

UNLOCKING THE VALUE OF REAL OPTIONS: HOW FIRM-SPECIFIC LEARNING CONDITIONS AFFECT R&D INVESTMENTS UNDER UNCERTAINTY

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Abstract

Research summary: Why do some firms increase R&D investments in the face of uncertainty, while others don't? Contrary to common wisdom, this study posits that uncertainty prompts firms to invest in R&D. The value to invest under uncertainty is, however, bounded by a firm's learning conditions (i.e., human capital, relatedness of innovation activities, and industry maturity). An empirical test on a cross-industry panel of 551 business divisions of manufacturing firms reveals how organization-environment interactions determine the firm-specific value to invest in learning prior to full-scale commercialization. The insights help to bridge real options theory and the learning literature.

Managerial summary: Uncertainty about the market environment makes taking investment decisions in R&D and the commercialization of new products a challenge: should firms "wait and see" until uncertainty resolves to avoid of the risk of betting on the wrong product or commit further resources regardless? Our analysis suggests that manufacturing firms often take a mixed approach ("act and see"). While deferring investments in the commercialization of new products, they undertake further R&D to inform decision-making by insights which would else be unavailable. However, we show that the benefit of such practice depends on the learning conditions of the individual firm. What is risky for firms with disadvantages in human capital and technology development is value-enhancing for firms with good foundations for learning through R&D.

INTRODUCTION

Firm-differences in allocating resources to research and development (R&D) activities have long captured the interest of organizational theorists and strategic management scholars (e.g., Helfat, 1994a, 1994b; Greve, 2003; Cuervo-Cazurra and Un, 2010). Seminal studies emphasize the path-dependent nature of search processes that can cause persistence in R&D spending (Nelson and Winter, 1982) and stability in R&D intensity over time (Chen and Miller, 2007). Patel and Pavitt (1997), however, observe that a considerable variance of resources allocated to R&D is unexplained and suggest that this relates to firm-specific managerial decisions made under uncertainty. Those decisions can serve a critical role in attaining entrepreneurial rents, which are the rewards for being prepared to act in the face of uncertainty (Knight, 1921; Rumelt, 1987).

Empirical studies find that dynamically adjusting R&D investments to the level of uncertainty generates value (Oriani and Sobrero, 2008; Levitas and Chi, 2010). The underlying theory predicts a negative effect of demand uncertainty on investment (McDonald and Siegel, 1986; Dixit and Pindyck, 1994) and assumes that firms from the same industry react to changing market conditions in similar ways. However, recent work finds a positive relationship between uncertainty and R&D investments (Bromiley, Rau, and Zhang, 2017) and emphasizes the role of firm-heterogeneities in valuing and capitalizing on uncertain opportunities (Klingebiel, 2012; Trigeorgis and Reuer, 2017), suggesting so far neglected sources of heterogeneity in explaining R&D investments. This spurs the question: *Why do some firms increase R&D investments in the face of uncertainty, while others don't?*

The literature on resource allocation decisions in the field of strategy and organization has largely built on the assumption that uncertainty can be resolved by undertaking R&D (e.g., Cohen and Levinthal, 1994) or negotiated with the environment (Cyert and March, 1963).

However, firms also face uncertainties that are largely unaffected by their actions and may resolve over time (Folta, 1998). Consequently, as firms of an industry often operate in the same market environment but have different abilities to learn about their risks, they differ in relative sources of uncertainty. It is this *total* uncertainty (including both unsystematic and systematic components) that managers worry about and act on (Amram and Kulatilaka, 1999). Hence, the combined effect of firm-specific learning abilities and industry-wide uncertainty is pertinent to managerial valuation of investment decisions and could be a source of heterogeneity in R&D investments across firms.

Building on the real options literature, we study resource allocations to R&D activities as learning investments that yield information on superior ways to combine organizational and technological elements to exploit uncertain market opportunities (Brown and Eisenhardt, 1998: 151; Amram and Kulatilaka, 1999; Kogut and Kulatilaka, 2001). We posit that, while uncertainty about current market demand lowers investments in the production of new products, it motivates firms to undertake further R&D activities as the latter can reduce earnings surprises and facilitate informed decision making unavailable for others who wait. Furthermore, we argue that the value to invest in learning is firm-specific because the expected outcomes are bounded by a firm's learning conditions, which are determined by a firm's human capital, the relatedness of innovation activities, and the industry maturity.

Using a cross-industry panel data of 551 business divisions of manufacturing firms, we find support for our arguments. The insights from the study contribute to the literature in important ways. First, we advance the literature on real options by providing arguments that explain why firms might find it beneficial to take an "act-and-see" approach under conditions of uncertainty rather than "wait and see". The insights challenge the widely-held assumption of

R&D as being risky and provide further explanations for the positive, statistically significant coefficients found in recent empirical work on the relationship between uncertainty and R&D intensity (Bromiley *et al.*, 2017).

Second, by interacting industry-wide demand uncertainty with factors that determine firm-specific learning, we specify organization-environment interactions that bound the *ex-ante* value of investing under total uncertainty as a source of idiosyncratic investment decisions in R&D. As these interactions help identify the effect of learning that relates to real options (Folta, 2005), the findings shed light on the relative contribution of real options theory and expand the literature that considers demand conditions as industry-level determinant of a firm's R&D spending (e.g., Cohen and Levinthal, 1990). Our theory helps to bridge the disconnection between rational future-oriented managerial choice under uncertainty, and actual real-life decisions. What can at first appear as behavior that is irrational (i.e., invest under uncertainty), may for some firms in fact be a sensible value-enhancing investment decision.

