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RESOURCE ALLOCATION STRATEGY FOR INNOVATION PORTFOLIO MANAGEMENT

RONALD KLINGEBIEL[1]* and CHRISTIAN RAMMER[2]
[1] *Warwick Business School, University of Warwick, Coventry, UK*
[2] *Centre for European Economic Research, Mannheim, Germany*

Our study demonstrates empirically that the choice of resource allocation strategy affects innovation performance. Allocating resources to a broader range of innovation projects increases new product sales, an effect that appears to outweigh that of resource intensity. In addition, we find that the performance benefit of breadth is higher for firms that allocate resources selectively at later stages of the innovation process. This breadth-selectiveness effect is greatest for firms intending to create relatively more novel products, departing further from their knowledge base. Based on these results, we theorize that breadth increases performance because it spreads firms' bets on unproven innovative endeavors. Limiting resource commitments by selecting out deteriorating projects prevents an escalation in the costs of breadth. This advantage increases with the uncertainty implicit in greater innovative intent. The paper thus contributes to theory of how resource allocation strategies influence performance outcomes of innovation project portfolios.

INTRODUCTION

In today's fast-moving markets, new products are more likely to fail than succeed. Nonetheless, competitive pressure requires firms to continue investing in product innovation projects, even if, initially, little is known about their commercial viability (Brown and Eisenhardt, 1997; Hauser, Tellis, and Griffin, 2006). Allocating scarce resources to uncertain innovation endeavors is thus a daunting task for many organizational decision makers.

Despite its managerial relevance, resource allocation strategy has scarcely featured in research on innovation performance. Standard input-output models do not account for heterogeneity in resource allocation (c.f. Crépon, Duguet, and Mairesse, 1998; Mairesse and Mohnen, 2002). The models' principal input factor tends to be innovation expenditure, which conceals variations in how these resources are allocated. However, pouring more money into bad projects does not necessarily increase performance.

Our aim in this paper is to test the effect of different resource allocation strategies on innovation performance, particularly in terms of new product sales. As resource allocation is a core activity for managers of innovations portfolios, this study adds to a growing body of literature that delineates how organizational differences in the strategic management of innovation impact upon performance (Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2010, 2011; Li and Atuahene-Gima, 2001).

One strategy available to managers is to allocate resources to a broad range of innovation projects. Greater breadth might cover a greater spectrum of future consumer preferences, hedging bets on individual new product projects (Sorenson,

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*Correspondence to: Ronald Klingebiel, Warwick Business School, Coventry CV4 7AL, UK. E-mail: ronald.klingebiel@wbs.ac.uk

2000). Unfortunately, the paucity of available data has limited empirical analysis of resource allocation breadth and potential performance effects. Related research found that innovation performance increases the wider companies search for information (Laursen and Salter, 2006; Leiponen and Helfat, 2010). That greater breadth may be advantageous is also an implicit assumption in conceptual and computational models of the new product development process (Cooper, Edgett, and Kleinschmidt, 2001; Ding and Eliashberg, 2002; Roberts and Weitzman, 1981).

But literature also suggests that there may be disadvantages for firms that undertake greater numbers of innovation attempts, including reduced managerial attention to individual projects, diminished strategic focus, heightened organizational complexity, and lowered incentives (Boudreau, Lacetera, and Lakhani, 2011; Klingebiel, 2010; Sull, 2003). It is thus worth asking not only whether resource allocation breadth improves innovation performance but also under which conditions it is more likely to do so.

The first consideration is timing. The disadvantages of breadth are pronounced in the later stages of the development process, where commitment and resource requirements are more substantial (Loch and Kavadias, 2007). Firms that explore a broad range of early-stage projects but select out some projects in later stages avoid an escalation of the disadvantages of breadth. Later-stage selection decisions should be better informed, as more becomes known about projects' commercial viability as time goes on. This paper thus tests for the performance effect of breadth conditional on selectiveness.

A second consideration is the innovative intent associated with the project portfolio, i.e. how ambitious the firms' innovation objectives are. More innovative intent indicates a greater share of novel projects, which are relatively distant from the firm's established knowledge and capability base. This poses a problem for resource-allocation decision making. Firms engaged in projects intended to upgrade existing products benefit from signals that are clearer and easier to interpret than firms aiming to extend product lines or expand into new market segments (Normann, 1971). As a result, innovative endeavors of the latter, more ambitious firms frequently generate disappointing sales, even if returns to the occasional success are higher (Hauser *et al.*, 2006; Shane and Ulrich, 2004). We therefore posit that the higher risk of decision-making error makes firms with greater innovative intent benefit more from a broader project portfolio than their less ambitious peers. And since there is greater scope for learning from uncertainty resolution when pursuing novel projects (e.g. Eggers, 2012; Huchzermeier and Loch, 2001), we argue that they also benefit more from complementing breadth with later-stage selectiveness.

To test these predictions, we use data from the German section of the EU-wide Community Innovation Survey (CIS). CIS data are appropriate because they include direct measures of firms' innovation performance, namely sales generated from new products. We were fortunate in being able to append further questions to the standard questionnaire, capturing firms' strategies for allocating resources to projects in their innovation portfolio.

Results show that breadth has a significant positive direct impact on innovation performance. Interestingly, its performance effect is more significant than that of increased project investment. Beyond this, we show that the effect of breadth is context-dependent. Firms achieve greater performance improvement if they allocate broadly at first and then also discontinue projects in later stages. When comparing sales generated from improved, new-to-firm, and new-to-market products, the effects are most pronounced for new-to-market sales. Testing for differences in the effect of breadth with regard to innovative intent corroborates this finding: more ambitious innovators derive greater benefit from breadth than their peers with lower innovative intent. The use they can make of breadth increases further if they also engage in selectiveness.

Our theoretical contribution lies in the delineation of how heterogeneity in firms' resource allocation policies explains variance in performance outcomes. Innovation performance is not only determined by the amount of resources spent on innovation, but also by the way in which these resources are allocated. We theorize how resource allocation breadth leads to higher new product sales and how this effect varies depending on selectiveness and innovative intent. The combination of breadth plus selectiveness provides a resource allocation strategy for coping with the challenge of incomplete knowledge in innovation portfolio management. This is particularly

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important for more ambitious innovators, who face greater levels of uncertainty.

We proceed with a discussion of extant literature to develop our four hypotheses. This is followed by the delineation of our empirical approach, results, and limitations. We conclude with a discussion of the implications for theory.

THEORY

The success of a firm's suite of innovative activities is a function of the amount and quality of resources dedicated to the task. Variables consistently linked with innovation performance include innovation expenditure and human capital (Crépon *et al.*, 1998; Mairesse and Mohnen, 2002). Given that only a fraction of innovation efforts are successful (Hauser *et al.*, 2006), however, the performance relationship is more complicated than that. Commercial uncertainty shortens the period within which managers, no matter how intelligent or well resourced, can confidently predict key determinants of innovation success, such as future customer preferences, technological standards, or competitive landscapes. Often, the time-to-market for new product developments exceeds this period (Griffin, 1997; Hauser *et al.*, 2006). Therefore, when firms allocate scarce resources to innovative endeavors, they run the risk of misjudging the prospects of success. Projects that initially look promising may ultimately fail, and projects that seem unconvincing at first may eventually succeed.

To deal with this challenge, firms often organize their innovation activities in portfolios of projects (Brown and Eisenhardt, 1995; Hauser *et al.*, 2006; Shane and Ulrich, 2004). The generation and prioritization of project variants are key concerns for portfolio managers (Loch and Kavadias, 2007). It is therefore striking that while the performance effect of heterogeneity in firms' strategies for allocating resources to innovation projects has received conceptual attention (Ding and Eliashberg, 2002; Roberts and Weitzman, 1981), there has been little empirical research. It is our objective to address this gap.

Resource allocation in innovation project portfolios influences the type of projects a firm pursues, how many, and for how long. Decision making typically occurs at successive points along the firms' product innovation process (Kester *et al.*, 2011; Schmidt, Sarangee, and Montoya, 2009). In this paper, we are interested in the extent to which three dimensions of resource allocation strategy influence the innovation portfolio performance, measured in terms of new product sales, that firms can hope to achieve: breadth, selectiveness, and innovative intent. By *breadth*, we mean the parallelization of innovation efforts, indicating a strategy of providing initial funding to several different projects. *Selectiveness* refers to resource allocation decisions in later stages of project development, indicating a strategy of deliberate discrimination between projects that warrant further resource allocation and those that do not. Finally, *innovative intent* describes the overall ambition associated with the portfolio of product innovation efforts, ranging from only minor improvements to existing products to novel forays into new market segments.

Prior observations suggest that firms display substantial variation in all three dimensions of resource allocation strategy (Cooper *et al.*, 2001; Griffin, 1997; Hauser *et al.*, 2006). In what follows, we develop hypotheses about the relationship between innovation performance and each of these aspects.

