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ADRESSING REPLICATION AND MODEL UNCERTAINTY: A BAYESIAN AVERAGING APPROACH APPLIED TO INNOVATION SURVEY DATA

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Abstract

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ABSTRACT: Many fields of strategic management are subject to an important degree of model uncertainty. This is because the true model, and therefore the selection of appropriate explanatory variables, is essentially unknown. Drawing on the literature on the determinants of innovation, and by analyzing innovation survey data for France, Germany and the UK, we conduct a 'large-scale' replication using the Bayesian averaging approach of classical estimators. Our method tests a wide range of determinants of innovation suggested in the prior literature, and establishes a robust set of findings on the variables which shape the introduction of new to the firm and new to the world innovations. We provide some implications for innovation research, and explore the potential application of our approach to other domains of research in strategic management.

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INTRODUCTION

Hubbard et al. (1998: 251) states that: 'The goal of science is empirical generalization, or knowledge development leading to some degree of understanding.' However, in many scientific fields, the integrity of the pertinent empirical literatures has been questioned based on what Rosenthal (1979) dubbed the 'file drawer problem,' which implies that journals may be dominated by papers reporting results with Type I errors (erroneous rejections of the null hypothesis), while null outcomes are filed away by researchers. In other words, when researchers 'search for asterisks' (Bettis, 2012), the published Type I error rates will be well in excess say of the prescribed, conventional 5 percent level of significance. Goldfarb and King (2016) report that between 24 and 40 percent of the findings published in the top five strategic management research journals are likely the result of chance rather than a reflection of true relationships.

According to Bettis (2012: 111) the strategic management field has certain institutional features which promote the file drawer problem, including (a) a bias against publication of replication studies, (b) non-reporting of so-called 'non-results,' and (c) the conviction held by many scholars, reviewers, and editors that all journal articles should both develop and test theory simultaneously which features introduce serious agency problems since the same authors are in charge of simultaneously developing and testing a theory. As indicated by Bettis and underscored by Hubbard et al. (1998), replication studies can help to reduce this problem by establishing a set of robust empirical results. In addition, even if researchers do not (to use Bettis's terminology) 'search for asterisks', statistical tests by nature produce Type I errors. The result is that, generally and in the field of strategic management in particular, we know too little about which results are empirically generalizable, and hence whether they potentially add to our understanding. It should be noted that meta-analysis is of little help in this context; since it usually is based on the body of published results, it will reproduce the publication bias problem in the underlying studies (Borenstein, Hedges, Higgins, and Rothstein, 2009).

The lack of robust empirical results in strategic management research may be due in part to their being 'many scholars in strategic management examining independent (and dependent) hypotheses in different subsamples of major databases (e.g., patents and Compustat), blissfully ignorant of each other' (Bettis, 2012: 110). However, in principle when researchers work on similar datasets, and use similar or identical dependent variables, the robust (and less robust) results can be extracted, while controlling for a host of other factors. Currently there are many standard datasets available that provide information on firm-level economic variables (e.g. Compustat), strategic alliances (Schilling, 2009), and patents (Hall, Jaffe, and Trajtenberg, 2001), and data on innovation processes and outcomes based on the various national Community Innovation Surveys (CIS) all of which are collected according to a standardized procedure (Smith, 2005). The existence of such general datasets allow conduction of large scale replication studies by which we mean studies where a large number of different independent variables potentially can be included in a single empirical model using the same dependent variable.

However, in these large-scale replications as in most empirical applications, the true model, and therefore the appropriate selection of explanatory variables, is essentially unknown which leads to a phenomenon described as 'model uncertainty' (Chatfield, 1995; Hoeting et al., 1999; George and Clyde, 2004). Disregarding model uncertainty results in too small standard errors and over confidence in the statistical findings (Raftery, 1995; Hoeting et al., 1999). Additionally, it is model uncertainty that fundamentally facilitates the search for asterisks. Since the true model is unknown, there is a temptation for the researcher to argue for a model specification that results in variables significances which that suit the researcher's line of reasoning. This can lead to a plethora of models each different from the other which all try to explain the same phenomenon.

To address some of these problems, in this paper we suggest introducing a Bayesian Averaging of Classical Estimates (BACE) approach to tackle some of the problems related to uncertainty about the model structure in the context of large-scale replication studies, and to produce a set of empirically robust results. We draw on work on the strategic management of innovation which uses CIS data for its analyses (e.g., Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2010; Garriga, von Krogh, and Spaeth, 2013) to demonstrate the usefulness of this approach for strategic management research. Beyond a general contribution to the strategic management literature, we contribute in particular by providing a set of robust findings on the determinants of firm-level innovation performance. Our analysis is based on CIS data covering 7,841 firms in three major European countries (France, Germany and the United Kingdom). The analysis allows us to examine the robustness of a range of models employed in previous research.