BACKGROUND THEORY

Real options and learning investments

Although the literature provides robust theoretical (McDonald and Siegel, 1986) and empirical evidence (Episcopos, 1995; Price, 1995) that the level of uncertainty has a negative effect on investment, recent work in the context of R&D reveals that uncertainty can also encourage investments (Bromiley *et al.*, 2017). A possible explanation for such findings relates to the role of learning activities to narrow down uncertainty, as discussed in early work on real options (Roberts and Weitzman, 1981). Instead of wait and see until uncertainty resolves, a firm may undertake an initial investment in order to actively learn about uncertain variables prior to

making full-scale investments for commercial exploitation (Hurry, 1994; Kumaraswamy, 1996; Garud, Nayyar, and Shapira, 1997; Brown and Eisenhardt, 1998: 151; McGrath and MacMillan, 2000; Barnett and Dunbar, 2008).¹ Because an initial investment reveals information about the benefits of investing further, it provides a shadow value that lowers the expected cost of a project and increases the incentive to invest (Pindyck, 1993).

For a forward-looking decision maker it is *a priori* of interest to know when such learning investments are beneficial to the firm. As not all learning suffers from time diseconomies (Eisenhardt and Tabrizi, 1995), undertaking initial investments can provide an advantage vis-à-vis those who wait. Such investments create value when the outcomes cannot be easily duplicated by a wait-and-see approach. Seminal work suggests that residual uncertainty after learning has taken place prevents fast imitation by others (Lippman and Rumelt, 1982; Rumelt, 1987). However, as organizations show large variations in the rate at which they learn (Argote, 2013: 15), those who lack learning abilities may expect limited effectiveness of such investments and rather wait when facing uncertainty. Since uncertainty bounds learning and learning can reduce uncertainty, the value to invest in R&D is, therefore, determined by the link between uncertainty and a firm's expected learning rate (Ghemawat, 1991: 132).

Firm-specific value to invest in R&D under uncertainty

The decision problem puts a focus on the role of both firm-specific and industry-wide uncertainty. Managers worry about the consequences of both sources of uncertainty and act on them (Amram and Kulatilaka, 1999). Real options theory provides the unique feature of focusing

¹ The literature categorises such type of learning activities also as “learning-*before*-doing” (Pisano, 1994, 1997) or “learning-by-spending’ on R&D” (Lieberman, 1984: 227; Kim, 1998), which differ from “learning-by-doing” in the sense that this type of learning refers to learning from cumulative production (e.g., Argote, 2013).

on total uncertainty (unsystematic and systematic component) when predicting investment decisions (Folta, 2005). Despite extant work on learning and real options (Dixit and Pindyck, 1994; Smit and Trigeorgis, 2004), however, the link between idiosyncratic uncertainty reduction (i.e., firm-specific learning) and systematic risk in the context of R&D is not well understood. Studies at the firm-level either focus on exogenous uncertainty (e.g., Oriani and Sobrero, 2008; Levitas and Chi, 2010), limiting empirical verification to industry-level differences only, or examine the role of endogenous uncertainty reduction, which bounds the ability to identify a real option effect relative to alternative learning theories (Adner and Levinthal, 2004; Folta, 2005).

The dearth of insights on firm-differences in R&D investments and total uncertainty may be a consequence of implicit assumptions about the investments to capitalize on uncertain market opportunities. Studies commonly define investments in R&D as the creation of real options and investments in capital as the cost of exercising them (e.g., Sanchez, 1993; Levitas and Chi, 2010). However, beyond a direct impact of R&D (e.g., new products, technologies), R&D investments can also have an indirect impact by shaping a firm's learning curve, i.e., how cumulative output relates to cost (Lieberman, 1984; Pisano, 1994), which conditions the incentive to engage in R&D (Sinclair, Klepper, and Cohen, 2000). As demand uncertainty bounds the firm's value when facing a learning curve (Majd and Pindyck, 1989), a theory that explains the decision to invest in learning about superior ways to combine organizational and technological elements prior to exploiting market opportunities has to jointly take a firm's learning abilities, the uncertainty about demand, and the expected effect on the learning curve into consideration.

The findings on incentive-driven R&D have implications for examining the role of total uncertainty in our decision problem. Building on prior literature on uncertainty and learning

curves (Dixit and Pindyck, 1994), we argue that R&D investments under demand uncertainty prior to commercialization of new products can be explained by the shadow value that such activities yield. Beyond the level of uncertainty about demand, this shadow value is influenced by a firm's ability to learn about uncertain variables and to lower the cost of commercialization. Hence, both firm-specific and industry-wide sources of uncertainty are important for determining the idiosyncratic value to invest in R&D. Though anecdotal evidence suggest that learning abilities and uncertainty can influence the expected benefits of learning investments (Ghemawat, 1991; Pisano, 1997), and the use of amplifying pre-investments prior to commencing commercialization has been argued as a way to release the bounds of uncertainty (McGrath, 1997), the literature lacks empirical verification as to whether firm-specific decisions to invest in R&D under total uncertainty can be explained by a real option theory that incorporates learning.

In the following, we first develop our baseline hypothesis (H1) for the predicted main effect of uncertainty on R&D investment. In order to compare the effect of uncertainty for R&D expenditures from capital expenditures, we empirically examine the uncertainty-investment relationship for both types of investments. In order to isolate the effect of firm learning that relates to real options, we follow calls for research that suggested empirically examining the interaction between firm-specific learning abilities and uncertainty about the demand (Folta, 2005). Specifically, as effective learning is conditioned on the employees' scientific understanding (Nelson, 1982; Pisano, 1994), whether learning relates to what is already known (Cohen and Levinthal, 1990; Kogut and Zander, 1992), and an industry's maturity (e.g., Fiol and Lyles, 1985), we develop hypotheses (H2–H4) on how these three contingencies determine firm-differences in R&D investments under uncertainty.

HYPOTHESES DEVELOPMENT

As investments are (partly) irreversible, it has been argued that it pays to wait under uncertainty about the expected level of demand for new information before committing resources (e.g., McDonald and Siegel, 1986; Levitas and Chi, 2010). Thus, in line with a well-established literature and robust empirical findings, we can expect that an increase in uncertainty lowers the firm's capital expenditures allocated to the commercialization of new products.

In case of R&D investments, by contrast, we expect that the degree of industry-level uncertainty has a positive influence for several reasons. First, preemptive R&D investments under demand uncertainty provide the benefits of acquiring a strategic advantage (Kulatilaka and Perrotti, 1998). Such initial investments create options to take advantage of growth opportunities, increasing firm value under uncertainty and stimulating R&D investments (Oriani and Sobrero, 2008; Bloom, 2014; Kraft, Schwartz, and Weiss, 2017).

