heteroscedasticity consistent as well as robust to very general forms of cross-sectional and temporal dependance. As a robustness check we have also corrected the standard errors by double clustering as discussed in Petersen (2009). The benchmark results are however almost identical.[18]

[INSERT TABLE 4 ABOUT HERE]

Table 4 reports our benchmark results. In regressions (1)-(3) we include a dummy variable if R&D expenses are positive, whereas regressions (4)-(6) involve R&D expenses that are set to zero if they are missing. In regressions (2), (3), (5), and (6) we include interaction variables that are the product of an R&D dummy and firm-level volatility or firm-level skewness. For instance, RD_vol_firm equals firm-level volatility if the particular observation also involves R&D expenses. Otherwise it is set zero. There are several interesting findings: First, index volatility is significantly negative in all regressions, i.e. more global risk leads to lower firm values. This result is consistent with the findings of Ang, Hodrick, Xing, and Zhang (2006) that aggregate volatility risk is inversely related to stock prices. However, the situation is very different for firm-level volatility that is significantly positive in regressions (1)-(4). Notice that the significance decreases and the point estimate goes down by 50% if we include the interaction variable RD_vol_firm. Instead, this interaction variable turns out to be highly significant with larger coefficients than firm volatility in regressions (1) and (4). This shows that firm-level

[17] In our regressions, the maximum lag is two years.

[18] The corresponding regression results are available upon request.

volatility matters significantly more for R&D observations. The result supports our hypothesis that firm values are positively related to firm-level volatility due to growth options. Notice also that firm-level volatility is not significant any more if we include both the interaction variable RD_vol_firm and R&D expenses (regressions (5) and (6)). Besides, we document that firm-level skewness is highly positively significant in all regressions. Its significance remains the same even if we include the interaction variable RD_skew_firm, although the coefficient goes down by 50%. However, the loading of RD_skew_firm is more than twice as high than the loading for non-R&D observations (in regressions (3) and (6) measured by Skew_firm).[19] Another important finding is that capital expenditures (Invest) are only significant if we do not include the actual size of R&D expenses, which are very significant in the last three regressions. Therefore, creating growth options via R&D expenses is more pricing relevant than any of the effects that could be attributed to capital expenditures (see Section 2).[20] Notice also that, although the R&D dummy becomes insignificant in regressions (2) and (3) where we include interaction variables with this dummy, the significance of the amount of the R&D expenses is hardly affected if we include the interaction variables in regressions (5) and (6). This documents the relative importance of R&D expenses in this context.

Furthermore, the Treasury yield is significant and positive. Since this result holds no matter how we control for effects of R&D expenses, the Treasury yield seems to proxy for business cycles. As a robustness check, we have additionally included time dummies. In this case, the results are very similar except that Treasury10 becomes insignificant.

The other controls have the expected signs and go in the same directions as in Roll, Schwartz, and Subrahmanyam (2009):[21] Tobin's Q increases with size and decreases with ROA and leverage. This demonstrates that there is a size effect in the cross-section. Besides, since ROA is negatively significant, mature firm's with less growth options seem to be more profitable. The

[19] Chen and Petkova (2012) also suggest that firms with high skewness are likely to have growth options/ R&D expenditures. However, they examine the relation between R&D expenses and stock returns.

[20] McConnell and Muscarella (1985) find evidence that the announcement of capital expenditures positively affects firm values, but they do not control for R&D expenses.

[21] An exception is turnover. Here the comparison is more complicated since Roll, Schwartz, and Subrahmanyam (2009) include two liquidity variables, stock turnover and option trading activity.

interpretation of leverage as a measure of distance to insolvency appears to be more important than its disciplinary effect as discussed by Jensen and Meckling (1976). Finally, the dividend dummy is highly negatively significant, which suggests that firms that pay dividends waste money on non-profitable projects due to non-binding financial constraints and/or are mature firms with less growth options.

Additionally, as another piece of empirical evidence, we run benchmark regression (1) several times, each run with an additional interaction variable that interacts the R&D dummy with any of the explanatory variables.[22] As expected we find that the interaction variables with firm-level volatility and skewness are significant. Besides, the interaction variable with ROA is negatively significant, i.e. R&D firms are currently less profitable. On the other hand, the interaction variable with turnover is positively significant implying that R&D firms have more liquid stock. A remarkable result however is that only the interaction variable with firm-level volatility is able to knock out the significance of the R&D dummy. This underlines the importance of firm-level volatility as explanatory variable for firm value and Tobin's Q, in particular.

5 Systematic vs. Idiosyncratic Volatility

In the previous section, we have documented that Tobin's Q of an R&D observation has a significantly positive loading on firm-level volatility and that the corresponding loading for non-R&D observation is smaller and borderline significant. In this section, we explore whether this positive dependance can be attributed to systematic or idiosyncratic firm-level volatility. We also study whether there is a difference between R&D and non-R&D observations. The main reason for decomposing firm-level volatility is that for the valuation of (growth) options both systematic and idiosyncratic volatility matter, whereas idiosyncratic volatility is not priced according to the CAPM or APT. Therefore, the idiosyncratic part of firm-level volatility might be a cleaner measure than firm-level volatility, since the idiosyncratic part only influences the values of growth options and not discount rates. Furthermore, if R&D firms have more growth

[22]The corresponding table is available upon request.

options than non-R&D firms, they should have a higher and positive loading on idiosyncratic volatility.

In the following, we briefly discuss how firm-level volatility can be decomposed into a systematic and an idiosyncratic part. First, notice that this decomposition is model-dependent. We thus implement two models: a Fama-French three-factor model and a CAPM-style one factor model. In the three-factor model, we run for every firm fiscal year the following regression on daily data

$$r_t^i - r_t^f = \alpha^i + \beta^{M,i}(r^M - r^f)_t + \beta^{SMB,i} SMB_t + \beta^{HML,i} HML_t + \varepsilon_t^i,$$

where r_t^i is the daily return of firm i, r_t^f is the Fama riskfree rate, and $(r^M - r^f)_t$, SMB_t, and HML_t denote the returns on the three Fama-French factor portfolios (market, size, book). The idiosyncratic volatility (ivol) of year y is then defined as[23]

$$\sigma_y^{unsys} = \sqrt{\mathrm{Var}(\varepsilon_t^i)},$$

where t is in year y. Analogously, the systematic volatility of year y is given by

$$\sigma_y^{sys} = \sqrt{\mathrm{Var}(r_t^i - r_t^f - \varepsilon_t^i)}.$$

Notice that $\sigma_y^2 = (\sigma_y^{sys})^2 + (\sigma_y^{unsys})^2$, where σ_y is the volatility of firm i in year y. The one-factor model includes the market factor $r^M - r^f$ only. Since our regressions already control for size and leverage that are closely related to the size and book factor of the Fama-French model, considering a one-factor might be a reasonable alternative.