Resource allocation breadth

In new product development, resources are spread across a number of projects, covering various aspects of potential future customer preferences (Hauser *et al.*, 2006; Sorenson, 2000). The argument for breadth is that the more projects, the more aspects covered and, therefore, the higher the probability of at least some innovation success. As an illustration, Ding and Eliashberg (2002) anecdotally report that Sony pursued between 20 and 30 development projects in the area of videotape recorder technology in order to increase their chances of success with one of them. Even though empirical evidence of performance implications has yet to be presented, the rationale of spreading bets is argued to motivate managers to allocate resources broadly in such sectors as pharmaceuticals (McGrath and Nerkar, 2004), telecommunications (Keil, McGrath, and Tukiainen, 2009), venture capital (Guler, 2007), and in various consumer goods settings (Cooper *et al.*, 2001).

An analogous performance argument has been made with regard to breadth of search and objectives. More sources of innovation and a broader search pattern lead to better informed new product decisions (Katila and Ahuja, 2002; Laursen and Salter, 2006; Leiponen and Helfat, 2010). The greater the number of different objectives associated with product innovation activities, the greater the predicted performance (Leiponen and Helfat, 2010). There are, of course, substantial differences between information sources and development projects. The former constitutes search, the latter pursuit of opportunity. Incremental costs are much higher for additional projects. Nonetheless, the logic of search breadth further motivates our hypothesis on resource allocation breadth:

Hypothesis 1 (H1): Greater resource allocation breadth increases product innovation performance.

Selectiveness

Discontinuing projects that have advanced through the development pipeline is not unequivocally good for performance. One can imagine situations where firms hold sufficient resources to develop all their project ideas, which may all promise a positive return on investment. Selectiveness here would limit performance. Such situations, however, are less likely if a firm increases the breadth of the innovation projects it pursues (Hall, 2008). Therefore, instead of hypothesizing a direct performance effect of selectiveness, we argue that selectiveness provides a condition for an increased performance effect of breadth.

Prior research has touched upon the potential for overstretch through breadth, a disadvantage that might be usefully curtailed by selectiveness. For example, greater breadth may reduce managerial attention to a project, thus decreasing output quality (Laursen and Salter, 2006) although not all studies could replicate this countervailing effect (Leiponen and Helfat, 2010). Breadth in product innovation portfolios can also starve individual projects of sufficient resourcing, increase managerial complexity, reduce incentives, and hamper strategic focus and thrust more generally (Boudreau *et al.*, 2011; Klingebiel, 2010; Sull, 2003).

In view of these potential downsides, breadth might be more useful in some circumstances than others. A situation in which breadth stands to be more beneficial is one where resources can be withdrawn from projects that seem less promising over time. While breadth without selectiveness improves the odds of at least some success, breadth with selectiveness enables firms to react to information gained during new product development, reallocating resources from less to more promising endeavors. Similar logic has informed the design of several normative approaches to structuring new product development pipelines (Cooper *et al.*, 2001; Ding and Eliashberg, 2002; Nelson, 1961; Roberts and Weitzman, 1981), where broad exploration is succeeded by narrower commercialization.

The advantages of breadth derive from increasing the odds of including successful candidate products during initial project selection, when little is known about projects' commercial viability and exploration is relatively affordable. But this advantage diminishes over time. In the later stages of product development, project resource requirements increase, and managers can typically construct a better informed opinion about a project's commercial viability (Loch and Kavadias, 2007). Breadth is thus comparatively less useful and more expensive to maintain for projects in the later stages of development. If a firm's broad innovation project line-up translates directly into a broad new product portfolio, it benefits from a higher likelihood of offering blockbuster products but also suffers from offering more lacklusters.

The conjecture is that broadly allocating firms that disburse later-stage development resources selectively generate greater innovation performance. Selectiveness serves to ensure that fewer of those projects that increasingly look like they will deliver lackluster products reach the market. Resources originally marked for the development of projects with deteriorating prospects can be used by more promising candidate projects, thus increasing the quality of the final output from those projects. The idea is one of efficient failure (McGrath, 1999; Sitkin, 1992), which enables probing and learning (Brown and Eisenhardt, 1997). We thus expect a new product development process with broad allocation of small initial funds, and selective allocation of more substantial funds as commercial uncertainty resolves, to lead to greater performance than a process that commits funds to a fixed number of projects.

Despite the arguments for committing selectively when allocating resources broadly, selectiveness does not automatically follow from breadth. Managers of broader portfolios do not automatically engage in more selection, and vice versa

(Adner, 2007; Guler, 2007). For instance, breadth without selectiveness occurs if a deliberate pruning strategy does not exist (Hauser *et al.*, 2006; Loch and Kavadias, 2007); information is unavailable or not processed (Schulz, 2001; Sethi and Iqbal, 2008); or managers escalate prior commitments despite adequate information and policy (Green, Welsh, and Dehler, 2003; Schmidt and Calantone, 2002; Simester and Zhang, 2010).

We thus aim to test for the performance effect of firm-specific heterogeneity in selectiveness. Other things being constant, we hypothesize that broad resource allocation with selectiveness generates greater performance than breadth without selectiveness:

Hypothesis 2 (H2): The performance effect of resource allocation breadth is greater for selective firms.

Innovative intent

Firms vary in the degree of innovative ambition associated with their product development portfolios. Some firms concentrate on projects that closely relate to their existing products while others engage in a higher proportion of projects that are distant from their established knowledge and capability base (Hauser *et al.*, 2006; Shane and Ulrich, 2004). A firm in the latter category might intend to bring out novel products, enter new product categories or expand into new market areas. For these more ambitious endeavors, managers initially have less information to establish confidence in eventual product success (Normann, 1971). It is thus worth asking whether breadth's performance impact varies with a firm's innovative intent. Could breadth be of particular benefit to firms with more ambitious innovation objectives?

Before addressing this moderating effect of innovative intent, its direct effect on performance should briefly be considered. By itself, the mere intent to create products that are more novel in nature is an unlikely predictor of new product sales. Firms with more innovative intent might venture into lesser-known terrain and thus observe greater variability in outcomes than their less ambitious peers. But there need not necessarily be a significant difference in the average overall sales generated by project portfolios with greater and lesser innovative intent (Davis, Eisenhardt, and Bingham, 2009; Eisenhardt, Furr, and Bingham, 2010). On other dimensions of performance, however, there could be a discernible effect. One could imagine, for example, that trying harder to enter new product markets would help firms achieve this goal more often. Here, more innovative intent drives performance, and our paper controls for such direct effects. But our main focus is on the more intriguing theoretical question of whether firms with more innovative intent benefit more from breadth, given that the resource allocation challenge faced by these companies differs from that of their less innovative peers.

When managing portfolios with more innovative intent, decision makers have access to less reliable information about the performance potential of innovation projects than their counterparts at firms with more incrementally oriented innovation portfolios, for whom such knowledge is more readily available and learning from past experience is easier (Normann, 1971). A more ambitious innovation program thus reduces portfolio managers' capacity to predict projects' commercial viability. As a result, their initial project decision making is error-prone (More, 1982). Many of the new products based on project concepts that are more distant in terms of the knowledge and experience gained from past projects, generate disappointing sales, even if the occasional returns to successful novel products exceed those of their more mundane cousins (Dahlin and Behrens, 2005). Given this increased skew toward many lackluster products with occasional blockbusters, the pursuit of several avenues in parallel becomes more important in order to improve the odds of including at least one success. The spread-your-bets argument for H1 is thus particularly applicable to firms with more innovative intent. Therefore, we posit that innovation portfolios with more ambitious intent provide another setting in which the performance advantages of breadth are likely to outweigh its disadvantages. We hypothesize

Hypothesis 3 (H3). The performance effect of resource allocation breadth is greater for firms with more innovative intent.

Firms with more innovative intent may also differ from their counterparts in the extent to which they can reap the benefits of complementing breadth with selectiveness. They face two opposing tendencies. First, the lack of reliable decision signals for firms with more innovative intent

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means not only that they should cast a wider net initially but also that later-stage resource allocation choices are more consequential. During the time it takes to develop a new product, the high levels of uncertainty often decrease—endogenously, in the case of technological uncertainty (through trial and error [Fleming, 2001; Huchzermeier and Loch, 2001]), and exogenously, in the case of market uncertainty (through revelations as regards competitive landscape, customer preferences, and economic circumstances nearer the time of product launch [Eggers, 2012; Klingebiel and De Meyer, 2013]). Since firms with more innovative intent are less likely to identify the ultimately successful projects at the beginning of the development process, they benefit more from reacting to information that emerges with the decline of uncertainty. Here, selectiveness provides a mechanism to shift resources from some of the many ultimately doomed projects to the few remaining more promising projects. The logic is similar to that in H2, but the performance penalty of not pruning more innovative portfolios over time is more severe than that of not pruning less innovative portfolios.