Second, initial investments in the form of low-cost probes prior to committing to the full-scale commercial production can also be used to lower the variance in expected earnings and reduce the firm's sensitivity to changes in uncertain market environments (Chatterjee, Lubatkin, and Schulze, 1999). As not all learning pays off, and a project can be (temporarily) terminated or abandoned, the downsides of such learning investments under uncertainty are limited. In case initial investment reveals failure, however, learning what does not work is valuable when facing uncertainty (Sitkin, 1992; McGrath, 2011). It provides the possibility of making informed judgment about adding commitments to production capacity required to launching new products (Brown and Eisenhardt, 1998: 151). However, it should also be acknowledged that part of the reduction in uncertainty may depend on how well prior investments turned out. Hence, a firm

that did not invest in learning may be at a disadvantage, and a firm that did invest in learning in a prior regime (but it did not turn out well) may also be at a disadvantage.²

Third, beyond the benefits of lowering the variance of revenues and costs of commercialization, learning by R&D activities can also improve the starting point and steepen the learning curve of producing new products (Lieberman, 1984; Pisano, 1997). Such reduction in future costs increases firm value of holding the option to commercialize new products under uncertainty about demand (Majd and Pindyck, 1989). Under high uncertainty, a firm will make use of learning actions before commercialization because unpredictable jolts in uncertain market environments disrupt the stable learning environment required to realize learning effects from cumulative production. Conversely, when there is low uncertainty about demand, a firm refrains from using R&D pre-commitments because expected learning rates from cumulative production are higher compared to learning from R&D, limiting its preemption value (Smit and Trigeorgis, 2004: 317). Taken these arguments into consideration, overall, we assume that there is a positive relationship between uncertainty and investment in R&D.

Hypothesis 1: Uncertainty will have a positive effect on investment in R&D.

Uncertainty and human capital

A firm's learning abilities provide a boundary condition for gaining valuable information from learning investments prior to exploitation of uncertain market opportunities (Kogut and Zander, 1992; McGrath, 2001). Empirical work emphasizes that investments in R&D to establish and capitalize on a firm's options depend on the level of skills among employees (Cuervo-Cazurra

² We thank an anonymous reviewer for this insight.

and Un, 2010; Riley, Michael, and Mahoney, 2017). Well-trained engineers and scientists enable a firm to convert information and recognised opportunities into options through connecting product markets and research laboratories during the learning process (Nelson, 1982; Arora and Gambardella, 1994; Garud and Nayyar, 1994; Kim, 1998).

When faced with uncertainty, firms with strong human capital relative to those with low human capital will be more capable in making use of learning investments, reducing variance of uncertain variables and steepening the learning curve (Pisano, 1994; Brown and Eisenhardt, 1998). Therefore, when human capital is strong, an increase in uncertainty increases the value to invest in R&D. By contrast, when human capital is weak, an increase in uncertainty will increase the expected value from investing in R&D prior to full-scale commercial production to a lesser extent (relative to high human capital), due to higher private risks and lower expected learning benefits from additional R&D. In this case, investments in learning are expected to result in a low learn-to-burn rate, i.e., how quickly useful feedback under uncertainty is received relative to the cost of experimentation (Ghemawat, 1991), making additional R&D activities a costly proposition (Pisano, 1997) and rather increasing the incentive to wait. Thus, we expect that

Hypothesis 2: The positive effect of uncertainty on R&D investment will be accentuated for firms having stronger human capital.

Uncertainty and related variation

O'Brien and Folta (2009) point out that the value of real options can also be moderated by innovation strategies endogenously selected on how to compete in an industry as they help to “learn about and act upon unfolding opportunities in the industry” (p. 815). We argue that a firm that strives for an expansion of its product range within existing product lines accentuates the

value of investing in R&D under demand uncertainty. Empirical studies show that the learning rate is greatest when the object of learning relates to what is already known (Cohen and Levinthal, 1990), when firms put priority on producing new products that are more similar to existing ones (Egelman *et al.*, 2017), and when learning can be transferred between related problem domains (i.e., ‘related variation’, Schilling *et al.*, 2003). Conversely, learning becomes more difficult when learning environments are distant from the firm’s existing products (Teece *et al.* 1994; McGrath and Boisot, 2003).

When faced with demand uncertainty and learning conditions that relate to the existing product lines, the use of experimental probes can be an effective approach to explore uncertain futures (Brown and Eisenhardt, 1997, 1998). Beyond reducing earnings surprises by lowering the variance of revenues and cost of commercialization, this form of experimental learning also provides options of responding to uncertain futures. As these are likely to be similar to existing products, the correlation of the firm’s upside opportunities will be positive, increasing the firm’s value when facing high uncertainty about the market environment (Anand, Oriani, and Vassolo, 2007). Consequently, when pursuing an innovation strategy of high related variation (as opposed to low variation), an increase in uncertainty increases a firm’s investment in R&D.

An additional argument for the moderating effect of a firm’s innovation strategy on the uncertainty-investment relationship relates to the underlying knowledge needed to effectively leverage R&D. Deeper knowledge on cause-effect relationships due to prior experience from the firm’s main product lines makes learning-before-doing relatively productive (Pisano, 1994, 1996). When related variation is high, an increase in uncertainty about demand increases the value to invest in R&D prior to commencing production.

By contrast, when facing high uncertainty at low levels of related variation, investments in R&D are expected to have a low learn-to-burn rate (Ghemawat, 1991). In this case, a lack of prior knowledge makes learning before doing less effective (Pisano, 1994) and the firm is likely to face a lower learning rate (Sinclair *et al.*, 2000; Egelman *et al.*, 2017). Consequently, the firm's value of the option to commercialize new products is lower (Majd and Pindyck, 1989), leading to less investment in R&D. Furthermore, since experimental activity often involves experiencing falls, learning from failure is less likely to occur in novel areas than familiar domains (Sitkin, 1992). Because the R&D investments in case of failure are more likely to be sunk and acquired resources can be less likely redeployed to other projects, firms who face high uncertainty and pursue low related variation will keep investments in each round of funding to an absolute minimum (McGrath and MacMillan, 2000). Therefore, we argue that related variation strengthens the positive relation between uncertainty and investment in R&D.