[INSERT TABLE 5 ABOUT HERE]

Table 5 reports the regression results when we decompose firm-level volatility (Vol_firm) into a systematic part (Vol_ff_sys or Vol_capm_sys) and an unsystematic part (Vol_ff_unsys or Vol_capm_unsys) using the Fama-French model and the CAPM. The regressions labeled (2: FF) and (2: CAPM) should be compared with regression (2) repeated from Table 4, which involves an R&D dummy. Accordingly, regressions labeled (5: FF) and (5: CAPM) should be compared with regression

[23] See Ang, Hodrick, Xing, and Zhang (2006).

(5) repeated from Table 4, which involves the actual amount of R&D expenses (set to zero if missing) instead of an R&D dummy.

It turns out that only the interaction variables RD_vol_ff_unsys and RD_vol_capm_unsys measuring the effect of idiosyncratic volatility on R&D observations are highly significant with the expected (positive) sign. The loadings of non-R&D observations on unsystematic volatility are borderline significant with sizes being about half as big as the loadings of RD_vol_ff_unsys and RD_vol_capm_unsys. Taken together these results clearly indicate that volatility predominately matters through its idiosyncratic parts. This effect is highly relevant for R&D firms that have a lot of growth options.

Finally, notice that our previous results concerning the relevance of capital expenditures and R&D expenses are still intact: The size of R&D expenses is highly relevant and knocks out the significance of capital expenditures when we include the actual amount in the regressions. This can be seen in regressions (5: FF), and (5: CAPM).

6 Stock Returns

In the previous sections, we have documented that for R&D observations firm value increases with (idiosyncratic) firm-level volatility. In this section, we study the relation between (idiosyncratic) firm-level volatility and stock returns for R&D and non-R&D observations. Following a similar line of argument as before, the (contemporaneous) stock return of a firm with a lot of growth options should be positively related to idiosyncratic volatility. This is because a larger volatility increases the values of the growth options, which should materialize in positive stock returns. As already discussed in the introduction, Ang, Hodrick, Xing, and Zhang (2006) document the so-called ivol anomaly showing that value-weighted high ivol portfolios have significantly lower expected returns, i.e. lower returns in *future* periods.[24] Since we focus on growth options where from an option pricing point of view the relation between volatility

[24] See Fu (2009) for measurement issues in this context.

and value or returns is contemporaneous,[25] we consider contemporaneous realized stock returns. Therefore, we relate volatility to returns of the same period for which (idiosyncratic) volatility is calculated. This is in line with the previous panel regressions where we relate firm values to contemporaneous firm-level volatilities. Besides, the firms are grouped into equal-weighted portfolios since this approach is similar to the weighting scheme of panel regressions. We focus on firms in our sample that have a fiscal year ending in December and match monthly stock returns from CRSP to our data set. The Fama-French factors as well as the momentum factor stem from Kenneth French's website.

The trouble with idiosyncratic volatility as defined in Section 5 is that from a theoretical point of view there can be a systematic relation between returns and idiosyncratic volatility if there is an omitted variable in the Fama-French model. We however expect that firms with more growth options should have higher returns than firms with less growth options and thus the contemporaneous relation of idiosyncratic volatility and abnormal returns should be higher for firms with more growth options, i.e. R&D firms.

[INSERT TABLE 6 ABOUT HERE]

Each year we form equal-weighted portfolios on the basis of the size of idiosyncratic volatility computed from a Fama-French model. The ivol portfolios are arranged from low ivol to high ivol. Table 6 reports the alphas from regressions of the monthly excess portfolio returns on the three Fama-French factors for the fiscal year whose data is used to calculate the ivol on which the portfolios are based. This is performed for the whole sample and two sub-samples, R&D and non-R&D firm observations. We also report the results for a four-factor model with momentum.[26] Table 6 provides evidence that there is no significant contemporaneous ivol-return relation for the whole sample.[27] Although the alphas appear to be ordered, the alphas of the difference portfolio are not significant. These results change when we look at the sub-portfolios. For R&D observations, the ordering of the alphas goes away. If anything, the alphas

[25] See, e.g., Brennan and Schwartz (1985). In the model of Kogan and Papanikolaou (2012) there is also a relation between expected returns and growth opportunities.

[26] See Carhart (1997).

[27] Bali and Cakici (2008) show that this is also true for expected returns and equal-weighted portfolios.

show a hump-shaped pattern. In particular, for the four-factor model all alphas are positive and the point estimate of the difference portfolio is zero. On the other hand, for non-R&D observations we find the opposite: Alphas are ordered (except for a slight increase from portfolio two to three) and the alphas of the difference portfolio are significantly negative. Panel C of Table 6 also reports the robust Newey-West t-statistics of the diff-in-diff portfolio (difference portfolio of the difference portfolios) that is -1.77 for the three-factor model and -2.26 for the four-factor model. These results indicate that there is significantly negative contemporaneous ivol-return relation for non-R&D observations. Notice that these findings are driven by the two highest ivol deciles of the non-R&D observations. To summarize, our results support our above prediction that firms with growth options should have higher contemporaneous returns than firms with less growth options and that the contemporaneous ivol-return relation should be higher for firms with more growth options.

Table 6 also reports sample averages of several variables for each portfolio. Here in every month we calculate the equal-weighted average of the corresponding variable and then calculate the equal-weighted average across months.[28] Capx denotes the ratio of capital expenditures over lagged book value of assets.[29] All other variables are defined as in Section 3. It can be seen that sorting on ivol leads to several interesting patterns. Size is decreasing with idiosyncratic volatility both for R&D and non-R&D observations, which is in line with Bali and Cakici (2008) who consider the whole sample. Besides, R&D firms are bigger than non-R&D firms where the difference is the largest for low ivol and slightly U-shaped. Second, the sort on ivol also leads to a monotonous relation for firm-level volatility in both panels. The differences between Panel B and C are U-shaped for total and idiosyncratic volatility, i.e. R&D firms have smaller volatilities

[28]Accounting data is only annual, i.e. does not change within a year. Therefore, for these variables one can just calculate the equal-weighted averages over December averages. But also for the other variables the differences are negligible.