Potentially curtailing this benefit of selectiveness is a tendency for firms with more innovative intent to commit more type II errors, selecting out novel projects that should be kept (Garud, Nayyar, and Shapira, 1997). Even more ambitious firms are likely to have a mix of projects in their portfolio, some closer and some more distant to the existing knowledge base. When making later-stage decisions about the allocation of more substantial chunks of project funding, these firms might be biased toward keeping projects that match their existing knowledge base and sorting out projects with more ambitious premises (Chatterjee and Wernerfelt, 1991; Danneels, 2002). This is because managers often perceive unusual new product propositions more negatively than new product propositions that are similar to the existing line-up, even if their business case is promising (Christensen, 1997; Van de Ven, 1999). With false negatives being selected out, fewer novel projects remain and the likelihood of a firm generating the hoped-for blockbuster success is thereby diminished. In addition, such firms have more limited line-ups of incremental projects than their competitors with less innovative intent. It is thus that selectiveness might actually reduce the positive effect of breadth for firms with more innovative intent. Firms with less innovative intent are less affected by the biased selection of false negatives, because their portfolios contain fewer project candidates that significantly depart from the established knowledge stock.

We argue that the first tendency outweighs the second. Combining breadth and selectiveness allows firms to reduce the risk of type II errors because it delays the final project choice until more information is available. Breadth without selection would not achieve the same—firms' innovation resources are limited and project-resourcing requirements rise as projects progress through the new product development process. Firms with more innovative intent that initially allocate resources broadly are less likely to have sufficient resources to finance the completion of all projects and, therefore, face a stiffer penalty for making type I errors in a later stage of development than for making type II errors at that stage: failure to reduce project portfolio breadth means that insufficient resources are available to develop and bring to market adequately any projects, irrespective of whether they were optimal choices. We therefore expect selectiveness to have a positive effect on the breadth–performance relationship among firms with more innovative intent. And because, to these firms, breadth is already worth more than to the firms with less innovative intent (H3), we hypothesize

Hypothesis 4 (H4). Complementing breadth with selectiveness is more beneficial for firms with more innovative intent.

DATA AND METHODS

Sample

The data are drawn from the 2009 Mannheim Innovation Panel, which constitutes the German part of the European Community Innovation Survey (CIS).[1] The survey contains information on innovation for the period 2006–2008. In addition to the normal set of CIS items, the 2009 survey also contained specific questions on resource allocation, which are detailed below in the section on measures.

[1] For background detail, see http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/en/inn_esms.htm

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CIS data have been used in several economic articles and, more recently, have attracted attention from the management community (Cassiman and Veugelers, 2006; Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Leiponen and Helfat, 2010). CIS's main strength is the provision of direct measures of firm success in commercializing innovations[2] across a representative range of industries. These measures provide a powerful complement to traditional innovation measures of patenting activity.

The statistical agency of the European Commission, Eurostat, coordinates the CIS survey instrument. Eurostat harmonizes the core set of measures that are to be included in the survey of each participating country (most countries conduct the survey biannually). Basic definitions and the survey methodology rest on the so-called Oslo Manual: 'Proposed Guidelines for Collecting and Interpreting Technological Innovation Data' (OECD and Eurostat, 2005). It contains guidelines for collecting and interpreting innovation data and mandates extensive piloting and pretesting to ensure reliability and validity.

The advantages of using German CIS data is not only that it captures the innovation activity in Europe's biggest economy but also that German data collection goes beyond the baseline requirements of the Oslo Manual in several aspects. It surveys firms annually, creating a richer longitudinal record for consistency checks. It is one of only four CIS countries that provide an additional layer of quality through extensive nonresponse surveys. And its scientific advisory board periodically reviews and permits the inclusion of supplementary questionnaire items, such as ours on resource allocation. For these reasons, and despite a slightly lower response rate than in some other CIS countries, the German data are generally considered to be of high quality (Eurostat, 2009).

The German CIS is sponsored by the Federal Ministry of Education and Research. It is conducted by the Centre for European Economic Research, in cooperation with the Institute for Applied Social Science Research and the Fraunhofer Institute of System and Innovation Research. Questionnaire data are processed using semiautomated methods of data input. Each response is subject to comprehensive quality control, including a consistency check against responses by the same firm in previous survey waves. Since the German CIS is conducted annually and many firms participate regularly, survey respondents are familiar with the main concepts and definition of the survey and can rely on established accounting and reporting tools to provide the various data asked for in the questionnaire.

The downside of such survey data is the potential for common methods bias. The CIS questionnaire is designed with this in mind and makes it difficult for respondents to maintain logical associations between different input fields. To date, critical reviews of CIS measures have not flagged common method issues as a primary concern (Mairesse and Mohnen, 2007, 2010; Smith, 2005). Nonetheless, we conducted a Harman single-factor test (Podsakoff *et al.*, 2003). With the variables used in Model III of Table 2, principal component analysis rendered five factors with eigenvalues greater than 1 (17 factors if industry dummies are included), and no single factor explained more than 24 percent of the variance (11% with industry dummies). The strongest loadings of the dependent variable and our key input variables were on different components. These results do not change substantially if different dependent variables are included. Common method variance is thus not likely to be present. Our test results are also in line with those reported in prior CIS analyses (Leiponen and Helfat, 2010, 2011).

The gross target sample of the 2009 survey consists of 35,197 enterprises, including manufacturing as well as services-based firms. Stratification is by sector (56 sectors at the two-digit level of NACE rev. 2.0), size class (eight classes according to the number of employees), and region (West Germany and East Germany). Sample firms were contacted via mail survey, with an option to respond online. The survey was addressed to the executive officer in charge of innovation. Firms that did not respond within six weeks of being mailed the questionnaire received a telephone reminder and were sent another copy of the questionnaire. This was followed up again after a further six weeks. By the end of this process, 5,388 firms were classified as neutral losses: they could either not be contacted or were confirmed to have ceased operation. Out of the corrected

[2] In the CIS data, a commercialized product innovation is defined as a novel or significantly improved product or service introduced to the market. These are further classified as either new-to-market, new-to-a-firm's product portfolio, or improvements to the existing range of products.

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gross sample of 29,807 enterprises, 7,655 usable responses were received. The response rate of 25 percent is slightly below that of some other international samples (Cassiman and Veugelers, 2006; Leiponen and Helfat, 2010) but of the usual magnitude for Germany (Grimpe and Kaiser, 2010).

Sector and size composition of the net sample does not differ significantly from the gross sample, indicating that the net sample is representative in terms of the sector and size distribution of the German firm population. An extensive nonresponse survey of 4,829 enterprises was conducted by telephone. This revealed no substantial concerns other than a higher share of innovating firms among the nonresponding firms (63.1%), compared with the net sample of responding firms (54.3%). This information is used to recalculate weights for economic projections and policy analysis but is of limited concern for studies like ours (Janz *et al.*, 2001; Peters, 2008).

For the analysis, only a subsample of survey responses is used. We exclude 4,282 firms that reported conducting no product innovation activity during the observation period. Some 452 firms have fewer than 10 employees, the standard threshold for CIS analysis (Laursen and Salter, 2006; Leiponen and Helfat, 2010). We also drop 69 nascent firms that were founded during the observation period. After removing a further 1,432 observations due to missing values in at least one variable of interest, we end up with a final dataset of 1,420 firms. This final sample compares well with the overall respondent set: industry membership, age, size, new product sales, and innovation expenditure are similarly distributed. We also estimate the hazard rate of observations being included in our final sample. The model results, reported in greater detail below, are robust to the inclusion of a correction term (inverse Mills ratio), suggesting that our analysis is unaffected by sample selection bias (Berk, 1983; Groves *et al.*, 2009).

Measures

Dependent variables

Performance in product innovation is conceptualized as the extent to which a firm generates commercially successful new products, evidenced through revenue from new product sales in 2008. To account for potential differences in the novelty of the new products generated, we adopt the customary three categories: sales originating from new-to-market products (NTM), sales from new-to-the-firm products (NTF), and sales from all new and improved products (NEW). On average, 6 percent of our sample firms' sales are attributed to new-to-market products, 10 percent to new-to-firm products, and 25 percent to new and improved products. The operationalization and distribution of these variables are in line with prior CIS work (Laursen and Salter, 2006; Rammer, Czarnitzki, and Spielkamp, 2009).

All three measures contain raw values. They have the advantage of providing greater construct validity than ratios (e.g. new product sales/overall sales); a performance increase in absolute terms can be more directly interpreted as being related to a firm's innovation activities than an increase in relative terms. An increase in the ratio could be due to a firm selling more successful new products as well as to diminished sales of legacy products. Raw values for new product sales avoid this conflation. In addition, ratios can create extreme values for smaller firms and those with only a few products, problems that do not occur with raw values (Mairesse and Mohnen, 2010).