Hypothesis 3: The positive effect of uncertainty on R&D investment will be accentuated for firms pursuing innovation activities that are related to their existing product lines.

Uncertainty, related variation, and industry maturity

The level of maturity of an industry is likely to be an important boundary condition for the moderating effect of related variation on the uncertainty-investment relationship. For new markets, relatedness offers more benefits from an option when demand uncertainty is high than when it is low. But in mature industries, the potential gains are often smaller due to decreasing marginal gains. As examples, there is tremendous room in electric vehicles for efficiency gains compared to gas powered engines, or biotechnology vs. conventional pharmaceuticals. For both

examples, the latter, due to their maturity, most gains have been wrung out.³ Once industries mature, competition becomes more intense (e.g., Grimm, Lee, and Smith, 2006) and the variance increasing effect of exploring unrelated areas creates the capability to change position in the future (Kogut and Kulatilaka, 2001), increasing the chances to outcompete others (March, 1991; McGrath, 2001). Consequently, under uncertainty and low degrees of related variation as a firm's innovation strategy, an increase in industry maturity will increase investment in R&D, as these enable the firm to learn how to effectively switch from one capability to another. In contrast, when facing demand uncertainty and high degrees of related variation as firm strategy, an increase in industry maturity will lead to less investment in R&D. Therefore:

Hypothesis 4: Industry maturity will constrain the interaction effect between uncertainty and related variation on R&D investments, such that the interaction effect is weaker when industry maturity is high than when industry maturity is low.

METHODS

Sample and data

In order to test the theoretical framework, we constructed a sample at the German Economics & Business Data Center (EBDC) that provides a unique panel dataset by matching the Innovation Survey and the Business Climate Survey. These data are collected by the Munich ifo Institute. The Innovation Survey questionnaire provides qualitative data about innovation objectives and detailed quantitative information on the expenses devoted to discrete types of activities in the innovation process. It is carried out on an annual basis and the data are linked to those from the

³ We thank an anonymous reviewer for this insight.

Business Climate Survey via common company identifiers. The Business Climate Survey comprises managers' expectations about future developments of the business condition. Since the Business Climate Survey is carried out on a monthly basis, we average the monthly data points within years in order to obtain annual observations.

The data cover information on a representative sample of (mainly non-quoted, medium-sized) companies in the German manufacturing sector (Hönig, 2009). As opposed to datasets that focus on large, listed companies, this one has the advantage of including firms to which total risk is pertinent to investment decisions. For non-quoted, medium-sized companies, firm-specific risks are less likely to be diversified away by shareholders. Further, the data are less influenced by biases from the stock market, which typically rewards the management of systematic risk rather than unsystematic risk (Bettis, 1983). The data also have the advantage of providing time-series data on management expectations, which are typically hardly accessible in large number and often need to be measured by proxies (e.g., Chen, 2008). Finally, a study of firms from only one country provides the advantage of focusing on firm-level differences in learning abilities without the need to control for cultural differences, since earlier work finds national differences in those abilities to be influential for real-option decisions (Hurry, Miller, and Bowman, 1992).

At the time of access, the EBDC database comprised information on 4,397 business divisions of 3,972 firms during the period 1994 to 2008. Using business divisions as the unit of analysis conforms to previous work studying R&D expenses (e.g., Cohen and Levinthal, 1990). Since the information contained in the database is anonymous, it was not possible to match external micro-level data to the observations, however, we are able to link industry data from the Federal Statistical Office of Germany (Destatis) using the 3 digit NACE Rev. 1 industry classifier. After eliminating divisions with constantly zero R&D expenses and observations from

less than two consecutive years, we obtain a panel of 530 business divisions and a total of 1,537 observations. Because the data build on an unbalanced panel and can include abandoned projects as well as firms that did not survive, we assume that the sample is relatively unbiased towards successful firms.

Dependent variables

Similar to prior work on R&D investments at the firm-level (e.g., Cohen and Levinthal, 1990), we calculate our core dependent variable (*R&D*) by aggregating the research and development investment categories comprised by the EBDC data and dividing annual total R&D expenditure by total sales. In order to first test whether uncertainty has a negative effect on capital expenditures, as is commonly found in the literature, we follow prior work (Levitas and Chi, 2010) by defining capital expenditures as the expenditures made for investments in buildings, plants, and equipment needed for commencing production of new products. For the measure (*CapexNP*), we use annual aggregated expenditures and divide it by total sales.

Independent variables

Uncertainty

For the measure of uncertainty, we follow prior work that focuses on the randomness in demand, which influences prices and cost, and determines profitability (Folta and O'Brien, 2004). Specifically, we derived a proxy for uncertainty from estimating a statistical model of the process that determines the conditional variance of an aggregate indicator at the industry-level, such as price level or industry output. Various real-option studies measure the unpredictability of an indicator using autoregressive models to examine the difference between the actual

development of the indicator and a prediction of its development from the recent trend (Folta and O'Brien, 2004; Oriani and Sobrero, 2008). Following this line of research, we use a general autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986) that captures uncertainty while controlling for trends in the data and allowing for unique, time-varying approximations.

Specifically, we estimate GARCH (1,1) models on a time series of monthly industry sales at the 3-digit NACE level provided by Destatis for the period 1995-2008. Since limited time periods may bear efficiency problems in autoregressive models, we take four preceding years of monthly observations for each industry, resulting in a time series of 48 data points for each model. Similarly to Folta and O'Brien (2004), we calculate the square root of the monthly conditional variance generated from this model. To obtain year observations for our variable *uncertainty*, we average the monthly data points across years and industries.

Human capital

In order to proxy a firm's human capital, extant work has often used the expertise of a firm's employees (e.g., Mowery and Oxley, 1995; Keller, 1996; Cuervo-Cazurra and Un, 2010; Klingebiel and Adner, 2015). For our measure of *human capital*, we use the share of employees with a technical university degree. This information is provided by the EBDC data base.