[29]In our panel regressions, following Roll, Schwartz, and Subrahmanyam (2009) we have normalized R&D expenses and capital expenditures by sales. This ensures comparability with their results and also avoids a 'hard-wired' relation to Tobin's Q whose denominator is book value. Now, we normalize by lagged book value so that all variables are normalized by the same variable (flow variables by lagged book value and stock variables by book value). This is similar to Chen and Petkova (2012) who normalize R&D expenses by book value.

for very low and very high volatilities, but higher volatilities for intermediate volatility levels. For R&D observations the ivol portfolios are also monotonously ordered with respect to R&D expenses and high (idiosyncratic) volatilities go together with high R&D expenses.[30] Notice however that R&D observations do not systematically have higher idiosyncratic volatility than non-R&D observations. In particular, the average ivols in the two highest ivol portfolios are larger for non-R&D observations.

Tobin's Q shows a very similar pattern as R&D expenses: The mean values of all R&D portfolios (except for the second portfolio) are larger than of the non-R&D portfolios. Besides, they are monotonously increasing for the R&D observations, whereas they are almost flat around 1.5 for non-R&D observations. Therefore, the portfolio with the highest average ivol (non-R&D portfolio 10 in Panel C) has a smaller average Tobin's Q than 9 out of 10 R&D portfolios. In particular, its average ivol is more than 10 times larger than the average ivol of the first R&D portfolio which has a larger Tobin's Q, though. Notice however that for the whole sample Tobin's Q is (almost) monotonously increasing with ivol, which is also reported by Chen and Petkova (2012).

Furthermore, capital expenditures are systematically larger for non-R&D observations. Turnover increases in ivol and R&D firm observations have higher turnovers than non-R&D observations. Skewness is systematically smaller for R&D firm observations (except for the highest ivol portfolio where the difference is small, though) and has the tendency to increase with ivol for both sub-samples. Besides, R&D firms have less leverage and for non-R&D firms leverage is increasing in ivol, whereas there is no clear pattern for R&D firms. Finally, ROA is decreasing in ivol for both sub-portfolios and R&D firms have smaller ROA than non-R&D firms. This difference substantially widens from low ivol to high ivol portfolios.

To summarize, a single-sort on ivol leads to several systematic patterns for other firm-specific variables[31] and these patterns have different sizes for R&D and non-R&D firm observations.

[30] This is in line with the finding of Chen and Petkova (2012) who do not report results for non-R&D observations.

[31] These findings are related to the results of Kogan and Papanikolaou (2012). They show that that firm characteristics such as Tobin's Q, investment rates, earnings-to-price ratio, and ivol are correlated with firms'

Furthermore, in equal-weighted portfolios there is only a significantly negative contemporaneous ivol-return relation when we focus on non-R&D observations. Here the significantly negative alphas of the two highest ivol portfolios in Panel C of Table 6 drive the results. Focusing on the portfolio with the highest ivol and most negative alpha in Panel C, this portfolio consists of firms without contemporaneous R&D expenses that at the same time are on average the smallest, have the highest leverage[32] and the highest idiosyncratic volatility of all portfolios (non-R&D as well R&D). In the light of all these strong relations, our findings call for double sorts or panel regressions where we can simultaneously control for several factors.

[INSERT TABLE 7 ABOUT HERE]

Since there is a strong relation between firm-level volatility and R&D expenses, we now double sort firms, first with respect to idiosyncratic volatility then with respect to R&D expenses. This allows us to control for (idiosyncratic) volatility and to study the impact of R&D expenses on contemporaneous stock returns. We expect that for a given level of idiosyncratic volatility returns increase in R&D expenses since firms with high R&D expenses presumably have more growth options. Panel A of Table 7 reports portfolio alphas when we sort observations into 60 portfolios:[33] Every ivol portfolio is sorted into six sub-portfolios (zero R&D and five R&D portfolios). Since approximately half of our observations are non-R&D observations, the five R&D portfolios together are approximately as big as the zero R&D portfolio. It can be seen that our intuition is confirmed: In all cases, high R&D observations have higher alphas than low R&D or zero R&D observations. Additionally, in 12 out of 20 cases, the differences are even individually significant.

Panel B of Table 7 reports our results when we sort the observations of every ivol portfolio into five sub-portfolios ranging from low to high R&D industries. We then focus on low and high

exposures to the same common risk factor, which generates a significant share of variation in realized portfolio returns and captures cross-sectional differences in their risk premia.

[32] If leverage is interpreted as a proxy for (physical) default probability, then these firms also have the highest default probability.

[33] We use a Fama-French three-factor model. The results involving a momentum factor are similar and available upon request.

R&D industries, which both make up for approximately 20% of the firm-year observations in our sample. High R&D industries are defined as the following five industries:[34] Pharmaceutical Products (13); Measuring and Control Equipment (37); Medical Equipment (12); Electronic Equipment (22); and Computers (35). In these industries, on average more than 90% of the firm-year observations involve R&D expenses (see Figure 1). There is a large gap to the next industry, Chemicals, where less than 80% of the observations involve R&D expenses. Low R&D industries are defined as the following ten industries: Wholesale (41); Construction (18); Personal Services (33); Printing and Publishing (8); Entertainment (7); Candy and Soda (3); Retail (42); Restaurants, Hotels, Motels (43); Precious Metals (27); and Transportation (40). In these industries, on average less than 15% of the firm-year observations involve R&D expenses. Panel B of Table 7 shows that all high R&D industry portfolios have higher alphas than the corresponding low R&D industry portfolios.

Furthermore, note that the individual alphas of all high R&D portfolios in Panel A and B are positive. This is in sharp contrast to the whole sample and zero or low R&D portfolios where the portfolio alphas are positive (negative) for low (high) ivol portfolios and with few outliers monotonously decreasing over ivol portfolios. These findings provide additional evidence that R&D firms have larger positive alphas.

[INSERT TABLE 8 ABOUT HERE]

Although our double sorts control for idiosyncratic firm-level volatility, there might be other variables that systematically affect alphas. To control for additional variables, we now extract annual averages of alphas for all 60 portfolios that were also used in Panel A of Table 7. More precisely, for every equal-weighted portfolio we calculate the monthly alphas via Fama-French regressions and then compute annual averages by averaging over these monthly portfolio alphas for a particular year in the sample. Analogously, we calculate annual equal-weighted averages of all explanatory variables. We use all firm-specific variables that are also included in our benchmark regression (1).[35] Notice however that capital expenditures and R&D expenses are

[34] We use the definition of the 48 Fama-French industries. SIC codes are in brackets.