Independent variables

We introduce a new variable for resource allocation breadth. After reviewing relevant literature on new product development (Ding and Eliashberg, 2002; Loch and Kavadias, 2007; Roberts and Weitzman, 1981), we decided to ask CIS firms to report the number of innovation projects pursued during 2006–2008. Answers were then divided by firm size, because bigger firms have more projects. This normalizes our measure for resource allocation breadth and allows for meaningful comparisons across the range of sample firms, big and small.

Orthogonal to portfolio breadth is the amount of resources allocated per project. If a firm increases its overall innovation budget, it can afford either more projects or more resources per project. We operationalize project resourcing by dividing a firm's overall innovation expenditure (2006–2008) by the number of projects it pursued. By controlling for the level of project resourcing, it becomes possible to identify the separate performance effect of allocating resources to a broader range of projects.

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Selectiveness refers to a firm's policy of allocating resources discriminately as projects move through the innovation process. Selective firms differ from nonselective firms in that they show evidence of project discontinuations (Adner, 2007; Guler, 2007). Therefore, we aim to detect whether firms apply selection pressure to their product development process: the survey asked respondents to state the number of innovation projects discontinued during 2006–2008. From this we construct two categories for the selectiveness variable: a firm that completes all its projects is not selective; a firm that completes only a subset is selective. In our sample, 36 percent of firms were selective.

Because it may be easier for firms with more projects to discontinue at least one of them, we complement the above with a second operationalization of the selectiveness variable. As per this second operationalization, we consider as selective only those firms that discontinue at least 20 percent of their projects (or one in every five innovation projects). Twenty-nine percent of sample firms meet this criterion (71% are not selective). This second operationalization is more robust to a potential portfolio size bias, but it is employed for the purpose of robustness checks only. It is somewhat arbitrary to prescribe an optimal share of projects that ought to be pruned, and any such value is likely to vary across industries, firms, and time. In addition, we view the qualitative difference between a firm pruning a few projects and a firm pruning a few more as less relevant than that between a firm applying selective pressure and one applying none at all.

For innovative intent, our aim is to distinguish more ambitiously innovative firms from their less ambitious counterparts. We do this by looking at firms' stated innovation objectives (see Leiponen and Helfat, 2010). The CIS survey asked each firm to use a Likert scale (from 0 for not important at all/not used to 3 for very important) to evaluate the importance of a series of objectives, including two that are relevant for this study: 'Expand into new product category' and 'Enter new markets.' A firm scoring high on these two dimensions is more ambitiously innovative in that it aims to create new products that are dissimilar to its existing line-up. We use a composite score of the two objectives and designate all firms with the maximum sum score of 6 as having more ambitious innovative intent (547 observations), and a score of 4 or less as having less ambitious innovative intent (485 observations). We omit observations where the composite indicator equals 5, to get a more robust demarcation between the two types of firms.[3]

Note that innovative intent is measured at the aggregate portfolio level. It does not capture individual radical or disruptive innovations. Instead, our operationalization of innovative intent indicates to what extent firms generally aim to create products for the development of which they cannot easily rely on historic knowledge stocks. Furthermore, a benefit of our measure is that it limits success bias. Alternative operationalizations based on whether or not firms introduced new-to-market innovations entail conceptual conflation with success (Dahlin and Behrens, 2005; Kleinknecht, Van Montfort, and Brouwer, 2002). Our measure correlates with that alternative at the 0.05 percent level but avoids its success selection bias.

Control variables

Our model contains controls that are frequently included in models explaining innovation performance (Crépon *et al.*, 1998; Grimpe and Kaiser, 2010; Leiponen and Helfat, 2010; Mairesse and Mohnen, 2002). We use firm sales to account for size, because larger firms generate greater new product sales in absolute terms, all else being equal. To control for the quality of input to the innovation process, we measure the proportion of employees with a university degree. We further control for the extent to which firms carried out research and development on a continuous basis (yes/no). Whether firms were engaged in process innovation (yes/no) is also included, as this is a valuable organizational activity that it is not otherwise captured in our models on product innovations. One could also imagine variation in innovation performance that is due to firms' prior experience, for this reason we extracted information about firm age from the national registry. In addition, we control for variation in performance that may be due to the focal firm belonging to a group of companies. To account for new product success

[3] We conducted robustness tests with 5 included and results remained consistent. For more detail on the interpretation of the Likert-scales of innovation objective variables, see Cohen and Malerba (2001) and Leiponen and Helfat (2010).

that is due to marketing rather than substantive innovation, we include a measure of firms' marketing expenditure as reported for 2007. Finally, we include a set of 22 industry dummy variables representing groups of two-digit level NACE sectors. This is to control for potential industry-level variations in firms' capacity to generate innovation performance.

Estimation

Our data are censored, making Tobit analysis the estimation method of choice. We follow established designs for innovation performance models based on CIS (Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Leiponen and Helfat, 2010). We depart from this only in decomposing the usual innovation expenditure variable into portfolio breadth and project expenditure.

To assess the varying effect of breadth under different conditions, we conduct split-sample/split-variable analyses (Carpenter and Westphal, 2001; Cassiman and Veugelers, 2006; Terwiesch and Loch, 1999). This allows us to separate the effects of breadth under different conditions, testing for statistically significant differences without violating the econometric assumptions of nonlinear specifications such as Tobit (Ai and Norton, 2003; Hoetker, 2007).

Correlations are presented in Table 1. The table includes the overall number of projects that firms conducted before this variable is adjusted for firm size (this is for the purposes of transparency only; the unadjusted count is not included in the models). Firms with more projects are more likely to select out at least one project. The correlation of the unadjusted project count with our primary operationalization of selectiveness underlines the usefulness of robustness checks through a second operationalization that is less susceptible to portfolio size. Measuring selectiveness as a percentage (one in five projects discontinued) removes the significant correlation between the number of projects in the portfolio and selectiveness. In any case, the main variable of resource allocation breadth, which adjusts the count of projects for firm size, does not significantly correlate with either of the two operationalizations of selectiveness. This suggests that an increase in breadth that is not due to firm size does not automatically make a firm more selective. The absence of a correlation here supports the argument that there is firm-specific variation in the extent to which selectiveness is exerted in otherwise equally broad portfolios. As expected, innovative intent does not correlate with overall new product sales (NEW) and does correlate significantly with sales from more novel products (NTF, NTM).

All of our models use logarithmic transformations of the dependent variable. Innovation performance is strongly skewed in all three categories and; accordingly, the pattern observed in the empirical distribution is more fairly represented by lognormal distributions (see Laursen and Salter, 2006). Similarly, breadth, as well as the controls for firm size, innovation expenditure, and marketing expenditure enter the models in lognormal form.

We assume a partial lag between resource allocation and innovation performance by relating new product sales in 2008 to independent variables measured for the period 2006–2008. While there appears to be no consensus on the lag structure of innovation input and output (c.f. Mairesse and Mohnen, 2010), we ensured that our operationalization is in line with that of prior CIS studies (Cassiman and Veugelers, 2006; Grimpe and Kaiser, 2010; Laursen and Salter, 2006). Using a subsample of 256 firms for which such information was available, we also compared the results of two base models (c.f. Mairesse and Mohnen, 2010), one including 2008 values for the dependent variables and one including the values reported in the subsequent year. The 2009 model, with greater lag, explained 15 percent less variance than the 2008 model.

RESULTS

The results Tables 2–5 list marginal effects, rather than coefficients, plus standard errors. Table 2 reports the estimated effects on the three dependent variables in full-sample models. Using the recommended standard design (Mairesse and Mohnen, 2010), our Model I shows significance for size, innovation expenditure, continuous R&D, process innovation, and marketing expenditure. These observations are consistent with recent CIS studies (Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Leiponen and Helfat, 2010). From new product sales, through new-to-firm product sales, to new-to-market product sales, the quality of resources and continuous R&D become more