MODEL UNCERTAINTY AND MODEL AVERAGING

As noted above, in the context of the firm-level determinants of innovation as in most empirical applications, the true model is essentially unknown leading to model uncertainty (Chatfield, 1995) in the form of variable selection uncertainty (Hoeting et al., 1999; George and Clyde, 2004). Thus, at the outset it is unclear which predictors should be included in the regression model. Certainly, different sets of predictors and hence different models can lead to dramatically different conclusions. Also, neglecting model uncertainty and not addressing the dependence of the results on the chosen model leads to overconfident inferences based on statistical estimates (Raftery, 1995; Hoeting et al., 1999).

Model averaging techniques address model uncertainty and recognize that in addition to the model parameters, the structure of the model must also be estimated. Model averaging techniques achieve this without involving the common searching for asterisks problem, or the search for and selection of a single model with no description of the process leading to its selection (Chatfield, 1995; Brock et al., 2007). In sum, model averaging proposes a solution to model uncertainty based on several plausible models, by averaging over those models and drawing inferences based on their weighted averages. In other words, model averaging uses several models rather than a single model to make inferences (Cohen-Cole et al., 2012).

There are both non-Bayesian and Bayesian approaches to model averaging. Hansen (2007) and Hjort and Claeskens (2003) discusses several non-Bayesian approaches while Bayesian model averaging has been applied in diverse areas of economic research such as macroeconomic growth models (Durlauf, 2001; Crespo Cuaresma et al., 2010; Magnus et al., 2010), forecasting (Liu and Maheu, 2009; Wright, 2009), and agricultural economics (Tiffin and Balcombe, 2011). Applications of averaging approaches in management research are scarce, and there are very few examples in corporate finance (Avramov, 2002; Liu and Maheu, 2009; Pesaran et al., 2009) or entrepreneurship (Arin et al., 2015). To the best of our knowledge, model averaging has not been applied to micro data in the context of strategic management research, and model uncertainty has received insufficient attention.

THE INNOVATION PERFORMANCE LITERATURE

The strand of work on the determinants of innovation is one of the most extensive in the strategic management literature. Innovation is often seen as critical for firms to gain and sustain competitive advantage (Teece, 2007) and almost all classifications of strategy focus on the types and nature (or lack) of managers' innovative efforts (Miles and Snow, 1978; Porter, 1980). Studies of dynamic capabilities invariably emphasize the abilities of organizations to develop, sense, and seize opportunities for creating new products, processes, business models, and services (Helfat and Winter, 2011). First-mover (dis)advantage research is predicated on the value that firms can gain from innovating (Liebermann and Montgomery, 1998). Strategic alliances are most considered vehicles to enable innovation (e.g., Powell et al., 1996; Schilling and Phelps, 2007; Schilling, 2009).

In innovation studies, the key variables of traditional interest are firm size and research and development (R&D). Tests of the so-called Schumpeterian Mark II hypothesis which suggests that large firms are more innovative than small firms, have generated a rich stream of generally inconclusive and even contradictory evidence (Cohen, 1995). Over time, the focus of attention has shifted to firm age based on the realization that firm size frequently is related to firm age (Acs and Audretsch, 1988). However, research on the (dis)advantages of young and old firms in different industries is inconclusive, although it suggests some advantages for young firms in new industries, and mature firms in older industries (Sørensen and Stuart, 2000). It has for long been assumed that R&D investment helps firms to innovate, and that the benefits of R&D reside not only in the direct effects of new products, processes, and services but also in the building of firm absorptive capacity (Cohen and Levinthal, 1990). Yet, R&D investments, to a certain degree, may be determined endogenously by the intent to innovate, or may fail to generate significant value for the organization (Hall et al., 2010).

In recent years, interest in the benefits derived from external collaboration or search for innovative performance, has surged. Early work looked at the effect of formal external, collaboration on innovation performance (Powell et al., 1996; Ahuja, 2000) but shifted later to the impact of internal and external search (Katila and Ahuja, 2002; Laursen and Salter, 2006). Several scholars broadened the range of potential variables of interest to include appropriability strategy (e.g., Cohen, Nelson, and Walsh, 2000; Cassiman and Veugelers, 2002; Laursen and Salter, 2014, Ballot et al., 2015), managerial practices (e.g., Foss, Laursen, and Pedersen, 2011), internationalization (e.g., Basile, 2001; Cassiman and Golovko, 2011), mergers and acquisitions (e.g., Paruchuri et al., 2006; Puranam et al., 2006), among many others.

One of the challenges for innovation studies is the lack of data on innovation outputs across the economic system. In part, this reflects the lack of agreement on the definition of and operationalization of the concept of innovation. It is acknowledged that there are many different types of innovation (product, process, business model, service, modular, architectural, etc. and incremental versus radical for instance). Over the past 20 years due to the availability of NBER and other online resources (Hall et al., 2001), much research has focused on patents as the primary measure of innovation, leading to a spate of studies of patent-intensive industries, such as semiconductors, robotics, biotechnology, and pharmaceuticals.