[35] We do not include an average dividend dummy since this would act like a portfolio fixed effect.

now normalized by the lagged book value of a firm. All other variables are defined as in regression (1). Table 8 reports the corresponding panel regressions.

Regression (a1) acts as a benchmark and shows that the loading of firm-level volatility is significantly positive. Furthermore, R&D expenses significantly increase alphas, whereas capital expenditures have a small and insignificant coefficient. Firm-level skewness is very significant and positively related to the portfolio alphas, which is intuitive given the definition of (contemporaneous realized firm-level) skewness. Leverage as a measure of distance to insolvency is significantly negative. If we interpret leverage as a proxy for (physical) default probability, then the negative loading of leverage resembles the results by Campbell, Hilscher, and Szilagyi (2008). Finally, turnover, size, and ROA are positively significant.

In regressions (a2) and (a3), we decompose firm-level volatility using a Fama-French model.[36] It can be seen that in (a2) the loading on systematic firm-level volatility is insignificant, whereas in (a3) the loading on unsystematic firm-level volatility is significantly positive. This finding supports our previous results that idiosyncratic volatility is more important.

In regressions (a4)-(a6) we interact R&D expenses with all three variants of volatility (total, systematic, and idiosyncratic). In each regression, the interaction variable is very significantly positive. Besides, the corresponding volatility variable becomes insignificant. This finding supports our previous results that volatility matters the most for firms with a lot of growth options. Finally, although the systematic part of volatility is individually not significant in (a2), it becomes highly significant if interacted with R&D expenses.[37] This is not unreasonable since the values of growth options increase in all components of firm-level volatility.[38]

[36]The results for volatility decompositions generated by the CAPM are similar and available upon request.

[37]Notice that one should not compare the sizes of the point estimates since the means are different.

[38]We did not run a regression involving systematic and idiosyncratic volatility, since the results would be contaminated by collinearity and we have fewer observations than before. Regressions (a2) and (a3) however suggest that idiosyncratic volatility is more important than systematic volatility.

7 Conclusion

This paper studies to what extend firm value is related to growth options. We find strong evidence that Tobin's Q is significantly increasing in firm-level volatility. More importantly, by splitting the sample into R&D and non-R&D observations we show that this relation is to a large extend driven by the idiosyncratic part of firm-level volatility and is concentrated within R&D firm observations. These results complement earlier findings that idiosyncratic volatility is significantly priced in the cross-section of stock returns. On the other hand, we document that Tobin's Q is negatively related to index-level volatility as measured by the volatility of the S&P 500, which proxies for global risk.

Furthermore, we find that firm-level skewness is positively related to Tobin's Q which is also consistent with real options theory. Hence, our results provide strong empirical evidence that firm value is significantly affected by growth options. We also document that the actual amount of R&D expenses is more important for firm valuation than capital expenditures, which are not significant in regressions where both variables are included. This indicates that R&D expenses are a better proxy for the creation of growth options.

Besides, we study the relation of stock returns to realized contemporaneous idiosyncratic volatility and R&D expenses. In this case, there is a significantly negative relation for non-R&D observations, whereas for R&D observations the portfolio alphas are all positive if we use a four-factor model with momentum. We also document that the sub-samples of R&D and non-R&D observations are very distinct with respect to the sizes and patterns of R&D expenses and Tobin's Q. On the contrary, the average ivols of the portfolios are similar, which is in line with our previous result that the pricing effect of ivol matters the most if we interact ivol with an R&D dummy.

Double sorts controlling for ivol show that for high R&D observations all sub-portfolio alphas are positive and that all alphas of difference portfolios between high and low or zero R&D observations are positive as well. Running panel regressions of portfolio alphas on firm-level volatility as well as its idiosyncratic and systematic parts shows that volatility matters, but predominately through its idiosyncratic part. Besides, we again confirm that this effect is amplified via R&D expenses.

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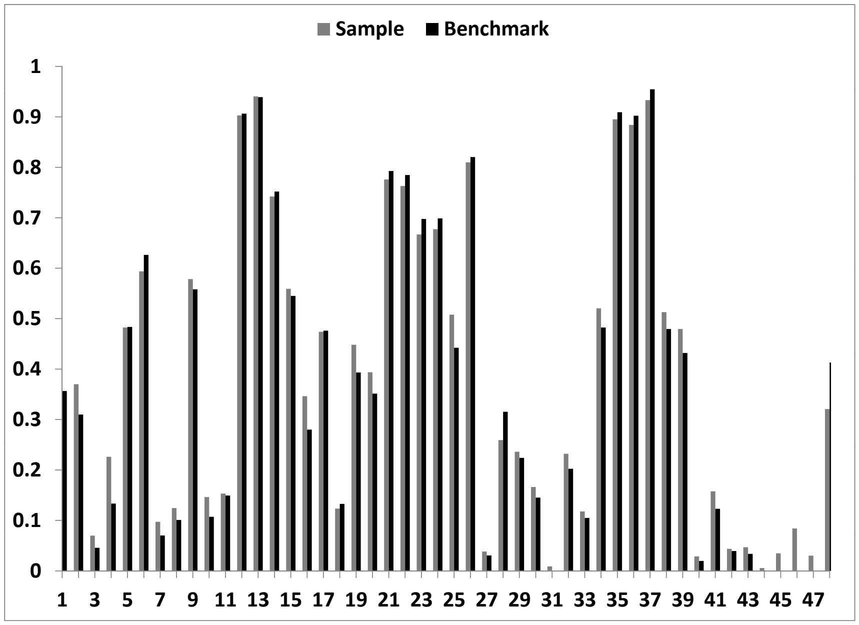

Figure 1: **Percentage of R&D Observations per FF-Industry**. This figure depicts the percentage of observations reporting R&D expenses per Fama-French industry. Sample refers to the whole sample, benchmark refers to the observations included in our regressions.

	Treasury10	Vol_sp
Mean	0.074	0.158
Median	0.072	0.138
Std. Dev.	0.028	0.072

Table 1: **Summary Statistics for the Macro Variables**. This table provides summary statistics for the macro variables from 1975 until 2009. Treasury10 denotes the yield of a Treasury bond with 10y maturity. Vol_sp denotes the annualized historical volatility of the S&P-500 calculated using index values of the last 250 trading days.