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Table 1. Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	New product sales (2008 €m, log)	1.00															
(2)	New-to-firm product sales (2008 €m, log)	0.64^{***}	1.00														
(3)	New-to-market product sales (2008 €m, log)	0.52^{***}	0.77^{***}	1.00													
(4)	Firm size (avg 2006–2008, sales in €m, log)	0.63^{***}	0.44^{***}	0.39^{***}	1.00												
(5)	Resource quality (2008, % staff w/ degree)	0.03	$0.08**$	0.09^{***}	-0.09^{**}	1.00											
(6)	Process innovation (2006–2008, yes/no)	−0.04	0.00	0.02	-0.19^{***}	0.14^{***}	1.00										
(7)	Continuous R&D (2006–2008, yes/no)	0.31^{***}	0.19^{***}	0.13^{***}	0.20^{***}	−0.00	$-0.07*$	1.00									
(8)	Firm age (years, in 2008, log)	0.27^{***}	0.26^{***}	0.31^{***}	0.18^{***}	0.07^{**}	0.20^{***}	0.07^{*}	1.00								
(9)	Part of group (2008, yes/no)	0.14^{***}	0.11^{***}	0.11^{***}	0.32^{***}	0.06^{*}	-0.24^{***}	0.02	−0.03	1.00							
(10)	Marketing expenditure (2008, % of sales, log)	0.35^{***}	0.22^{***}	0.18^{***}	0.53^{***}	−0.04	−0.03	0.10^{***}	0.11^{***}	0.09^{**}	1.00						
(11)	Innovation expenditure/portfolio (avg 2006–2008, % of sales, log)	−0.00	0.08^{**}	0.11^{***}	-0.33^{***}	0.15^{***}	0.31^{***}	0.06^{*}	0.36^{***}	-0.21^{***}	-0.12^{***}	1.00					
(12)	Innovation expenditure/project (avg 2006–2008, €m, log)	0.24^{***}	0.14^{***}	0.12^{***}	0.31^{***}	-0.06^{*}	0.01	0.07^{**}	0.05^{*}	0.08^{**}	0.14^{***}	0.15^{***}	1.00				
(13)	Innovation projects (2006–2008, # of projects, unadjusted)	0.25^{***}	0.25^{***}	0.27^{***}	0.27^{***}	0.03	−0.00	0.07^{**}	0.15^{***}	0.13^{***}	0.14^{***}	0.07^{**}	−0.02	1.00			
(14)	Resource allocation breadth (2006–2008, # projects, size-normalized, log)	-0.09^{***}	−0.03	−0.00	-0.23^{***}	0.06^{*}	0.04	−0.05	0.02	-0.07^{*}	-0.12^{***}	0.13^{***}	-0.06^{*}	0.36^{***}	1.00		
(15)	Selectiveness1 (2006–2008, projects discontinued, yes/no)	0.23^{***}	0.20^{***}	0.20^{***}	0.26^{***}	0.04	−0.03	0.08^{**}	0.17^{***}	0.12^{***}	0.20^{***}	0.02	0.01	0.14^{***}	−0.02	1.00	
(16)	Selectiveness2 (2006–2008, >20% discontinued, yes/no)	0.16^{***}	0.15^{***}	0.14^{***}	0.17^{***}	0.03	−0.01	0.04	0.12^{***}	0.10^{***}	0.14^{***}	−0.00	0.02	0.04	−0.03	0.86^{***}	1.00
(17)	Innovative intent (2006–2008, less/more radical)	0.03	0.11^{**}	0.09^{***}	-0.07^{*}	0.13^{***}	0.03	−0.03	0.06^{*}	−0.03	−0.04	0.11^{***}	−0.02	0.01	0.05	−0.01	0.00

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

significant. These changes across dependent variables are theoretically plausible as they indicate the greater challenges of generating truly novel product innovations. Age and group membership appear not to affect innovation performance significantly. The models' McFadden R^2 values indicate a level of fit that is comparable to prior CIS work (e.g. Laursen and Salter, 2006).

Breadth

Model II in Table 2 tests for the direct effect of resource allocation breadth. Here, innovation expenditure is entered on a per-project basis to separate its effect from breadth. The results for the control variables are in line with the reference model. The effect of breadth on innovation performance is positive and statistically significant. This effect is consistent across all further models and supports H1. Breadth's performance effect also seems to increase with the novelty of innovation output, though models with different dependent variables cannot readily be compared.

An interesting side observation in Model II is that the effect of innovation expenditure per project becomes less insignificant with greater novelty of products sold. It seems to suggest that the effect of overall innovation expenditure is mainly driven by the breadth of the project portfolio rather than by the magnitude of project investments.

This picture does not change when selectiveness and innovative intent are added to the model (Model III). Coefficients for the control variables, breadth, and expenditure hardly change. Selectiveness has no significant direct influence on any innovation performance variable. Selectiveness does not seem to affect breadth, which allays concerns over potential codetermination. Innovative intent shows no significant relationship with overall innovation performance (NEW), but there is a significance link with performance in more novel product categories (NTF, NTM). The latter observation simply reflects that firms who pursue more novel innovation projects are also more likely to sell products of greater novelty than firms who pursue less novel projects. In practical terms, this underlines that the split-sample analysis of breadth with more/less innovative intent ought to be restricted to models with NEW as dependent variable.

Selectiveness

Table 3 displays the results of the split-sample models used to test for the effect of breadth in subsamples of selective and nonselective firms, using the primary operationalization of selectiveness. The control variables show effects similar to the preceding models. The effect of breadth is positive significant for both, but the confidence level and the magnitude of the breadth effect are greater for selective firms. This offers support for Hypothesis 2.

To test whether the variation in marginal effects across subsamples is statistically significant, we computed the Z-score (Clogg, Petkova, and Haritou, 1995). For all three model specifications (NEW, NTF, NTM), the Z-score of breadth is significant. A log-likelihood test renders the same result. We further examined whether the assumption of running two separate models is correct, using the Chow test methodology (Chow, 1960). Results confirm this assumption for all three categories at the 0.1 percent-level. It suggests that, across the two subsamples, firms vary significantly in their capacity to generate innovation performance. To interpret the economic significance of the marginal effects, a cautious look at the mean variable levels offers some rough indications. An average firm with €100M in revenues, 15 product innovation projects, and €25M in new product sales might expect a two percent increase in new product sales (NEW) if it added an additional project to its portfolio and did not select out projects over time (*ceteris paribus*). If the same firm did select out projects, the expected increase in new product sales would rise to seven percent. The average new product sales boost through an extra project is greater if the portfolio is smaller and less pronounced if the portfolio is bigger, all else stable. It should be noted that marginal effects listed in the tables are indicative for at-mean values and are not constant in nonlinear Tobit models.

Innovative intent

In order to assess the moderating impact of innovative intent, we conducted similar split-sample analyses (see Table 4). The results for NEW, NTF, and NTM all show an insignificant performance effect of breadth for firms with less innovative intent and a significant positive effect for firms with more innovative intent. The

Table 2. Full sample models (H1)

	NEW: Model I	NEW: Model II	NEW: Model III	NTF: Model I	NTF: Model II	NTF: Model III	NTM: Model I	NTM: Model II	NTM: Model III
Firm size	0.913	0.835	0.838	0.840	0.758	0.753	0.944	0.810	0.716
	(0.043)***	(0.043)***	(0.051)***	(0.072)***	(0.073)***	(0.084)***	(0.104)***	(0.105)***	(0.124)***
Resource quality	0.241	0.377	0.288	0.404	0.656	0.800	0.971	1.384	1.435
	(0.312)	(0.314)	(0.364)	(0.522)	(0.525)	(0.606)	(0.766)	(0.771)*	(0.914)
Process innovation	1.092	1.192	1.231	0.710	0.864	0.848	0.486	0.701	0.687
	(0.117)***	(0.117)***	(0.133)***	(0.198)***	(0.198)***	(0.224)***	(0.290)*	(0.290)**	(0.336)**
Continuous R&D	0.387	0.629	0.480	0.828	1.187	1.056	1.823	2.365	2.385
	(0.134)***	(0.128)***	(0.146)***	(0.226)***	(0.216)***	(0.245)***	(0.336)***	(0.325)***	(0.376)***
Firm age	−0.093	−0.111	−0.105	−0.013	−0.040	−0.057	0.148	0.098	0.281
	(0.069)	(0.070)	(0.080)	(0.117)	(0.118)	(0.135)	(0.169)	(0.171)	(0.199)
Part of group	−0.003	0.043	−0.023	−0.266	−0.212	−0.003	−0.453	−0.367	−0.075
	(0.134)	(0.135)	(0.155)	(0.224)	(0.226)	(0.258)	(0.327)	(0.330)	(0.384)
Marketing expenditure	0.082	0.097	0.097	0.200	0.221	0.194	0.320	0.356	0.328
	(0.027)***	(0.028)***	(0.031)***	(0.047)***	(0.047)***	(0.053)***	(0.071)***	(0.072)***	(0.081)***
Innovation expenditure/portfolio	0.270	—	—	0.423	—	—	0.656	—	—
	(0.046)***	—	—	(0.079)***	—	—	(0.120)***	—	—
Innovation expenditure/project	—	0.036	0.039	—	0.001	−0.106	—	0.005	−0.051
	—	(0.021)*	(0.028)	—	(0.035)	(0.049)**	—	(0.049)	(0.070)
Resource allocation breadth	—	0.259	0.238	—	0.488	0.436	—	0.645	0.453
	—	(0.104)**	(0.108)**	—	(0.169)***	(0.174)**	—	(0.231)***	(0.240)*
Selectiveness	—	—	0.159	—	—	0.305	—	—	0.448
	—	—	(0.142)	—	—	(0.236)	—	—	(0.348)
Innovative intent	—	—	0.269	—	—	0.931	—	—	1.141
	—	—	(0.230)	—	—	(0.419)**	—	—	(0.328)***
McFadden R2	0.13	0.12	0.13	0.06	0.05	0.06	0.07	0.06	0.07
No. of observations	1,420	1,420	1,032	1,420	1,420	1,032	1,420	1,420	1,032
No. of left-censored observations	173	173	124	502	502	366	808	808	595
Log likelihood	−2,891.29	−2,903.39	−2,084.61	−2,840.83	−2,850.89	−2,041.99	−2,256.78	−2,268.04	−1,609.75

*p < 0.1; **p < 0.05; ***p < 0.01
Dependent variables: NEW: new product sales; NTF: new-to-firm product sales; NTM: new-to-market product sales. Industry dummies included.