In addition, innovation survey data have become a major resource for scholars seeking to understand the determinants of innovation in strategic management. The primary orientation of early work in this research stream was the effects of collaboration and external knowledge on innovation performance. Two particularly influential papers in this literature strand are Laursen and Salter (2006) and Cassiman and Veugelers (2006). Laursen and Salter (2006) use data from an innovation survey of United Kingdom manufacturing firms to suggest that firms' breadth and depth of external search are curvilinearly (inverted U-shape) related to their innovation performance. Cassiman and Veugelers (2006) focus on complementarities in the make or buy decision with respect to innovation, using data for Belgium. They show that there are strong complementarities between using in-house and external knowledge with respect to product innovation. These two papers — and others published before and after them — have spawned a stream of work on the costs and benefits of external search and collaboration for innovation performance, focusing on a range of firm-level contingencies which might moderate or mediate this relationship (Tether and Tajar, 2008; Leiponen and Helfat, 2010; Garriga et al., 2013; Love et al., 2014). Research shows that absorptive capacity may mediate the effect of external search and collaboration on performance (Escribano et al., 2009), the breadth of external search and its objectives have a mutual effect on innovative performance (Leiponen and Helfat, 2010), the obstacles to innovation can mediate the effect of external search on innovative outcomes (Garriga et al., 2013), and prior search and collaboration can shape future search and innovative outcomes (Love et al., 2014). More recently, Cassiman and Valentini (2015) suggest that the complementary benefits of buying and selling knowledge from outside the firm are very small due to the associated external engagement and internal coordination costs.

In addition to research on collaboration and search, several studies use data from innovation surveys to investigate issues such as the effects of innovation on survival (Cefis and Marsili, 2006), mergers and acquisitions (Cefis and Marsili, 2012), exporting (Cassiman and Golovko, 2011), rates of firm growth (Belderbos et al. , 2004), credit rating (Czarnitzki and Kraft, 2004), and profits (Leiponen, 2005b). These studies typically draw on innovation survey data combined with other information from national statistics agencies. The availability of innovation survey data has enabled research within several streams of the strategic management literature, and contributions that have deepened and extended our understanding of the determinants of innovation. These data are providing a broader perspective on the managerial behaviors and choices that shape innovation outcomes and the drivers of innovation in sectors where traditional measures of innovation such as patents and/or R&D, are less available.

However, research that relies on innovation surveys presents several challenges which have significant parallels with the wider problems related to strategic management research. First, although CIS-type innovation surveys are informed by prior theoretical and empirical research on the determinants of innovation, they are not underpinned by a single coherent theoretical framework. Their design and implementation are shaped by a set of guidelines, codified in the OECD (2005) Oslo manual but there is a lack of clarity on a theoretically appropriate model specification, leaving considerable leeway for researchers to define and create their own models. Second, this problem is compounded by the broad range of variables in a typical innovation survey which are considered inputs to the innovation process such as R&D, collaboration, sources of information, and appropriability instruments, as well as product, process, organizational, and marketing innovation outcomes. This allows researchers to select or exclude model variables. Since some survey variables are likely to be correlated, the exclusion of some of these appears justifiable. However, the cumulative effect of this diversity and choice is confusion about which variables should be included in an analysis. Third, the widespread availability of innovation survey data is resulting in many researchers working independently of one another, often using specific national samples. This could increase the risk of non-cumulative and contradictory research findings.

It can be seen that survey based innovation research is likely to involve many of the problems associated with strategic management research in general: Type I errors resulting (or not) from the hunt for stars, model uncertainty, partial and incomplete samples, and limited replication. However, innovation surveys have the advantage that the data are collected systematically and consistently over time, and in different contexts. Thus, innovation survey data and the research based on it are an ideal context to explore the potential for resolving some of the more general problems referred to above through a large-scale replication study which takes account of model uncertainty.

DATA AND MEASURES

In our analysis, we investigate model uncertainty in a range of studies that use CIS (or similar) data to explain innovation performance (e.g., Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2010; Garriga et al., 2013). As already indicated, our analytical variables are developed by focusing on the most influential papers in the relevant literature such as Laursen and Salter (2006) and Cassiman and Veugelers (2006). We assume that this studies helped to influence the modelling strategies adopted in subsequent work. We also include additional measures taken from Leiponen (2005a), Schmiedeberg (2008), Roper et al. (2008), Grimpe and Kaiser (2010), Love et al. (2014), and Ballot et al. (2015). The list of the variables examined in these studies is long, and the contexts vary; to render our analysis tractable, we include only the key variables from these studies and the core control variables in the innovation literature more broadly. Table Z1 lists the variables and the related innovation studies.