Related variation

A firm's learning rate is enhanced when a firm's main priority is on producing new products that are similar to existing product offerings (Egelman *et al.*, 2017), so a firm's engineers and scientists face over time different but related problems (Schilling *et al.*, 2003). In order to proxy

such related task variation, we use the EBDC survey data that provides information on the strategic priority of each firm's innovation activities. We measure *related variation* as the respondents' ratings of innovation activities within the extant product range (0 = no; 1 = weak; 2 = strong; 3 = very strong) in the current year. A level of three would suggest that the innovation activities build on existing skills or knowledge sets, and that new opportunities explored in the learning process are strategically central to the business (Lynn, Morone, and Paulson, 1996; McGrath and MacMillan, 2000).

Industry maturity

Industry life cycles are characterized by decreasing growth rates. The more mature an industry becomes, the less it grows. Such dynamics can influence a firm's option values (Bollen, 1999) and R&D activities (e.g., Klepper, 1996). To proxy *industry maturity*, we calculate the difference between the greatest past growth rate and the actual growth rate of total industry sales, both at the three-digit NACE Rev.1 level.

Control variables

We include factors that could influence R&D expenses beyond the model variables and control for firm, industry, and time effects. First, scholars have emphasized the importance of abandonment for limiting downside risk and resource reallocation for real option studies (e.g., Dixit and Pindyck, 1994; Adner and Levinthal, 2004). Therefore, in line with recent empirical work (Klingebiel and Adner, 2015), we created a dummy variable (*Project discontinuation*) that reflects whether the firm discontinued innovation projects (1= discontinued; 0 otherwise), as a proxy for reallocation of resources to other projects.

Second, we control for expected market conditions, since firms tend to enter markets when they expect favorable market environments (e.g., Kim and Kogut, 1996), and those expectations can influence investments in R&D (Bromiley, 1991). In the Business Climate Survey, managers are asked about their expectations on future changes in the business situation on a three point scale (worse, better, or unchanged). To operationalize the variable *expected growth*, we average these expectations per year. Values greater than zero indicate favorable market developments, and values below zero indicate unfavorable market developments.

Third, given that R&D investments tend to be distant and uncertain, and performance improvements from increased R&D intensity are not immediate, managers may cut R&D expenses when under pressure to meet performance forecasts. As empirical work finds that a performance gap relative to forecasts relates to a firm’s R&D intensity (Gentry and Shen, 2013), we control for *performance gap*. The EBDC data provide detailed information on managers’ expectations and, therefore, enables us to measure the performance gap relative to forecast based on those expectations directly. The monthly EBDC survey comprises respondents’ expectations about the developments of ‘commercial operations’ in the following six months as well as their appraisals of the ‘state of business’ in the current month, both measured on a three-point scale (worse, unchanged, or better). They allow us to compare their ex-ante predictions of the business development with their ex-post assessments of the business development (Hönig, 2009). Firms facing differences between predictions business developments and real outcomes are facing a performance gap. The performance gap relative to forecast by a firm *f* at time *t* is given by:

$$P_{f,t} = \left| E_{f,t,n} - \frac{1}{n} \sum_{n=1}^n A_{f,t+n} \right|,$$

where $E_{f,t,n}$ denotes the expected business development over n future periods, and the subtraction term contains the mean of $A_{f,t+n}$ representing the assessments of the current business situations across n periods. For each firm, we calculate the performance gap $P_{f,t}$ in every month of the observation period and average them across years. In line with Gentry and Shen (2013), we took the absolute value. We lag the variable *performance gap* by one year as the related time span reaches six months into the future.

At the industry level, we control for *industry productivity* as measured by the sales/employees ratio. Industry productivity may be related to the firm's tendency to undertake R&D projects (e.g., Lim, 2015; Zhou and Wu, 2010). Finally, we include year dummies in order to control for changes in our dependent variable that are related to the macro-environment (Chen, 2008).

Analytical approach

Empirical evidence suggests that firms use previous year's R&D budget and set it up or down (O'Brien and David, 2014), or that budgets can be routinized as a fixed percentage of sales (Chen, 2008). Having routinized procedures for determining R&D spending implies that firm's R&D investments are largely influenced by previous year's spending. In order to avoid biases in parameter estimates, it is important to take this into account in the regressions. Therefore, similar to prior studies that explain R&D expenses (e.g., Lim, 2015; Vissa, Greve, and Chen, 2010), we use Arellano-Bond dynamic panel data estimation in our analysis (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). This method simultaneously controls for autoregression and firm-level effects that may influence R&D spending. Thus, we include the control variable *lagged R&D* which accounts for potential stability in the allocation of resources

to R&D over time. We employ the robust two-step difference generalized methods of moments (GMM) estimator which provides consistent estimates and corrects for autocorrelation. The Arellano-Bond tests for autocorrelation applied in our GMM models indicate the absence of serial autocorrelation as the AR2 tests are insignificant. Since the hypotheses predict interaction effects, we mean-centered the variables to account for potential multicollinearity between direct and interaction effects (Aiken and West, 1991).

RESULTS

Descriptive statistics and a correlation matrix are presented in Table 1. The mean and standard deviation of *R&D* intensity show similar values to earlier studies (e.g., Greve, 2003; Cuervo-Cazurra and Un, 2010; O'Brien and David, 2014). As our sample shows R&D intensities far below 100 percent, the data are apparently in line with our theoretical model which relates to firms that focus on production and sales activities, not R&D specialists (Chen and Miller, 2007; Lim, 2015).

The mean and standard deviation of *uncertainty* in our data is higher than in earlier work on the value-creating effect of R&D investments under uncertainty (Oriani and Sobrero, 2008: mean 0.05/ sd 0.04). Our measure of *human capital* (the share of employees with a technical university degree) is, on average, lower to similar studies on R&D investments using the share of employees with more than a secondary degree (Cuervo-Cazurra and Un, 2010: mean 8.7/ sd 10.27). As can be seen in Table 1, the pairwise correlations across the set of variables are small. We used ordinary least square regressions to test for multicollinearity. The mean variance inflation factor is 1.01 and the individual variance inflation factors are all below 2. Overall, we conclude that multicollinearity is not a concern.