Table 3. Split-sample models: selectiveness (H2)

	NEW: no selectiveness	NEW: selectiveness	NTF: no selectiveness	NTF: selectiveness	NTM: no selectiveness	NTM: selectiveness
Firm size	0.706	1.067	0.632	1.003	0.775	0.980
	(0.057)***	(0.073)***	(0.096)***	(0.124)***	(0.144)***	(0.171)***
Resource quality	0.468	0.171	0.524	0.680	1.242	1.219
	(0.392)	(0.513)	(0.659)	(0.863)	(1.000)	(1.211)
Process innovation	1.488	0.577	0.911	0.748	0.793	0.661
	(0.144)***	(0.200)***	(0.245)***	(0.340)**	(0.370)**	(0.482)
Continuous R&D	0.600	0.635	1.185	1.087	2.340	2.389
	(0.157)***	(0.220)***	(0.265)***	(0.374)***	(0.408)***	(0.546)***
Firm age	−0.069	−0.173	−0.093	0.051	0.149	0.027
	(0.090)	(0.111)	(0.152)	(0.188)	(0.229)	(0.263)
Part of group	0.261	−0.401	−0.002	−0.582	−0.378	−0.336
	(0.174)	(0.216)*	(0.293)	(0.366)	(0.442)	(0.514)
Marketing expenditure	0.071	0.133	0.187	0.239	0.352	0.341
	(0.034)**	(0.046)***	(0.059)***	(0.080)***	(0.092)***	(0.115)***
Innovation expenditure/ project	0.073	−0.017	−0.017	0.005	0.001	0.011
	(0.029)**	(0.030)	(0.051)	(0.049)	(0.074)	(0.067)
Resource allocation breadth	0.236	1.044	0.403	2.181	0.498	3.707
	(0.108)**	(0.422)**	(0.176)**	(0.701)***	(0.243)**	(0.962)***
Z-score (breadth)	5.69**		11.69***		17.91***	
Chow test chi value	57.54***		41.46*		39.76*	
McFadden R2	0.11	0.14	0.04	0.07	0.05	0.07
No. of observations	911	509	911	509	911	509
No. of left-censored observations	124	49	355	147	565	243
Log likelihood	−1,844.09	−1,034.43	−1,756.11	−1,077.55	−1,321.28	−931.97

*p < 0.1; **p < 0.05; ***p < 0.01
Dependent variables: NEW: new product sales; NTF: new-to-firm product sales; NTM: new-to-market product sales; Ind-dum. incl.

breadth effect's insignificance for firms with less innovative intent renders a Z-test comparison unnecessary. Regardless, H3 cannot be confirmed in its stated form. Rather than a diminished performance effect of breadth, firms with less innovative intent witness no significant effect at all; the benefit of broad resource allocation seems reserved to firms with more innovative intent.

The results in Table 4 need to be interpreted with caution, however. Although firms with greater innovative intent tend to have a greater share of relatively more novel projects within their portfolio, it is difficult to ascertain whether the significant effects for breadth are driven by them or by less novel projects. This is potentially most problematic for NEW, which is why comparing effects with the NTF and NTM model is informative, where the proportion of novel projects in firms' portfolios is higher. Unfortunately, the NTF and NTM models have another imperfection: they include a potentially confounding effect through innovative intent's positive correlation with more novel product output. To address this issue, we ran a second, alternative model specification, splitting the breadth variable according to innovative intent. This means that there are two breadth variables: one that equals breadth if firms have less innovative intent and otherwise 0, and one that equals breadth if firms have more innovative intent, otherwise 0. We then add innovative intent as a control, so that its direct effect on NTF and NTM is captured. The results reflect those in Table 4, with breadth being significant and positive only for firms with more innovative intent.

To assess H4, we continued with this specification and separated samples once more by selectiveness (see Table 5). Combining the split-variable approach for innovative intent with a

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Table 4. Split-sample models: innovative intent (H3)

	NEW: less innovative intent	NEW: more innovative intent	NTF: less innovative intent	NTF: more innovative intent	NTM: less innovative intent	NTM: more innovative intent
Firm size	0.799	0.866	0.770	0.827	0.885	0.610
	(0.086)***	(0.060)***	(0.157)***	(0.096)***	(0.233)***	(0.142)***
Resource quality	0.322	0.266	1.308	0.613	4.530	0.702
	(0.627)	(0.424)	(1.133)	(0.680)	(1.766)**	(0.986)
Process innovation	1.588	0.997	1.146	0.733	0.454	0.837
	(0.227)***	(0.159)***	(0.414)***	(0.258)***	(0.630)	(0.391)**
Continuous R&D	0.264	0.741	0.656	1.320	2.341	2.515
	(0.246)	(0.172)***	(0.445)	(0.280)***	(0.692)***	(0.436)***
Firm age	−0.107	−0.090	0.084	−0.191	0.384	0.222
	(0.133)	(0.097)	(0.240)	(0.158)	(0.356)	(0.239)
Part of group	−0.051	0.089	0.023	−0.005	−0.197	0.141
	(0.258)	(0.189)	(0.469)	(0.304)	(0.710)	(0.455)
Marketing expenditure	0.135	0.052	0.151	0.233	0.312	0.335
	(0.047)***	(0.041)	(0.087)*	(0.067)***	(0.137)**	(0.103)***
Innovation expenditure/project	0.062	0.010	−0.142	−0.100	−0.066	−0.068
	(0.041)	(0.037)	(0.079)*	(0.061)	(0.112)	(0.092)
Resource allocation breadth	−0.031	0.235	1.116	0.422	0.822	0.494
	(0.539)	(0.098)**	(0.945)	(0.154)***	(1.462)	(0.217)**
McFadden R2	0.12	0.16	0.04	0.08	0.06	0.08
No. of observations	485	547	485	547	485	547
No. of left-censored observations	73	51	211	155	315	280
Log likelihood	−1,005.88	−1,049.81	−920.67	−1,098.84	−682.12	−914.95

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$
Dependent variables: NEW: new product sales; NTF: new-to-firm product sales; NTM: new-to-market product sales; Ind-dum. incl.

split-sample approach for selectiveness provides an intuitive 2×2 of marginal effects of breadth for less/more innovative and selective/nonselective firms. Breadth is positive significant for firms with more innovative intent, and the effect increases if these firms also engage in selectiveness. A Z-test for breadth with more innovative intent suggests that the differences in marginal effects of the selective and nonselective subsample models are significant. More innovative firms appear to benefit from combining breadth with selectiveness, which supports Hypothesis 4. A side observation is that firms with low innovative intent can increase new-to-firm or new-to-market product sales if they complement breadth with selectiveness, even though this may not be their principal objective. This result adds nuance to the findings for Hypothesis 3.

To assess the extent to which a decision-maker bias to select out false negatives might have existed at those firms with more innovative intent that engaged in selectiveness, we sought an indication of the kind of projects that managers were more likely to discontinue. To do this, we looked at the overall novelty of new product output. In the NEW model of Table 5, selective firms with more innovative intent saw an average of 25 percent of all new product sales come from new-to-market offerings (i.e. from relatively more novel projects that were not selected out). This compares to 21 percent for nonselective firms with more innovative intent. Assuming uniform project returns, these numbers suggest that sample firms with higher innovative intent did not necessarily display a bias toward selecting out more novel projects.