[Table Z1, just about here]

The empirical analysis uses firm-level innovation survey data from the 4th CIS for France, Germany and the United Kingdom (Smith, 2005; Mairesse and Mohnen, 2010). The innovation outcome variables refer to 2004, and the independent variables refer to 2004 or the period 2002-2004. We restrict our sample to the 7,841 manufacturing firms in the data set. The sectoral break down is displayed in Table Z2.

[Table Z2, just about here]

Dependent variables

The construction of the variables and their relation to relevant literature are presented in Table Z1. We measure innovation performance by the share of sales based on innovation, defined as the share of sales of new products in 2004 over total sales in that year. We use two variants of the innovation performance measure depending on the novelty of the innovation: based on logarithmic transformation, INNOWORLD is the share of sales of products new to the world, while INNOFIRM captures the share of sales of products new to the firm.

Potential predictors

All independent variables refer to the period 2002-2004 unless stated otherwise. For details of how the individual variables are calculated and how they are used in the literature, see Table Z1.

Search: Firms' innovation search activities are captured by BREADTH and DEPTH. We integrate particular information flows from users or from competitors through the variables USER and COMPINFO. The value of information from the science system is captured by BASICINFO and from publicly available sources by PUBINFO.

Collaboration: Patterns of innovation collaboration are captured by a collaboration dummy variable COLLAB, and by a variable indicating collaboration depth COLDEPTH.

R&D: R&D activities are reflected by total R&D expenditure as a share of sales in year 2004.

Markets: The firm's main market is indicated by INTMKT FOR international and NATMKT FOR national. The reference category is regional market.

Appropriability strategy: IPF and IPNF are formal and informal appropriability strategy, respectively.

Obstacles to innovation: We include financial obstacles to innovation (OBSFIN), knowledge obstacles to innovation (OBSKNOW), and market obstacles to innovation (OBSMKT).

Make or buy: We include three dummy variables for innovation related make or buy decisions — MAKEONLY, BUYONLY, MAKEBUY with no make or buy decision as the reference category.

Firm demographics: Firm size is measured as the log of the number of employees (LOGEMP) in year 2004. STARTUP indicates firm foundation between 2002 and 2004. We also include 11 sector dummies for main sectors of activity. French, German and United Kingdom firms are differentiated by three country dummies.

Table Z3 provides summary statistics of the variables. Appendix Table A1 presents the correlations among the potential predictors.

[Table Z3, just about here]

MODEL SPECIFICATIONS AND RESULTS

Tobit regressions

In the first step, we employ Tobit regressions to estimate the effects of our predictors on innovation performance since the dependent variables are bounded between 0 and 4.62 (Leiponen, 2005a; Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Schmiedeberg, 2008; Leiponen and Helfat, 2010). Based on the variables defined above and including some second order terms and some interactions, we build the main models in Laursen and Salter (2006), Cassiman and Veugelers (2006), and Schmiedeberg (2008). In Table X1 and Table X2 models (1) and (2) reproduce Laursen and Salter's (2006) models I, II, IV. Model (3) is equivalent to model (7) in Cassiman and Veugelers (2006), and model (4) is inspired by model (2) in Schmiedeberg (2008). Models (5) and (6) include all the variables included in models (1) to (4). Our findings are generally comparable to the those reported in Laursen and Salter (2006), Cassiman and Veugelers (2006), and Schmiedeberg (2008). However, note that in the analyses reported in Tables X1 and X2 the significance of the coefficients depends on the model's overall structure, that is, on the variables included in the regressions. In particular, six variables change from being significant to being insignificant depending on which other variables are included in the analysis of share of sales of innovations new to the world (BASICINFO, COLDEPTH2, RD, NATMKT, LOGEMP, STARTUP×RD). In the case of the models explaining sales of innovations new to the firm, six variables also change from being significant to being insignificant depending on which other variables are included in the analysis. These variables include the variables DEPTH, USER, PUBINFO, NATMKT, OBSFIN, LOGEMP.

[Table X1, just about here]

[Table X2, just about here]

Accounting for model uncertainty

The variables in the regression models gain or lose significance depending on which other variables are included in those models. This finding highlights that the coefficient estimates in each of the models in Tables X1 and X2 must be interpreted conditional on the assumption that in each case, the estimated model is the 'true' model. The true model is the model which is characterized by the predictors appropriate to explain innovation performance.