	Tobin	Vol_firm	Skew_firm	Turn_firm	Invest	Size	Roa	Leverage	Div_dum	RDexp
Panel A: All Observations										
Mean	1.840	0.616	0.176	0.005	0.237	-0.344	0.008	0.210	0.380	0.423
Median	1.283	0.512	0.202	0.002	0.043	-0.518	0.067	0.170	0.000	0.000
Std. Dev.	2.235	0.432	1.382	0.009	2.099	2.220	0.261	0.210	0.485	5.202
Panel B: R&D Observations										
Mean	2.212	0.628	0.139	0.006	0.199	-0.063	-0.028	0.163	0.361	0.911
Median	1.462	0.534	0.198	0.003	0.043	-0.300	0.061	0.120	0.000	0.045
Std. Dev.	2.781	0.430	1.333	0.010	2.012	2.280	0.323	0.186	0.480	7.611
Panel C: Non-R&D Observations										
Mean	1.519	0.606	0.208	0.004	0.269	-0.587	0.040	0.250	0.396	0.000
Median	1.171	0.494	0.204	0.002	0.042	-0.712	0.070	0.220	0.000	0.000
Std. Dev.	1.550	0.433	1.422	0.008	2.170	2.137	0.187	0.220	0.489	0.000

Table 2: **Summary Statistics for Firm Specific Variables**. This table provides summary statistics for the firm specific variables. Tobin is the ratio of market value to book value. Vol_firm is a firm's historical volatility of the stock returns. Skew_firms is a firm's historical skewness of the stock returns. Turn_firm is the daily turnover of the shares of stock as a percentage of stocks outstanding. Invest is the ratio between capital expenditures and sales of a firm. Size is the logarithm of a firm's market capitalization deflated by CPI as reported by the Bureau of Labor Statistics. Roa is the return on assets defined as income before extraordinary items plus interest divided by lagged book value. Leverage is ratio between long-term debt and book value of assets. Div_dum is an indicator variable for whether a firm pays a dividend. RDexp is the ratio between RD expenses and sales. Invest, Roa, Leverage, and RDexp are winsorized at the 0.1% level. There are 106,219 observations coming from 12,935 firms. We have 49,244 observations including R&D expenses and 56,975 observations not including R&D expenses. The observations range from 1975 to 2009.

	Tobin	Treasury10	Vol_sp	Vol_firm	Skew_firm	Turn_firm	Invest	Size	Roa	Leverage	Div_dum	RDexp
Panel A: All Observations												
Tobin	1.000											
Treasury10	-0.080	1.000										
Vol_sp	-0.016	-0.286	1.000									
Vol_firm	0.086	-0.170	0.197	1.000								
Skew_firm	0.035	0.100	-0.074	0.053	1.000							
Turn_firm	0.141	-0.274	0.113	0.138	-0.050	1.000						
Invest	0.056	-0.005	0.006	0.047	0.002	0.016	1.000					
Size	0.133	-0.229	0.029	-0.437	-0.070	0.221	-0.017	1.000				
Roa	-0.268	0.116	-0.068	-0.346	0.005	-0.077	-0.118	0.231	1.000			
Leverage	-0.081	0.010	0.026	0.031	-0.007	-0.040	0.017	-0.007	-0.009	1.000		
Div_dum	-0.128	0.168	-0.074	-0.428	0.015	-0.124	-0.055	0.411	0.254	-0.032	1.000	
Panel B: R&D Observations												
Tobin	1.000											
Treasury10	-0.086	1.000										
Vol_sp	-0.013	-0.302	1.000									
Vol_firm	0.122	-0.193	0.223	1.000								
Skew_firm	0.059	0.086	-0.071	0.069	1.000							
Turn_firm	0.140	-0.266	0.098	0.158	-0.041	1.000						
Invest	0.070	-0.026	0.009	0.043	-0.004	0.030	1.000					
Size	0.091	-0.179	0.010	-0.443	-0.081	0.203	-0.011	1.000				
Roa	-0.317	0.144	-0.076	-0.370	-0.019	-0.079	-0.145	0.243	1.000			
Leverage	-0.050	0.039	0.013	-0.002	-0.008	-0.046	0.002	0.015	-0.038	1.000		
Div_dum	-0.180	0.205	-0.088	-0.449	0.007	-0.154	-0.051	0.438	0.282	0.035	1.000	
RDexp	0.124	-0.071	0.016	0.087	-0.011	0.042	0.611	-0.034	-0.269	-0.006	-0.087	1.000
Panel C: Non-R&D Observations												
Tobin	1.000											
Treasury10	-0.058	1.000										
Vol_sp	-0.031	-0.272	1.000									
Vol_firm	0.033	-0.148	0.173	1.000								
Skew_firm	0.016	0.109	-0.077	0.041	1.000							
Turn_firm	0.104	-0.282	0.130	0.114	-0.057	1.000						
Invest	0.052	0.009	0.005	0.052	0.006	0.005	1.000					
Size	0.170	-0.263	0.044	-0.444	-0.057	0.227	-0.018	1.000				
Roa	-0.083	0.067	-0.053	-0.343	0.031	-0.036	-0.100	0.279	1.000			
Leverage	-0.060	-0.034	0.046	0.065	-0.015	0.003	0.022	0.020	-0.041	1.000		
Div_dum	-0.053	0.135	-0.061	-0.408	0.019	-0.085	-0.060	0.402	0.231	-0.095	1.000	