Insert Table 1 about here

Model 1 (Table 2) first examines whether uncertainty has a negative effect on capital expenditures for new products (*CapexNP*). In line with prior findings on manufacturing investments (e.g., Episcopos, 1995; Price, 1995; Levitas and Chi, 2010), uncertainty has a negative effect on *CapexNP*. As previous work in the real options literature also suggests that entry depends on the expectations about market opportunities (Kim and Kogut, 1996), it is worth mentioning that the positive and statistically significant effect of a firm's expected market growth on *CapexNP* parallels prior literature.

In Models 2–5, we test our predictions with *R&D* as dependent variable. Model 2 is the base model with the control variables. The negative effect of *related variation* on *R&D* suggests that, on average, fewer resources are allocated to R&D when the firm pursues innovation activities that relate to the main product line. This finding is in line with Penrose's (1959) view that the less familiar the activities that support the expansion strategy, the higher the efforts required to obtain required information. The relation between *industry maturity* and *R&D* is negative and statistically significant, suggesting that, on average, firms invest less in the research and development (and commercialization; see Model 1) of new products when industries are more mature.

In Model 3, we test the relation between *uncertainty* and *R&D*. Contrary to the finding of *CapexNP*, we expect that this relation is positive. A positive influence of *uncertainty* of *R&D* suggests that firms tend to increase investment in learning when uncertainty increases, as the R&D activities enable the firm to reveal information about the benefits of investing further.

Model 3 indicates that *uncertainty* has a positive effect on *R&D* ($p < 0.001$), providing support for Hypothesis 1. In practical terms, it implies that a one standard deviation above the mean is associated with about 5% increase in *R&D* intensity after controlling for firm and industry variables.

Even though the results from Model 3 are at the firm-level, the uncertainty-investment relation may mask firm differences because the measure for uncertainty is at the industry-level (e.g., Folta, 2005). Therefore, we add in Model 4 the interactions of uncertainty with the firm-specific learning conditions (*human capital* and *related variation*). Regarding *human capital*, we expect that *human capital* strengthens the relation between *uncertainty* and R&D intensity, suggesting that the level of skills among a firm's employees increases the R&D intensity at mean values of uncertainty. Model 3 indicates that the coefficient of the interaction term of *human capital* and *uncertainty* is positive and significant. The level of significance is modest ($p = 0.087$). However, in the full model, in which the substantive variables of the theoretical framework are present simultaneously (Cohen *et al.*, 2003) and all moderation hypotheses are tested, the level of significance is high ($p < 0.001$), providing support for Hypothesis 2. Effects size analysis suggests that when *human capital* is high (95th percentile), *uncertainty* at the highest degree yields 1.96 times higher *R&D* intensity than the lowest degree of *uncertainty*. By contrast, when *human capital* is low (5th percentile), the highest degree of uncertainty yields only 1.66 times higher *R&D* intensity.

With respect to firm-level differences that relate to the innovation strategy, we observe that the interaction of *uncertainty* and *related variation* is positive and significant ($p < 0.001$), providing support for Hypothesis 3. The coefficient of *related variation* remains negative and significant, but relatedness seems to enhance the positive influence of uncertainty on investment

in *R&D*. In practical terms, when *related variation* is at the 95th percentile value, *uncertainty* at its highest value yields significantly higher (2.8 times) *R&D* intensity than *uncertainty* at the lowest value does. By contrast, when *related variation* is low (5th percentile), the increase from the lowest to the highest level of *uncertainty* yields only about 66% increase in *R&D* intensity.

However, our theoretical model argues that this interaction effect is contingent on the maturity in the industry. In Model 5, we add the three-way interaction of *uncertainty*, *related variation*, and *industry maturity*. Hypothesis 4 predicts that *industry maturity* reduces the moderating effect of *related variation* on the relationship between *uncertainty* and *R&D* intensity. Consistent with our expectation, the coefficient estimate of this interaction term is negative and significant ($p < 0.01$). Thus, Hypothesis 4 is supported. The effect size estimation shows that when both *industry maturity* and *related variation* take their highest values, an increase from the lowest to the highest degree of *uncertainty* results in a decline in *R&D* intensity of about 12%. However, when *industry maturity* takes its lowest value and *related variation* takes its highest, the highest level of *uncertainty* yields a 3.5 times higher *R&D* intensity than the lowest level of *uncertainty*. In all models, the direct effect of *uncertainty* and the effects between *uncertainty* and the moderators show stable results, indicating support for our theoretical framework.

Insert Table 2 about here

DISCUSSION

Starting from the observation that unexplained variance in *R&D* activities might be rooted in future-oriented, firm-specific managerial choice under *uncertainty* (Patel and Pavitt, 1997), this

paper sought to understand why some firms increase R&D investments in the face of uncertainty, while others do not. Building on the literature on real options theory and learning, we study whether a forward-looking decision model that considers a firm's learning conditions can explain heterogeneities in R&D investments under uncertainty. Contrary to common wisdom, which mainly builds on insights from manufacturing investments, we find in the context of R&D, that the uncertainty-investment relationship is positive. We also find that a firm's human capital and the firm strategy of pursuing innovation activities that relate to the main product focus enhance the positive effect of the uncertainty on the allocation of resources to R&D activities. However, the effect of related variation is weakened by industry maturity. Our findings help advance the understanding of how firms manage uncertainty and have implications for theory and management practice.