In our analysis we account for model uncertainty and modify the BACE approach in Sala-i-Martin et al. (2004) and Jones and Schneider (2006), to accommodate the Tobit regressions required for the dependent innovation performance variable. Put simply, the BACE averages over the entire model space $\{M_1, \dots M_k, \dots M_\kappa\}$ consisting of κ models, where each model consists of a different set of predictors. After regressing the κ models the BACE approach computes the weighted average of the estimation results with weights that have a clear Bayesian foundation because model averaging can be considered a special case of Bayes's rule (Sala-i-Martin et al., 2004). Our averaging weights is the posterior model probability $P(M_k|D)$:

$$P(M_k|D) = \frac{P(D|M_k) \cdot P(M_k)}{\sum_{j=1}^{\kappa} \quad P(D|M_j) \cdot P(M_j)}$$

where $P(D|M_k)$ essentially measures how well M_k explains the data, and $P(M_k)$ is the prior model probability which captures our prior belief in model M_k. The averaging then gives rise to the posterior mean of the parameter estimate β:

$$E(\beta|D) = \sum_{k=1}^{\kappa} P(M_k|D) \cdot \beta^k$$

where β^k is the estimated coefficient conditional on model M_k. Using Bayes factors $B_{k0} = P(D|M_k)/P(D|M_0)$ and α_k as the prior model odds, the posterior model probability $P(M_k|D)$ can be written as:

$$P(M_k|D) = \frac{\alpha_k \cdot B_{k0}}{\sum_{r=0}^{\kappa} \alpha_r \cdot B_{r0}}$$

where the index k refers to model M_k and the index 0 refers to one fixed model M_0 as the reference. For the Tobit regressions Hoeting et al. (1999: 388) recommend the Bayesian Information Criterion (BIC) to approximate the Bayes factor:

$$B_{k0} = exp(-0.5BIC_k + 0.5BIC_0)$$

Since this specifies the Bayes factors B_{k0} we need only to specify the prior model odds as $\alpha_k = P(M_k)/P(M_0)$. Our prior model probability is:

$$P(M_k) = \prod_{j=1}^{z} \pi_j^{\delta_{kj}} (1 - \pi_j)^{1-\delta_{kj}}.$$

where z is the number of all potential predictors in the analysis, δ_{kj} is an indicator for variable j to be part of the model M_k, and π_j denotes the prior probability that β_j is not zero. We use $\pi_j = 0.5$ for all j. Robustness checks with $\pi_j = 0.3$ and $\pi_j = 0.7$ reveal that the choice of this parameter does not qualitatively change the findings. The findings are available from the authors upon request.

As the set of predictors that are included in the analysis also contain interaction terms such as the interaction STARTUP×RD of STARTUP and RD, we must modify the above assumption slightly. We cannot assume that inclusion of the variables a priori is independent. In the case of interactions, say A×B, between two so-called parent variables A and B we apply a strong heredity principle (Chipman, 1996). This requires that whenever the interaction variable A×B is included in the regression, all parent variables A and B, also have to be included. If this principle is violated, the analysis of the interaction effects may produce misleading findings as illustrated by the discussion in and between Masanjala and Papageorgiou (2008), Crespo Cuaresma (2011), and Papageorgiou (2011). Since the squared term included in the analysis is the interaction of the variable A with itself (A×A), we use the same strong heredity principle when including the second order terms of the variables in the model. Technically, we account for the strong heredity principle by setting $P(M_k) = 0$ for all k where M_k violates the principle.

Given the final number of variables that will be included in the analysis, the first step would — were we to fully enumerate the whole model space — require us to estimate 2^{29} (= 540 million) Tobit models. Even with access to high performance computation facilities this model space is prohibitive for a full enumeration. Instead, we implement a Markov Chain Monte Carlo Model Composition (MCMCMC or MC^3) algorithm to search the model space and collect information from the relevant parts of the posterior model distribution. The object of the MC^3 is to approximate the posterior model distribution. We implement a Metropolis-Hastings algorithm to search the model space in a stepwise manner.

The algorithm replaces a given model M_i by an alternative model M_j with the probability

$$P_{ij} = \min\{1, \frac{P(M_j|D)}{P(M_i|D)}\}$$

The distribution of the models then converges to the distribution of the posterior model probabilities $P(M_i|D)$. To generate an alternative model M_j, based on the current model M_i, we implement a birth-and-death sampler and reversible-jump samplers. The birth-and-death sampler selects one of the potential 29 variables randomly. If this variable is part of the current model M_i then the alternative model M_j is generated by dropping the variable. If the variable is not yet part of the current model then the alternative model M_j is created by including the variable. The reversible-jump sampler generates an alternative model by birth-death with a 50% probability. In all other cases a variable that is already in the current model is removed and a variable that is not part of the current model is added to the model (Green, 1995; Madigan and York, 1995).

We carry out 600,000 MC^3 iterations and discard the first 300,000 iterations as so-called burn-in steps. The analysis is based on the results of the remaining 300,000 MC^3 iterations. The burn-in steps are required for the algorithm to focus on the most important parts of the model distribution. The correlation between the posterior model probability and the frequency of the model in the MC^3 chain is a measure of how well the MCMC converges. Our analyses are based on MCMC runs that yield a correlation of more than 0.998 which indicates excellent convergence.

Results of the model averaging

Tables Y1 and Y2 report the results of the model averaging analysis. They show the respective determinants of the share of sales of radical innovations and innovations new to the firm respectively. We use 29 potential predictors including several interactions and second order terms. Note that in addition to the 29 potential predictors all models include the sector and country dummies. These results are not reported in the tables.