Robustness and sensitivity

Interpreting changes in raw values for the dependent variables in our models provides greater validity than focusing on ratios, but it comes with the disadvantage of having to include size as a control, which then explains a substantial

Table 5. Split-sample/split-variable models: selectiveness and innovative intent (H4)

	NEW: no selectiveness	NEW: selectiveness	NTF: no selectiveness	NTF: selectiveness	NTM: no selectiveness	NTM: selectiveness
Firm size	0.712	1.112	0.633	1.084	0.612	1.020
	(0.066)***	(0.090)***	(0.113)***	(0.146)***	(0.171)***	(0.206)***
Resource quality	0.522	−0.148	0.419	1.147	1.122	1.272
	(0.441)	(0.627)	(0.755)	(1.007)	(1.160)	(1.458)
Process innovation	1.402	0.848	0.928	0.611	0.859	0.430
	(0.161)***	(0.240)***	(0.278)***	(0.392)	(0.424)**	(0.568)
Continuous R&D	0.628	0.127	1.279	0.600	2.503	2.343
	(0.174)***	(0.260)	(0.299)***	(0.424)	(0.468)***	(0.639)***
Firm age	−0.043	−0.216	0.013	−0.173	0.447	−0.001
	(0.101)	(0.130)*	(0.175)	(0.211)	(0.265)*	(0.298)
Part of group	0.185	−0.376	0.049	−0.185	−0.233	0.254
	(0.194)	(0.258)	(0.331)	(0.420)	(0.506)	(0.601)
Marketing expenditure	0.081	0.109	0.169	0.202	0.266	0.453
	(0.038)**	(0.053)**	(0.065)**	(0.088)**	(0.103)***	(0.132)***
Innovation expenditure/ project	0.062	−0.084	−0.081	−0.189	−0.025	−0.172
	(0.031)**	(0.066)	(0.055)	(0.108)*	(0.079)	(0.156)
Innovative intent	0.013	0.546	0.727	1.334	0.671	1.640
	(0.170)	(0.447)	(0.292)**	(0.402)***	(0.252)**	(0.577)***
Breadth: less innovative intent	−0.341	1.358	0.614	1.077	−1.424	2.598
	(0.513)	(0.966)	(0.850)	(0.561)*	(1.664)	(1.200)**
Breadth: more innovative intent	0.252	0.964	0.409	1.805	0.431	3.287
	(0.112)**	(0.493)*	(0.184)**	(0.785)**	(0.256)*	(1.093)***
Z-score (breadth: more innovative)	3.39*		6.37**		12.28***	
McFadden R2	0.11	0.15	0.05	0.08	0.06	0.09
No. of observations	676	356	676	356	676	356
No. of left-censored observations	89	35	265	101	421	174
Log likelihood	−1,347.32	−715.61	−1,284.94	−739.48	−965.73	−626.37

*p < 0.1; **p < 0.05; ***p < 0.01
Dependent Variables: NEW: new product sales; NTF: new-to-firm product sales; NTM: new-to-market product sales; Ind-dum. incl.

portion of the overall variance. To check for multicollinearity, we inspected the variance inflation factors of uncensored models. For the main independent variables, variance inflation factors do not exceed 1.7, which alleviates concerns of multicollinearity. To further check for model distortions through size, we reviewed semipartial correlations. For the input variables reported as significant in the models above, semipartial correlation values range from 0.05 to 0.22, while those of size range between 0.19 and 0.34. These figures confirm that the independent variables explain nontrivial portions of the overall model variance (Budescu, 1993).

We then ran our model designs again, this time with ratios as dependent variables. Dividing new product sales by overall sales reduces the influence of size as a control variable. Results of the ratio models were consistent with those reported above, suggesting that hypothesized effects of breadth are independent of size (Kleinknecht *et al.*, 2002). The effects are strong enough to show, even though ratios as dependent variables are influenced by more causal factors than raw values.

In addition, we ran probit models with an alternative operationalization of innovation success: whether or not firms were able to launch a new product (e.g. Leiponen and Helfat, 2010). When using such a dummy variable for NEW, NTF, and NTM, results are largely consistent with the main Model III in Table 2. Though useful as a robustness check, models with dummy dependent variables cannot be interpreted in the exact same manner. Instead of estimating continuous innovation performance differentials, the models predict the likelihood of product launch. Since a large majority—86 percent of all sample firms—launched some kind of new product, the effect of breadth is less pronounced for NEW. A single project can often suffice for a product launch, given the many nonselective firms.

We also inspected to what extent path dependency might bias results. One way to do this is to include lagged dependent variables (Burton, Lauridsen, and Obel, 2002; Leiponen and Helfat, 2010). This changes the interpretation from nominal performance to change in performance, and it introduces high levels of correlation between the lagged variable and the error term, potentially distorting coefficient estimates (Honoré, 1993; Honoré and Kyriazidou, 2000). Nonetheless, with the results remaining stable, inclusion of a lagged dependent variable can provide further confidence in the robustness of our analysis. Unfortunately, the CIS survey's year-to-year respondent churn means that we have information about past success for only a subset of sample firms. Nonetheless, the results of a lagged dependent variable model on the basis of these fewer observations still compare well with Model III in Table 2.

We extended this line of analysis by probing for reverse causality. There is no obvious theoretical reason to suspect higher-performing firms of allocating resources more broadly or selectively or to have more innovative intent. Nevertheless, we ran reverse regression models for a subset of firms for which preobservation period performance data are available. We find no statistical significance for the effect of prior innovation performance on subsequent portfolio breadth, selectiveness, or innovative intent.

Another potential concern is about size and its influence on covariates. We sought to corroborate our results on selectiveness with models that use the alternative operationalization of selectiveness, where portfolio size is less of a potential issue. Results are consistent with the primary operationalization of selectiveness. Breadth is significant throughout, and the differences in marginal effects between selective and nonselective firms are also significant. The Chow test proves significant in the NEW models only, most likely due to the greater imbalance in subsample size that comes with the alternative operationalization of selectiveness. Overall, these second sets of results further support H2.

We then also analyzed the results of subsamples separated by size and find no statistically significant difference in the effect of breadth. In addition, we checked if the observed effects are confined to smaller portfolios where variation in the number of projects makes a disproportionate difference. When restricting the sample to firms with portfolios of more than five innovation projects and using a specification that follows Model III in Table 2, results hold throughout.

Finally, we inspected whether our results are driven by specific industries. All our models already control for principal industry membership. Beyond that, we reran models with an augmented operationalization of breadth; namely, one that normalizes the measure by the industry's average breadth. Results remained consistent. We then reviewed the results from a split-sample analysis, where one group contained firms in technology-intensive manufacturing industries (Chemicals/Pharmaceuticals, Electronics/Electrical, Machinery/Equipment, and Vehicles) and all remaining sectors. Coefficient differences were insignificant.

DISCUSSION

Increasing the quality and quantity of innovation resources is not a sufficient answer to the challenge posed by commercial uncertainty inherent in most of today's innovation endeavors. A firm's performance in innovation also depends on how it allocates the available resources. By showing this empirically, this research deepens our understanding of the determinants of product innovation performance. The model results indicate that, when firms' overall innovation expenditure is separated into resource allocation breadth and project resourcing, breadth significantly impacts performance, independent of resourcing. This effect is stronger for firms that allocate resources selectively and for those with more ambitious innovative intent. As discussed below, these findings have implications for theory of organizational resource allocation and innovation portfolio management.

Resource allocation breadth and innovation performance

There is evidence of a positive relationship between innovation performance and the allocation

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of resources across a broader range of innovation projects. We attribute this effect to a mechanism of spreading bets on innovation. Because managers have to commit resources before the performance implications of these commitments are fully understood, greater resource allocation breadth improves the odds of success. Portfolio managers who hedge the vagaries of investing in ideas with unproven potential stand to benefit from greater overall market success.

This extends the literature on the strategic management of innovation by delineating resource allocation breadth as a predictor of innovation performance. The underlying mechanism may apply even more widely. Breadth can spread other kinds of commercial bets too; and it increases the likelihood that at least some firm investments will turn out to be successful, a mechanism that could also explain prior findings in adjacent fields; namely, in the areas of product variety (Bordley, 2003; Lancaster, 1990; Sorenson, 2000) and search breadth (Laursen and Salter, 2006; Leiponen and Helfat, 2010). It confirms the assumptions behind computational models of project funding (e.g. Ding and Eliashberg, 2002; Roberts and Weitzman, 1981). And it opens up areas for future research into the reasons for why some managers might choose/not choose to allocate resources as broadly as suggested.

In our models, breadth also proves a more significant predictor of innovation performance than the magnitude of resource investment, a key variable in economic models (Crépon *et al.*, 1998; Mairesse and Mohnen, 2002). When separating overall innovation resourcing into the breadth and intensity of resource allocation, the results indicate that spreading resources across a greater number of projects is more important than increasing project resourcing. An innovation manager who contemplates resource allocation might thus be advised to err on the side of spreading resources thinly, rather than concentrating substantial resources on an insufficient number of new product candidates. Our finding suggests that innovation is about getting the right new products at least as much as it is about getting new products right.

Breadth and selectiveness

We also show that the positive relationship between breadth and performance is not uniform across firms. We find significant differences in the extent to which selective and nonselective firms benefit from increased breadth. The effect of breadth on all three categories of new product sales is greater with selectiveness.