Table 3: **Correlation Matrix for R&D and Non-R&D Observations**. This table reports the correlations between the relevant variables. The correlations are calculated on the basis of 49,244 observations including R&D expenses and 56,975 observations not including R&D expenses. The observations range from 1975 to 2009. Invest, Roa, Leverage, and RDexp are winsorized at the 0.1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Treasury10	4.080***	4.097***	4.127***	4.329***	4.192***	4.223***
	(3.78)	(3.80)	(3.82)	(3.93)	(3.84)	(3.86)
Vol_sp	-1.681***	-1.717***	-1.710***	-1.664***	-1.713***	-1.705***
	(-3.92)	(-4.09)	(-4.08)	(-3.95)	(-4.04)	(-4.02)
Vol_firm	0.311**	0.151*	0.158*	0.329***	0.134	0.143
	(3.20)	(2.07)	(2.10)	(3.29)	(1.64)	(1.74)
Skew_firm	0.081***	0.080***	0.040***	0.079***	0.079***	0.039***
	(7.40)	(7.44)	(5.17)	(7.14)	(7.37)	(5.07)
Turn_firm	10.262***	9.853**	9.880**	10.632***	9.758**	9.788**
	(3.36)	(3.28)	(3.28)	(3.44)	(3.23)	(3.22)
Invest	0.021***	0.022***	0.022***	0.001	0.007	0.007
	(3.58)	(3.63)	(3.66)	(0.22)	(1.08)	(1.09)
Size	0.288***	0.289***	0.289***	0.300***	0.290***	0.290***
	(7.80)	(7.82)	(7.83)	(7.85)	(7.86)	(7.87)
Roa	-2.305***	-2.267***	-2.264***	-2.313***	-2.206***	-2.202***
	(-11.61)	(-11.29)	(-11.27)	(-11.92)	(-10.86)	(-10.84)
Leverage	-0.767***	-0.753***	-0.755***	-0.900***	-0.756***	-0.757***
	(-6.20)	(-6.16)	(-6.18)	(-7.04)	(-6.50)	(-6.52)
Div_dum	-0.729***	-0.729***	-0.730***	-0.750***	-0.731***	-0.732***
	(-10.18)	(-10.34)	(-10.36)	(-10.43)	(-10.52)	(-10.54)
RD_dum	0.294***	0.067	0.061			
	(6.18)	(1.01)	(0.87)			
RD_vol_firm		0.374***	0.358***		0.427***	0.404***
		(3.52)	(3.39)		(6.63)	(6.50)
RD_skew_firm			0.092***			0.094***
			(6.40)			(6.55)
RDexp				0.019***	0.016***	0.016***
				(4.12)	(3.75)	(3.82)
Intercept	1.981***	2.080***	2.082***	2.121***	2.097***	2.096***
	(16.63)	(19.02)	(18.90)	(18.47)	(17.26)	(17.31)
R^2	0.157	0.159	0.159	0.155	0.160	0.161

Table 4: **Benchmark Regressions**. The table reports the results of panel regressions of Tobin's Q on selected variables. All regressions are based on 106,219 observations coming from 12,935 firms. There are 49,244 observations including R&D expenses and 56,975 observations not including R&D expenses. Financial firms and utilities are excluded from the sample. The sample ranges from 1975 to 2009. Invest, Roa, Leverage, and RDexp are winsorized at the 0.1% level. Robust Driscoll-Kraay t-statistics are reported in brackets. Asterisks correspond to the following p-values: $*p < 0.05, **p < 0.01, ***p < 0.001$.

	(2)	(2: FF)	(2: CAPM)	(5)	(5: FF)	(5: CAPM)
Treasury10	4.097***	4.134***	4.132***	4.192***	4.223***	4.221***
	(3.80)	(3.65)	(3.61)	(3.84)	(3.69)	(3.65)
Vol_sp	-1.717***	-1.600***	-1.623***	-1.713***	-1.584***	-1.610***
	(-4.09)	(-4.13)	(-4.29)	(-4.04)	(-4.08)	(-4.23)
Skew_firm	0.080***	0.079***	0.079***	0.079***	0.079***	0.079***
	(7.44)	(7.37)	(7.43)	(7.37)	(7.23)	(7.31)
Turn_firm	9.853**	10.036***	10.013***	9.758**	9.971***	9.931***
	(3.28)	(3.61)	(3.50)	(3.23)	(3.56)	(3.44)
Invest	0.022***	0.022***	0.022***	0.007	0.007	0.007
	(3.63)	(3.63)	(3.61)	(1.08)	(1.09)	(1.06)
Size	0.289***	0.292***	0.291***	0.290***	0.292***	0.292***
	(7.82)	(7.45)	(7.43)	(7.86)	(7.53)	(7.49)
Roa	-2.267***	-2.265***	-2.266***	-2.206***	-2.204***	-2.205***
	(-11.29)	(-11.30)	(-11.28)	(-10.86)	(-10.88)	(-10.86)
Leverage	-0.753***	-0.748***	-0.750***	-0.756***	-0.745***	-0.749***
	(-6.16)	(-6.23)	(-6.23)	(-6.50)	(-6.61)	(-6.61)
Div_dum	-0.729***	-0.728***	-0.728***	-0.731***	-0.729***	-0.729***
	(-10.34)	(-10.46)	(-10.43)	(-10.52)	(-10.63)	(-10.58)
RD_dum	0.067	0.030	0.041			
	(1.01)	(0.35)	(0.48)			
Vol_firm	0.151*			0.134		
	(2.07)			(1.64)		
RD_vol_firm	0.374***			0.427***		
	(3.52)			(6.63)		
Vol_ff_sys		-0.291			-0.322	
		(-0.81)			(-0.85)	
Vol_ff_unsys		0.190			0.194	
		(1.94)			(1.89)	
RD_vol_ff_sys		0.547			0.594	
		(1.14)			(1.62)	
RD_vol_ff_unsys		0.312***			0.318***	
		(4.18)			(5.50)	
Vol_capm_sys			-0.222			-0.265
			(-0.65)			(-0.73)
Vol_capm_unsys			0.176*			0.177
			(1.98)			(1.87)
RD_vol_capm_sys			0.440			0.517
			(1.00)			(1.53)
RD_vol_capm_unsys			0.334***			0.347***
			(4.01)			(6.29)
RDexp				0.016***	0.016***	0.016***
				(3.75)	(3.75)	(3.76)
Intercept	2.080***	2.081***	2.078***	2.097***	2.079***	2.082***
	(19.02)	(18.49)	(18.30)	(17.26)	(17.06)	(17.03)
R^2	0.159	0.159	0.159	0.160	0.160	0.160

Table 5: **Regressions with Volatility Decomposition**. The table reports the results of panel regressions of Tobin's Q on selected variables. Firm volatility is decomposed into a systematic and an unsystematic part. Regressions (2: FF) and (5: FF) uses a decomposition coming from a three-factor Fama-French model, whereas regressions (2: CAPM) and (5: CAPM) uses a decomposition coming from a one-factor CAPM. The results can be compared with regressions (2) and (5) where volatility is not decomposed (also reported in Table 4). All regressions are based on 106,219 observations coming from 12,935 firms. There are 49,244 observations including R&D expenses and 56,975 observations not including R&D expenses. Financial firms and utilities are excluded from the sample. The sample ranges from 1975 to 2009. Invest, Roa, Leverage, and RDexp are winsorized at the 0.1% level. Robust Driscoll-Kraay t-statistics are reported in brackets. Asterisks correspond to the following p-values: $*p < 0.05, **p < 0.01, ***p < 0.001$.