The first columns in Tables Y1 and Y2 report the posterior inclusion probability (PIP) of the variable. The PIP is the sum of the probabilities of those models that include this particular predictor. Essentially, the PIP is the sum of the weights $P(M_k|D)$ used for the averaging process. The PIP addresses model uncertainty directly. It represents the probability of each of the potential predictors to be part of the true model.

As a guideline for interpreting the PIP of a predictor, the literature suggests the following conventions (Kass and Raftery, 1995): a PIP between 0.50 and 0.75 is regarded as weak evidence, a PIP between 0.75 and 0.90 is interpreted as positive evidence. A PIP between 0.90 and 0.99 indicates strong evidence, and a PIP larger than 0.99 is considered decisive evidence that the variable is part of the true model. This enables us to judge the relevance of the variable for explaining innovation performance.

The second columns in Tables Y1 and Y2 present the direction and magnitude of the parameter estimates; they report the mean parameter estimate for all the models that include the corresponding variable. Finally columns (3) and (4) in both tables give an indication of the robustness of the estimate of the effect. Column (3) presents the fraction of the models with a positive parameter estimate when the variable is included, and column (4) reports the fraction of the models with a significant parameter estimate when the variable is included in the model.

To explain the share of sales innovations new to the world (Table Y1) the model averaging approach provides decisive evidence for USER, COLDEPTH×RD, INTMKT, IPF, IPNF, MAKEONLY and MAKEBUY being related to the dependent variable and weak evidence for COLLAB and OBSMKT. With exception of OBSMKT we find a positive relationship, indicated by the mean of the coefficient conditional on inclusion (column (2)). For OBSMKT we find a negative mean coefficient estimate. All the coefficients are estimated rather precisely; conditional on their inclusion the coefficients are always significant as indicated in table Y column (4). We found no evidence that any of the other variables in the model is associated with innovation performance.

[Table Y1, just about here]

In Table Y2 model averaging provides decisive evidence that BREADTH, BREADTH2, COMPINFO, COLDEPTH, MAKEONLY and MAKEBUY are associated with the share sales of innovations new to the firm since the PIP is larger than 0.99 in those cases. For OBSMKT we find weak evidence. With the exception of BREADTH2 all of the mean coefficient estimates are positive. We find an inverse U-shaped relationship between BREADTH and innovation performance with the downward sloping arm starting at around 7 and covering about 60% of the observations in the data set.

[Table Y2, just about here]

DISCUSSION

In the strategic management, inferences are made from empirical models that are largely ad hoc creations of a particular setting and information set, and of a particular choice of theoretical framework. This practice is fostered by model uncertainty where the true model is unknown, which encourages a model specification which produces significant variables that support the researcher's line of reasoning. This approach has led to a degree of contradictory and inconsistent findings and limited cumulative development of knowledge on the core aspects of strategic behavior.

Using the case of innovation survey data, this paper used Bayesian Averaging of Classical Estimates to improve coherence and consistency across a range of studies using the same underpinning data set. The aim was to both replicate prior research and to suggest an approach that lifts the veil on the model underlying numerous studies using the same data. The approach involves integrating data from three different countries and testing a range of variables against these data to determine which of the variables in the literature remain valid when accounting for model uncertainty.

Our analysis shows that some variables are closely related to the firm's innovation performance. We look first at the case of radical (new to the world) innovations and then the case of innovations that are new to the firm. In the case of products that are new to the world, user involvement is central which is in line with the literature on user innovation (von Hippel, 2005). We found also that international market involvement is associated with sales of products that are new to the world in line with the findings for exporting and innovation (Cassiman and Golovko, 2011). It appears also that a firm's approach to capturing rents from its innovative efforts through formal and informal appropriability strategies are were associated with higher levels of radical innovation (Cohen et al., 2000; de Faria and Sofka, 2010). Interestingly, we found little evidence supporting the importance of some more traditional innovation variables such as R&D and firm size, or more recent ones such as collaboration and Laursen and Salter's breadth of external search variables. However, collaboration depth is significant when interacted with internal R&D which is consistent with the idea that absorptive capacity shapes the benefits of external engagement (Escribano et al., 2009). We found evidence also that decisions about R&D and the firm's boundary are important variables in all the models, providing some support for Cassiman and Veugelers's (2006) analysis in the case of Belgium.

In the case of innovation new to the firm, we found strong evidence that external search breadth is associated with innovation. This result is consistent with Laursen and Salter (2006) and research on openness and innovation such as Leiponen and Helfat (2010), Garriga et al. (2013), and Love et al. (2014). We found support also for the notion of an inverted U-shaped relationship between openness and innovation, consistent with this prior literature. The analysis emphasized that collaboration matters for explaining new to the firm products (Belderbos et al., 2004). Moreover, the organizational boundary to innovation is a predictor of innovation new to the firm since the make or buy decision influences innovation outcomes which is again consistent with Cassiman and Veugelers (2006). However, we found little support for the more traditional variables such as firm size, R&D, and firm age, or appropriability strategy, obstacles to innovation, and market orientation.