We theorize that pruning the project portfolio mitigates the disadvantages of greater resource allocation breadth, while maintaining its advantages. Selectiveness makes pursuing a broad resource allocation strategy more economical, due to two dynamics: resource needs are lower for early-stage development projects than for later-stage projects, and commercial viability is less clear for early-stage projects than for later-stage projects (c.f. Hauser *et al.*, 2006; Loch and Kavadias, 2007). It thus makes sense to allocate resources broadly in the early stages of the development process, while being more selective in later stages. It allows for greater exploration when projects' commercial viability is still unclear and for more focus when commercial viability is better established. Consistent with these predictions, we find that high performers in innovation combine resource allocation breadth with selectiveness.

The difference in effect between selective and nonselective firms also suggests that breadth may carry disadvantages. Research indicates that these could include lack of strategic focus and diseconomies of scale (Ghemawat and Costa, 1993; Klingebiel, 2010). Another downside of breadth is that project managers' motivation may decrease with increased competition for innovation resources (Garcia and Tor, 2009). Although we are unable to trace specifically the ways in which breadth could be detrimental, our results indicate that any potential disadvantages of breadth are better offset when firms allocate selectively in the later stages of product development.

Our findings resonate with broader conceptualizations of strategic responsiveness, according to which efficient adaptation mechanisms influence performance, such as low-cost probes (Brown and Eisenhardt, 1997) and learning through failure (McGrath, 1999; Sitkin, 1992). A combination of breadth with selectiveness appears to provide firms with such a mechanism when it comes to managing innovation portfolios. It offers an explanation for performance differentials that are rooted in firms' strategies for allocating resources to innovation projects.

This paper also supports initial conceptualizations (Klein and Meckling, 1958; Marschak

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and Nelson, 1962; Nelson, 1961) and qualitative research on funnel-style innovation management (Cooper *et al.*, 2001; Wheelwright and Clark, 1992). With breadth and selectiveness being key features of such funnels, our paper would suggest that firms employing funnels outperform their peers. At the same time, our findings run counter to a recent study reporting disadvantages to stage-gate funnels (Sethi and Iqbal, 2008).

Innovative intent

A firm's strategy of pursuing more ambitious projects within the product innovation portfolio has the predicted relationship with performance: our models show no significant effect on overall sales from new products and a significant positive effect on sales from new-to-firm and new-to-market products. More interesting for our study, however, is innovative intent's moderating influence on the relationship between breadth, selectiveness, and performance.

The descriptive statistics show that, on average, firms with a more ambitious portfolio do not allocate resources more broadly. Those that do, however, reap performance rewards. The base models already indicate a significant positive effect of breadth, which rises with the novelty of product output for which sales are measured. Since we cannot formally test coefficient differences across models with different dependent variables, we extend this line of analysis through the separate innovative intent variable. The results confirm that firms with more innovative intent see greater benefit from breadth. In fact, (nonselective) firms with less innovative intent do not see any at all.

Our contribution to the literature here is that firms with greater innovative ambition are more successful in achieving their objectives if they maintain a broader project portfolio. Our interpretation is that greater novelty means managers have less information about a new product's commercial viability when making initial resource allocation decisions. Therefore, firms have greater success in generating novel products when they allocate resources broadly. Breadth improves their chances of satisfying future customer preferences that are not fully known in the early stages of new product development.

Firms with less ambitious innovation intent can rely more on established knowledge than can firms with more ambitious portfolios. The former are less likely than the latter to misjudge the commercial prospects of an innovation project in the early stages of development. As a result, firms operating portfolios containing more incremental projects have less to gain from breadth than firms with portfolios consisting of more novel projects. Incrementally oriented firms can make more informed project-resourcing decisions at the beginning of the new product development process. They are thus less likely to see substantially improved product hit rates that could offset the additional costs that come with breadth, such as increased organizational complexity, lack of strategic focus, and less motivated project managers (Boudreau *et al.*, 2011; Klingebiel, 2010). For firms with more innovative intent, however, the lack of information during initial resource allocation means that spreading bets can substantially enhance product hit rates and eventual innovation performance.

Furthermore, our analysis of selectiveness shows that firms with more innovative intent that allocate both broadly and selectively achieve the highest innovation performance. We think this is also due to the higher probability of failure for more novel projects. Where this is the case, it is important to select out projects for which new information suggests deteriorating commercial prospects, so that limited resources can be reassigned to more promising project candidates. If resources are not reassigned, the penalty for firms with more innovative intent is harsher than for their less innovative peers.

A possible decision-maker bias toward errors of omission based on conservative and inert selection criteria (Garud *et al.*, 1997; Van de Ven, 1999) seems not to play a dominant role for firms with more innovative intent. From our data, we cannot identify the exact choice set of each portfolio manager. But if the problem of selecting out false negatives were overwhelmingly present, we would expect selective firms to see a lower share of new-to-market product sales, relative to their total innovation output. The data contradicts this, providing support for earlier work, which could not confirm a relationship between a project's degree of novelty and its propensity to be selected out (e.g. Danneels and Kleinschmidt, 2001). If a decision-making bias were present, we would also expect to find comparatively lower performance for selective firms that are more

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ambitiously innovative. Finding the opposite, we suggest that the high failure rate of more ambitious innovation endeavors renders some later-stage selection imperative, despite any remaining risk of errors of omission.

Uncertainty may surround novel projects until their market launch. Nonetheless, managers are likely to be able to glean at least some additional information during product development. Updates on technological developments, consumer trends, or competitors' actions, for example, can change managers' perception of projects' commercial viability. Our results suggest that translating altered perceptions into transfers of at least some resources from disappointing to more promising projects ought to trump fear of selecting out the wrong project. For firms with more innovative intent, the initial likelihood of any particular novel idea becoming a successful new-to-market innovation may be so low that selectiveness is a necessary resource safeguard to complement breadth. Here, weeding out projects over time improves innovation performance.

In addition to the literature on the strategic management of innovation, our paper complements that on the management of new product development portfolios and stage-gate processes. The latter traditionally focuses on the composition of a firm's innovation portfolio at different points in time (see Cooper, 2008; Loch and Kavadias, 2007). By delineating the varying effects of innovation project portfolio breadth under different conditions, we link heterogeneity in resource allocation strategy with performance differentials. The suggestion is that managers of new product development portfolios generally benefit from allocating resources more broadly, especially if this approach is accompanied by selectiveness and more innovative intent.

Limitations and future research

There is ample space for future work on firm-level heterogeneity unexplored in this paper. One interesting source of difference is the quality of ideas that are fed into the innovation process, something for which we cannot currently control, other than through consideration of the education level of firm employees. Further sources of heterogeneity that might be fruitfully examined include industry-level differences in innovation routines, the nature of innovation projects, or returns to innovation efforts. At present, these are accounted for only through a series of industry dummies, which also do not capture potential membership of multiple industries. Future research may be able to measure some of these differences more directly. Conversely, single-industry contexts may offer the opportunity to study in more detail the causal chain between portfolio resource allocation breadth and performance. Such studies may be able to identify various sources of innovation uncertainty and trace the reasoning for project discontinuations, both of which could moderate the relationships we propose.

One could also investigate in finer detail the relationship between the extent of selectiveness and the potential impact of common decision-making biases in selecting out particular types of projects. The levels of selectiveness used for this paper may be below a tipping point beyond which decision bias against more novel projects, for example, might begin to inhibit firms' innovation performance. In this regard, the disruptiveness of innovation may be another important dimension of inquiry. Our work measures short-term performance only, but disruptive innovations may require time to take off. Research with a longer-term view could potentially account more accurately for the performance effect of breadth and selectiveness in industries where disruption occurs. Finally, it is worth noting that our measure of innovative intent is an aggregate portfolio-level construct. We can neither isolate individual projects of disruptive or radical nature nor specify the exact composition of firms' project portfolios. Future work might usefully seek to scrutinize particular outlier innovations in more detail and their effect on the relationship between resource allocation strategy and performance of the overall portfolio.

CONCLUSION

Innovation portfolio management provides an exemplary setting in which competitive pressure requires resource allocation decisions to be made before outcomes are fully understood. As a consequence, innovation efforts are prone to failure, regardless of how heavily resourced they each might be. This paper investigates how different strategies for the allocation of resources to product innovation projects allows firms to cope with this

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challenge. We find that breadth in resource allocation increases innovation performance, more so than does resource allocation intensity. The effect is particularly strong for sales of more novel products. We also show that the performance effect of breadth varies in different contexts. Firms can expect greater new product sales through breadth if they allocate resources selectively and if their portfolio is more ambitiously innovative.

We contribute by explaining innovation performance differentials with firms' choices of resource allocation strategy. We theorize that breadth can increase the chances of success and that selectiveness can contain some of the disadvantages that come with breadth. A firm that follows a dual policy of resource allocation breadth and selectiveness is able to respond to new information more effectively, a feat that is particularly important for portfolios with more innovative intent.

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