Implications for theory

This paper contributes to answering a question that strategic management researchers have sought to answer since inception of the field: how do firms behave in their environment and why do firms differ (Rumelt, Schendel, and Teece, 1994). We contribute to this literature by studying firm-specific drivers of strategic investment decisions in the face of uncertainty. The insights address recently reviewed challenges regarding real options in strategic management (Trigeorgis and Reuer, 2017). More specifically, we explain heterogeneous firm behavior in R&D and provide arguments on when learning investments prior to production yield value and when a firm should rather wait to invest. Linking such initial investments to the option of commercializing new products (see also: Bowman and Hurry, 1993; McGrath, 1997; Garud *et al.*, 1997) and understanding the benefits of such learning-type investments complements research that has

largely focused on the role of creating and exercising R&D options under exogenous uncertainty (e.g., Oriani and Sobrero, 2008; Levitas and Chi, 2010). Thus, exploring the link between learning abilities, total uncertainty, and pre-investments in the context of R&D, informs us on how to strengthen and *manage* real options in the face of uncertainty. Furthermore, by revealing how interactions between firm-specific learning conditions and demand uncertainty influence investment decisions, we answer prior calls that suggested complementing real options research by the role of learning (e.g., Folta, 2005, 2007; Li *et al.*, 2007; Trigeorgis and Reuer, 2017).

Our findings on the role of learning investments under total uncertainty also contribute to the literature on risk management. First, in line with Bettis' (1983) conundrum #1 on unsystematic risk management (p. 408), our findings suggest that both firm-specific uncertainty and systematic uncertainty are crucial for explaining R&D investments. While delaying commitments to producing new products when facing (industry-wide) demand uncertainty, initial investments allow firms to reduce firm risk (e.g., Chatterjee *et al.*, 1999). However, by revealing that interactions between a firm's learning abilities and demand uncertainty motivate heterogeneous firm behavior, our insights suggest that some uncertainty is endogenous to some firms while it is beyond any control to others. This explains why some firms tend to proactively manage uncertainty to lower risk while others prefer to wait until uncertainty resolves.

Second, these insights provide an explanation for recent empirical findings that challenge the common practice of using R&D intensity as a proxy for a firm's risk taking (Bromiley *et al.*, 2017). As risk theory particularly applies to innovation expenditures that are relatively large and represent efforts to change the organization (Greve, 2003), we argue that beyond aforementioned firm-specific abilities, the direction of the uncertainty-investment relationship may also depend on the type of innovation activities. By distinguishing (Model 1 vs Model 3, see Table 2)

between innovation expenses that relate to R&D from those that relate to commencing production of new products (*CapexNP*), we show that demand uncertainty has contrary effects on both types of investments. This suggests that different types of innovation expenses underlie different motivations, implying for future studies a cautious use of R&D budgets to proxy for risk taking.

Finally, the insights from our study contribute to the literature on incentive-driven R&D (e.g., Cohen and Levinthal, 1990; Sinclair *et al.*, 2000). Building on findings on the role of R&D for a firm's learning curve (Lieberman, 1984; Pisano, 1994; Sinclair *et al.*, 2000) and research that combined demand uncertainty with learning curves (Majd and Pindyck, 1989), we contribute to the literature by specifying how demand uncertainty and firm-specific learning conditions jointly determine when the incentives to *learn before doing* increase. By interacting learning abilities with demand uncertainty, we identify real option effects that relate to firm learning as suggested by Folta (2005). Obviously, part of a firm's absorptive capacity is built by investing in real options.

In the light of the illustrative example of Hyundai Motor Company's history in developing its absorptive capacity (Kim, 1998), our theory provides a nuanced understanding of earlier findings. Prior to committing irreversible investments to the next stage of the innovation process, Hyundai leveraged trial-and-error learning to lower unsystematic uncertainties. Our theory suggests that it is the uncertainty after the oil crisis (e.g., uncertainty about the future demand of cars) that increased the incentives to shift learning orientation from "learning by doing" in production to "learning by research" and increase R&D investments (Kim, 1998: 514). In order to elevate the prior knowledge base and support the learning process, the company secured the availability of well-trained human resources and pursued innovation activities that

support a product expansion that relates to the main line of business. Hyundai's internal learning conditions enhanced the upside value of investments in R&D under demand uncertainty, while limiting the downsides by reducing variance and mean of its cost through experimentation. It appears that option values have guided those investment decisions. Once markets became favorable, the automobile producer increased sales, achieved high market shares, and caught-up with rivals (Kim, 1998). Hyundai's entrepreneurial approach to creating opportunities in unpredictable environments has enabled the firm to capitalize on uncertainty (Shim and Steers, 2012).

Practical implications

As an important implication for management, our study challenges the belief that firms ought to invest in R&D only under stable prospects or that R&D is per se risky for a firm. Popular business literature recommends using experimentation before committing to full-scale commercialization of uncertain market opportunities (e.g., Brown and Eisenhardt, 1998; McGrath and MacMillan, 2000; Ries, 2011). While our findings support the notion that uncertainty can encourage firms to invest in learning, we provide managerial insight on when such activities have less potential to generate firm value. When facing demand uncertainty, decision-makers who aim at using a trial-and-error process to learn about connections between technological capabilities and markets have to take the firm's human capital, innovation strategy, and industry maturity into consideration. Learning conditions facilitate limiting the downsides and enhancing the upsides of a firm's real options. Further, as allocating resources to R&D activities is accompanied by the challenge that R&D projects generate immediate costs while there are no immediate cash flows from investing, such investments have to be motivated by the

benefits of learning about connections between markets and capabilities and positioning the firm for exploiting uncertain market opportunities. Project managers who seek to receive funding from upper management may emphasize the importance of linking R&D with a firm's options to highlight value-creating effects of pre-investments.

In order to make better-informed strategic decisions, companies may combine real options, uncertainty, and risk management in their scenario planning process (Miller and Waller, 2003; Klingebiel, 2012: 312). By constructing scenarios, managers can analyze how plausible states of the world influence real-option exposures. Including firm-specific factors into real option analysis enables an 'apple-to-apple' comparison of a firm's possible strategic opportunities (Amram and Kulatilaka, 1999). However, this recommendation also includes a caveat: since market valuations of real options can differ from managerial valuations (Folta and O'Brien, 2007) and markets care about systematic risk rather than unsystematic risk (Bettis, 1983; Chatterjee *et al.*, 1999), firms seeking external funding for managing uncertainty need to raise market's perception of the value to invest in additional R&D activities. Our combined framework of firm-specific factors and uncertainty can help enhance the market's understanding of when learning investments (e.g., R&D pre-commitments) can enhance the firm's value.