Our results suggest that the models underlying the production of innovations that are new to the world and new to the firm are different and may require different modeling strategies. They suggest also that some of the findings from the more recent literature on the determinants of innovation related to the make or buy decision, external search breadth, and collaboration, are central to explaining product innovation, especially when for innovations new to the firm.

Implementing model averaging techniques on innovation survey data allows us to estimate the parameters and the structure of the innovation performance model simultaneously. These estimation approaches help to overcome model uncertainty. We show the potential for Bayesian Averaging of Classical Estimators in particular, and Bayesian Model Averaging in general, across a range of strategic management contexts. We noted the special value of the technique as a tool for conducting large-scale replication studies in contexts where a relatively large number of studies (with many potentially competing explanatory variables) uses the same or similar datasets while relying on the same dependent variable. Although the proposed technique cannot be applied in the same way across all fields of strategic management, there are several areas where its application could potentially be fruitful. These include innovation studies relying on citation weighted patents as the dependent variable, internationalization studies which typically use firm-level exports as the dependent variable, the numerous strategy studies which rely on firm-level profits (such as return on assets), and work that uses firm-survival as the dependent variable.

However, our approach has some limitations. First, we assume that the chosen econometric model — in our case the Tobit — is the correct specification. We do not use the methodology to cross check the appropriateness of the functional form of the model. Second, our approach assumes that the 'true' model can be built from a subset of the potential predictors included in the analysis. So our findings should be interpreted contingent on this assumption. However, this assumption is weaker and less strict than any of the assumptions made implicitly or explicitly in the empirical strategic management literature. Third, and perhaps obviously, Bayesian Model Averaging of cross-sectional data does not help to resolve the endogeneity issues related to innovation data (and strategic management generally). It might be that more innovative firms are of better inherent quality (in terms of management, routines, etc.), and therefore cross sectional data may in part reflect an omitted variable which would help to explain both their use of different innovation strategies and their different innovation performance. It might also be the case that innovation performance drives strategic choice which in turn, drives innovation. In the absence of evidence from panel data it is difficult to make strong inferences about the effects of particular variables on innovation outcomes. Fourth, our approach relies on the information contained in the CIS dataset and might suffer from errors of omission such as exclusion of important additional variables, and/or commission such as design and measurement errors emerging from the questionnaire. The approach proposed in this paper is appropriate for environments with relatively stable research design and limited use of supplementary data.

Despite the above limitations, we believe that the use of large-scale replication could resolve many of the problems identified in strategic management and may encourage more thought about the most appropriate analytical model.

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Table Z1: Description of the variables used

Variables	Description	Used in
INNOWORLD, INNOFIRM	Sales share of products new to the world or new to the firm respectively. Logarithmic transformation.	Laursen and Salter (2006); Cassiman and Veugelers (2006); Schmiedeberg (2008); Love et al. (2014); Leiponen and Helfat (2010); Roper et al. (2008); Leiponen (2005a); Grimpe and Kaiser (2010); Garriga et al. (2013); Ballot et al. (2015)
BREADTH	Number of sources of information sources used by the firm. The knowledge sources include: internal sources, suppliers, customers, competitors, consulting firms, universities, governmental research organizations, conferences, publications, business associations (0-10)	Laursen and Salter (2006); Love et al. (2014); Leiponen and Helfat (2010); Garriga et al. (2013)
DEPTH	Number of sources of information sources used to a high degree by the firm. The knowledge sources include: internal sources, suppliers, customers, competitors, consulting firms, universities, governmental research organizations, conferences, publications, business associations (0-10)	Laursen and Salter (2006); Garriga et al. (2013); Ballot et al. (2015)
USER	Firm uses customer information to a high degree (0/1)	Laursen and Salter (2006); Garriga et al. (2013)
COMPINFO	Importance of competitors as information source on a scale of 1 (low) to 3 (high) (0-3)	Cassiman and Veugelers (2006); Roper et al. (2008)
BASICINFO	Importance of universities and research institutes relative to suppliers and customers as information sources (0.00-1.00)	Cassiman and Veugelers (2006)
PUBINFO	Importance of publications and conferences, relative to suppliers and customers as information sources (0.00-1.00)	Cassiman and Veugelers (2006)
COLLAB	Firm is involved in innovation collaboration (0/1)	Laursen and Salter (2006); Schmiedeberg (2008); Garriga et al. (2013); Ballot et al. (2015)
COLDEPTH	Number of partner types used for innovation collaboration. Partner types include: suppliers, customers, competitors, consulting firms, universities, governmental research organizations (0-6)	Laursen and Salter (2006); Grimpe and Kaiser (2010); Schmiedeberg (2008)
RD	RandD expenditure as a share of sales (0.00–1.00)	Laursen and Salter (2006); Cassiman and Veugelers (2006); Schmiedeberg (2008); Love et al. (2014); Leiponen and Helfat (2010); Roper et al. (2008); Leiponen (2005a); Grimpe and Kaiser (2010); Garriga et al. (2013); Ballot et al. (2015)
INTMKT	Main markets of the firm are international (0/1)	Laursen and Salter (2006); Ballot et al. (2015)
NATMKT	Main markets of the firm are national (0/1)	Laursen and Salter (2006);
IPF	Number of formal methods for protection for innovation including the registration of designs, trademarks, or patents and the use of copyrights (0/1)	Cassiman and Veugelers (2006); Ballot et al. (2015)