	Low	2	3	4	5	6	7	8	9	High	HL	
Panel A: All Observations												
Alpha_ff3	0.002*	0.002	0.002*	0.002**	0.002**	0.002	0.001	-0.002	-0.004	-0.005	-0.007	
	(2.06)	(1.93)	(2.03)	(2.67)	(2.74)	(1.81)	(0.96)	(-0.98)	(-1.71)	(-1.38)	(-1.73)	
Alpha_ff4	0.002*	0.002*	0.002*	0.002**	0.003**	0.002*	0.002	-0.000	-0.001	-0.003	-0.004	
	(2.48)	(2.38)	(2.50)	(2.98)	(3.28)	(2.09)	(1.80)	(-0.02)	(-0.49)	(-0.67)	(-1.08)	
Size	2.285	1.715	1.121	0.604	0.192	-0.306	-0.694	-1.148	-1.691	-2.524		
Vol_ff_unsys	0.194	0.261	0.314	0.368	0.429	0.496	0.576	0.677	0.832	1.317		
Vol_firm	0.227	0.295	0.348	0.404	0.466	0.533	0.611	0.709	0.860	1.338		
RD	0.019	0.018	0.020	0.025	0.036	0.051	0.064	0.074	0.082	0.074		
Capx	0.076	0.085	0.094	0.098	0.104	0.108	0.101	0.102	0.091	0.077		
Tobin	1.563	1.546	1.547	1.612	1.739	1.877	1.913	1.952	2.040	2.064		
Turn_firm	0.003	0.004	0.004	0.004	0.005	0.005	0.005	0.005	0.005	0.005		
Skew_firm	0.104	0.105	0.118	0.154	0.150	0.159	0.143	0.166	0.267	0.502		
Leverage	0.202	0.213	0.222	0.224	0.222	0.212	0.214	0.210	0.229	0.260		
Roa	0.095	0.091	0.082	0.079	0.067	0.041	0.005	-0.060	-0.087	-0.191		
Panel B: R&D Observations												
Alpha_ff3	0.002*	0.002	0.001	0.002*	0.004*	0.004*	0.002	-0.000	-0.002	-0.001	-0.003	
	(2.02)	(1.63)	(1.75)	(2.43)	(2.26)	(2.48)	(1.65)	(-0.19)	(-0.75)	(-0.24)	(-0.60)	
Alpha_ff4	0.002*	0.002*	0.002**	0.003**	0.005**	0.005**	0.004**	0.001	0.000	0.002	0.000	
	(2.51)	(2.00)	(2.71)	(3.05)	(3.01)	(3.07)	(2.69)	(0.65)	(0.16)	(0.48)	(0.06)	
Size	2.973	2.221	1.482	0.865	0.361	-0.128	-0.575	-1.052	-1.538	-2.319		
Vol_ff_unsys	0.191	0.254	0.311	0.373	0.437	0.505	0.583	0.679	0.821	1.255		
Vol_firm	0.230	0.293	0.350	0.414	0.479	0.546	0.623	0.712	0.850	1.277		
RD	0.035	0.038	0.045	0.066	0.088	0.111	0.124	0.136	0.159	0.161		
Capx	0.074	0.074	0.073	0.075	0.074	0.076	0.076	0.073	0.068	0.055		
Tobin	1.646	1.592	1.652	1.883	2.145	2.291	2.335	2.338	2.504	2.647		
Turn_firm	0.003	0.004	0.004	0.005	0.006	0.006	0.006	0.006	0.005	0.006		
Skew_firm	0.047	0.072	0.072	0.083	0.108	0.144	0.101	0.116	0.235	0.506		
Leverage	0.179	0.184	0.183	0.173	0.163	0.164	0.152	0.153	0.170	0.201		
Roa	0.097	0.090	0.072	0.064	0.043	0.004	-0.037	-0.130	-0.182	-0.284		
Panel C: Non-R&D Observations												
Alpha_ff3	0.002	0.001	0.003**	0.002*	0.002	0.001	-0.001	-0.003	-0.005*	-0.009*	-0.010**	-0.007
	(1.90)	(1.63)	(2.72)	(2.34)	(1.16)	(0.48)	(-0.80)	(-1.08)	(-2.15)	(-2.34)	(-2.62)	(-1.77)
Alpha_ff4	0.002*	0.002*	0.003**	0.003**	0.002	0.001	-0.001	-0.001	-0.003	-0.007	-0.008*	-0.009*
	(2.14)	(2.13)	(2.76)	(2.88)	(1.24)	(0.73)	(-0.35)	(-0.32)	(-1.07)	(-1.68)	(-2.02)	(-2.26)
Size	1.520	1.268	0.842	0.418	0.078	-0.378	-0.832	-1.234	-1.828	-2.696		
Vol_ff_unsys	0.199	0.268	0.319	0.368	0.422	0.486	0.564	0.671	0.840	1.363		
Vol_firm	0.225	0.299	0.351	0.400	0.456	0.519	0.594	0.699	0.864	1.383		
RD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Capx	0.080	0.097	0.111	0.119	0.133	0.129	0.130	0.131	0.118	0.090		
Tobin	1.488	1.492	1.500	1.481	1.478	1.461	1.455	1.467	1.512	1.602		
Turn_firm	0.002	0.003	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004		
Skew_firm	0.173	0.144	0.172	0.195	0.150	0.213	0.140	0.236	0.310	0.488		
Leverage	0.229	0.239	0.252	0.261	0.264	0.268	0.269	0.275	0.287	0.310		
Roa	0.094	0.092	0.089	0.084	0.081	0.068	0.046	0.021	0.016	-0.106		

Table 6: **Alphas of Portfolios Constructed on the Basis of Ivol**. Equal-weighted portfolios are formed each year on the basis of the size of idiosyncratic volatility computed from a Fama-French model. The ivol portfolios are arranged from Low ivol to High ivol. The table reports the alphas, Alpha_ff3, from *contemporaneous* regressions of the monthly excess portfolio returns on the three Fama-French factors for the fiscal year whose data is used to calculate the ivol on which the portfolios are based. Also reported are the alphas of a four-factor model with momentum, Alpha_ff4. HL refers the difference portfolio between high ivol firms and low ivol firms. In column HL of Panel C (right-hand side of alpha of HL), we also report the alpha of the diff-in-diff portfolio (HL of non-RD observations minus HL of RD observations). Sample averages of other variables are also reported. RD denotes the ratio of R&D expenses over lagged book value of assets. Capx denotes the ratio of capital expenditures over lagged book value of assets. All other variables are defined as in Table 2. The sample period is from 1975 to 2009. Only firms with fiscal year ending in December are included. Robust Newey-West t-statistics are reported in brackets. Asterisks correspond to the following p-values: $*p < 0.05, **p < 0.01, ***p < 0.001$.