Limitations and future research

Several limitations of our study need to be mentioned. First, our study is limited to demand uncertainty and learning investments, yet different types of uncertainties can influence the value of options (e.g., Huchzermeier and Loch, 2001) and such learning investments can relate to multiple options (Oriani and Sobrero, 2008). Future studies could explore the role of learning investments for different types of options and extend our insights to different types of

technological environments. Second, since unsystematic risk can also be influenced by competitors' actions (Bettis, 1983), firm differences in investment in new capabilities under uncertainty may also relate to focal competitor moves, such as market entry or imitation (McGrath, 1997). Combining different learning-type investments to uncover information and influence competitive behavior will provide interesting avenues to study resource allocation decisions (McGrath, Chen, and MacMillan, 1998). Third, the generalizability of our insights across national contexts might be limited due to the single-country context of this study. Prior work has suggested that differences in investment decisions might be rooted in different cultures and logics (Hurry *et al.*, 1992; O'Brien and David, 2014). Thus, research on the role of cross-country differences for investment decisions under uncertainty is needed. Fourth, there might be a bias against basic research that occurs at the corporate level, since such expenses are not included in our R&D variable that is measured at the business-unit level. The sample is representative of the German economy and, therefore, contains only few large firms with multiple business units. The R&D departments of these business units respond to changes in their market environments while the corporate research unit pursues overall, long-term projects. In these few cases, firm differences might exist in the division of labor between business and corporate research units. The study controls for at least part of these effects at the object level using a dynamic panel model.

Conclusion

We present and empirically test a framework that integrates real options research with the theory of learning to explain R&D investments under uncertainty. Most applications of real options theory assume that firms are homogenous actors, suggesting that firms in an industry respond to

changes in uncertainty in identical ways. Our theorizing points to the critical role of firm-specific learning conditions as boundary conditions that determine whether a firm yields value from investing in R&D under total uncertainty. The insights provide a better understanding of firm-specific investment patterns in R&D. We contribute by providing fresh insight into how total uncertainty (including both unsystematic and systematic components) can influence strategic investment decisions. What seems to be a behavior that is irrational (i.e., invest under industry-wide uncertainty) may for some firms in fact be a quite sensible value-enhancing investment decision.

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TABLES

Table 1. Descriptive statistics and correlation matrix ^a

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1 R&D	1.92	2.59	0	33.75	..1.00									
2 CapexNP	0.48	1.73	0	39.89	0.24**	1.00								
3 Uncertainty	0.14	0.10	0.05	0.95	0.07**	-0.02	1.00							
4 Human capital	5.95	19.55	0	100	0.03	-0.00	0.01	1.00						
5 Related variation	2.16	0.94	0	3	0.07**	-0.00	0.00	0.05*	1.00					
6 Industry maturity	1.97	0.12	0.44	2.57	-0.10**	-0.10**	-0.02	-0.05	-0.00	1.00				
7 Industry productivity	199.43	105.53	58.44	1068.60	-0.04	0.00	-0.02	0.04	0.06*	-0.12**	1.00			
8 Expected growth	1.92	0.40	1	3	-0.03	0.03	0.09**	-0.08**	-0.05*	0.07**	-0.06*	1.00		
9 Performance gap	0.52	0.33	0	2	0.02	0.01	-0.00	-0.01	0.02	0.04	-0.02	-0.02	1.00	
10 Project discontinuation	0.08	0.07	0	1	-0.02	-0.04	-0.03	-0.00	0.05	0.01	-0.03	-0.03	0.01	1.00

^a $N = 1,591$

* $p < 0.05$

** $p < 0.01$

Table 2. Dynamic panel data estimation of investment in R&D and CapexNP ^a

	Model 1 (CapexNP)	Model 2 (R&D)	Model 3 (R&D)	Model 4 (R&D)	Model 5 (R&D)
Uncertainty × Related variation × Industry maturity					-2.871* (1.367)
Uncertainty × Industry maturity					5.199*** (1.374)
Uncertainty × Related variation				2.024*** (0.369)	1.882*** (0.255)
Uncertainty × Human capital				0.026† (0.015)	0.049*** (0.012)
Related variation × Industry maturity					-1.331*** (0.199)
Uncertainty	-1.491*** (0.373)		2.913*** (0.656)	3.524*** (0.701)	4.145*** (0.598)
Human capital	0.001* (3.40e-04)	-0.002 (0.001)	-0.002† (0.001)	-0.002† (0.001)	-0.003* (0.001)
Related variation	-0.015 (0.015)	-0.068* (0.036)	-0.098** (0.039)	-0.106*** (0.039)	-0.087* (0.038)
Industry maturity	-0.704*** (0.033)	-(0.274)* (0.148)	-0.567*** (0.189)	-0.558*** (0.189)	-0.073 (0.169)
Industry productivity	0.005*** (5.17e-04)	-0.002* (0.001)	-0.008*** (0.002)	-0.008*** (0.002)	-0.007*** (0.002)
Expected growth	0.159*** (0.034)	-0.082 (0.085)	-0.090 (0.090)	-0.068 (0.094)	-0.031 (0.098)
Performance gap	-0.055† (0.031)	-0.031 (0.093)	-0.059 (0.101)	-0.062 (0.108)	-0.031 (0.105)
Project discontinuation	-0.144*** (0.045)	-0.165 (0.127)	-0.133 (0.132)	-0.210 (0.108)	-0.193 (0.144)
Lagged dependent variable	0.179*** (0.005)	-0.014* (0.007)	-0.024*** (0.008)	-0.029*** (0.008)	-0.027*** (0.008)
Year dummies	included	included	included	included	included
No. of obs.	1,591	1,591	1,591	1,591	1,591
No. of units	551	551	551	551	551
Wald Chi squared	50,456.56***	622.27***	1,190.63***	1,314.79***	971.51***
AR1/AR2 p-value	0.007/0.498	0.000/0.802	0.000/0.892	0.000/0.842	0.000/0.643

^a Standard errors in parentheses; † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.