Panel A: Six R&D Expenses Sub-Portfolios					
Portfolio:	Zero R&D	Low R&D	High R&D	HL R&D	HZ R&D
Low	0.001	0.001	0.003*	0.001	0.001
	(1.76)	(1.36)	(2.51)	(1.22)	(1.38)
2	0.001	-0.000	0.005**	0.006*	0.004*
	(1.62)	(-0.04)	(3.09)	(2.37)	(2.10)
3	0.002*	-0.001	0.003*	0.005	0.001
	(2.34)	(-0.70)	(1.97)	(1.68)	(0.57)
4	0.002*	-0.002	0.009***	0.012***	0.007**
	(2.38)	(-1.19)	(4.94)	(3.64)	(3.00)
5	0.002	-0.002	0.008***	0.010**	0.006*
	(1.76)	(-0.80)	(3.35)	(2.89)	(2.10)
6	-0.001	-0.002	0.012***	0.014***	0.013***
	(-0.46)	(-1.03)	(3.82)	(4.29)	(3.47)
7	0.000	-0.004	0.006	0.009*	0.005
	(0.22)	(-1.53)	(1.60)	(2.02)	(1.06)
8	-0.003	-0.003	0.007*	0.010*	0.010*
	(-1.23)	(-0.93)	(2.11)	(2.39)	(2.25)
9	-0.004	-0.007	0.005	0.012	0.009
	(-1.52)	(-1.84)	(0.83)	(1.77)	(1.53)
High	-0.008*	-0.007	0.006	0.013	0.014*
	(-2.11)	(-1.20)	(0.85)	(1.87)	(2.01)

Panel B: Two R&D Industry Sub-Portfolios			
Portfolio:	Low R&D Industries	High R&D Industries	HL R&D Industries
1	0.001	0.004***	0.003***
	(0.94)	(3.78)	(3.49)
2	0.001	0.005***	0.004*
	(0.97)	(3.51)	(2.16)
3	0.001	0.004**	0.003
	(0.83)	(3.13)	(1.62)
4	0.002	0.003**	0.001
	(1.33)	(2.87)	(0.75)
5	0.000	0.004*	0.004
	(0.07)	(2.09)	(1.43)
6	-0.001	0.007**	0.007*
	(-0.29)	(2.78)	(2.15)
7	-0.003	0.003	0.006
	(-1.06)	(1.53)	(1.55)
8	-0.004	0.002	0.006
	(-1.20)	(0.68)	(1.22)
9	-0.007*	0.000	0.007
	(-2.21)	(0.05)	(1.69)
10	-0.003	0.005	0.007
	(-0.54)	(0.92)	(1.57)

Table 7: **Alphas of Double-sorted Portfolios Constructed on the Basis of Ivol and R&D**. In Panel A, equal-weighted portfolios are formed each year on the basis of the size of idiosyncratic volatility computed from a Fama-French model and R&D expenses (normalized by lagged book value). The ivol portfolios are arranged from Low ivol to High ivol (in rows). The alphas of the R&D portfolios are in columns. HL R&D (HZ R&D) denotes the difference portfolio of high R&D observations minus low R&D observations (observations with zero R&D). In Panel B, equal-weighted portfolios are formed each year on the basis of the size of idiosyncratic volatility computed from a Fama-French model and R&D vs. non-R&D industries. The ivol portfolios are arranged from Low ivol to High ivol (in rows). The R&D portfolios are in columns. The first column reports the alphas for low-R&D industries, the second for high-R&D industries, and the third the difference portfolios. Both panels report the alphas from *contemporaneous* regressions of the monthly excess portfolio returns on the three Fama-French factors for several periods relative to December of the end of the fiscal year whose data are used to calculate R&D expenses and the ivol on which the portfolios are based. The sample period is from 1975 to 2009. Only firms with fiscal year ending in December are included. Robust Newey-West t-statistics are reported in brackets. Asterisks correspond to the following p-values: $*p < 0.05, **p < 0.01, ***p < 0.001$.

	(a1)	(a2)	(a3)	(a4)	(a5)	(a6)
Skew	0.011**	0.011**	0.011**	0.010**	0.011**	0.010**
	(2.99)	(3.38)	(2.92)	(2.90)	(3.19)	(2.85)
Turn	0.638**	0.671**	0.675**	0.717**	0.753**	0.756**
	(2.84)	(3.22)	(2.87)	(3.13)	(3.33)	(3.11)
Capx	0.014	0.002	0.014	0.016	-0.001	0.016
	(0.84)	(0.13)	(0.84)	(1.02)	(-0.05)	(1.04)
RD	0.036***	0.034***	0.036***			
	(4.13)	(3.89)	(4.10)			
Size	0.003***	0.002***	0.003***	0.003***	0.002***	0.003**
	(4.38)	(3.74)	(4.07)	(3.92)	(4.30)	(3.63)
Roa	0.020*	0.016*	0.019*	0.021*	0.018***	0.020*
	(2.42)	(2.30)	(2.36)	(2.75)	(5.41)	(2.42)
Leverage	-0.014*	-0.011	-0.014*	-0.021**	-0.013	-0.022**
	(-2.21)	(-1.72)	(-2.14)	(-2.91)	(-1.46)	(-2.97)
Vol_total	0.010**			0.007		
	(2.88)			(1.89)		
Vol_sys		0.021			0.004	
		(1.13)			(0.22)	
Vol_unsys			0.010*			0.007
			(2.58)			(1.69)
RD_vol_total				0.037***		
				(3.97)		
RD_vol_sys					0.160***	
					(5.37)	
RD_vol_unsys						0.036**
						(3.54)
Intercept	-0.012***	-0.009*	-0.011***	-0.008*	-0.006	-0.008*
	(-3.97)	(-2.31)	(-4.00)	(-2.50)	(-1.45)	(-2.47)
R^2	0.177	0.172	0.176	0.180	0.184	0.177

Table 8: **Regressions of Abnormal Returns on Selected Variables**. The table reports the results of panel regressions of the abnormal return on 60 equal-weighted portfolios that are double sorted on idiosyncratic volatility computed from a Fama-French model and R&D expenses (normalized by lagged book value). The portfolios are identical to the ones used in Panel A of Table 7. The explanatory variables are equal-weighted as well. Financial firms and utilities are excluded from the sample. The sample ranges from 1975 to 2009. Robust Driscoll-Kraay t-statistics are reported in brackets. Asterisks correspond to the following p-values: $*p < 0.05, **p < 0.01, ***p < 0.001$.