IPNF	Number of informal methods of protection for innovation, including secrecy, complexity of design, or lead time advantage (0/1)	Cassiman and Veugelers (2006); Ballot et al. (2015)
OBSFIN	Lack of finance inside or outside the firm is 'very important' or 'important' (0/1)	Roper et al. (2008); Ballot et al. (2015)
OBSKNOW	Lack of qualified personnel, lack of information on technology, or lack of information on markets are 'very important' or 'important' (0/1)	Cassiman and Veugelers (2006); Ballot et al. (2015)
OBSMKT	Market domination by established enterprises or uncertain demand for innovative goods and services are 'very important' or 'important' (0/1)	Cassiman and Veugelers (2006); Ballot et al. (2015)
MAKEONLY	Internal RandD activities (0/1)	Cassiman and Veugelers (2006)
BUYONLY	Acquisition of technology through external RandD contracts, purchase of machinery for innovation, purchase of knowledge through patents, licensing etc. (0/1)	Cassiman and Veugelers (2006)
MAKEBUY	Internal RandD activities and acquisition of technology through external RandD contracts, purchase of machinery for innovation, purchase of knowledge through patents, licensing etc. (0/1)	Cassiman and Veugelers (2006)
LOGEMP	Logarithm of the number of employees	Laursen and Salter (2006); Love et al. (2014); Leiponen and Helfat (2010); Roper et al. (2008); Leiponen (2005a); Grimpe and Kaiser (2010); Garriga et al. (2013); Ballot et al. (2015)
STARTUP	Firm was a startup in the three years of the observation period (0/1)	Laursen and Salter (2006); Garriga et al. (2013)

Table Z2: Sectoral distribution (in percent)

Sector	Total (N=7,841)	France (N=3,681)	UK (N=2,398)	Germany (N=1,762)
Food	11,49	15,65	9,92	4,94
Textile	6,19	8,23	4,3	4,48
Pulp and Paper	11,07	9,51	12,76	12,03
Chemicals	8,79	10,38	5,88	9,42
Rubber and plastics	6,39	5,73	7,17	6,7
Metal	3,99	4,56	3,67	3,23
Fabricated metal	12,09	10,65	12,34	14,76
Equipment	9,81	9,05	9,01	12,49
Electronics	16,55	13,39	17,47	21,91
Transportation equipment	7,78	8,29	8,51	5,73
Other manufacturing	5,85	4,56	8,97	4,31
Total	100	100	100	100

Table Z3: Summary statistics

	All three Countries (N=7,841)				France (N=3,681)				UK (N=2,398)				Germany (N=1,762)			
Variables	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
INNOWORLD	1.075	1.330	0.00	4.62	1.188	1.356	0.00	4.62	1.045	1.312	0.00	4.62	0.883	1.276	0.00	4.62
INNOFIRM	1.290	1.374	0.00	4.62	1.230	1.369	0.00	4.62	1.453	1.423	0.00	4.62	1.158	1.268	0.00	4.62
BREADTH	6.887	2.741	0	10	6.288	2.928	0	10	7.470	2.339	0	10	7.343	2.581	0	10
DEPTH	1.653	1.386	0	10	1.519	1.246	0	10	1.802	1.618	0	10	1.729	1.294	0	8
USER	0.385	0.487	0	1	0.311	0.463	0	1	0.470	0.499	0	1	0.427	0.495	0	1
COMPINFO	1.376	0.966	0	3	1.186	0.974	0	3	1.591	0.924	0	3	1.478	0.927	0	3
BASICINFO	0.349	0.526	0.00	1.00	0.369	0.619	0.00	1.00	0.276	0.357	0.00	1.00	0.404	0.498	0.00	1.00
PUBINFO	0.700	0.604	0.00	1.00	0.751	0.727	0.00	1.00	0.608	0.433	0.00	1.00	0.720	0.495	0.00	1.00
COLLAB	0.395	0.489	0	1	0.474	0.499	0	1	0.326	0.469	0	1	0.323	0.468	0	1
COLDEPTH	0.991	1.605	0	6	1.090	1.619	0	6	0.992	1.722	0	6	0.781	1.374	0	6
RD	0.062	1.025	0.00	1.00	0.060	1.204	0.00	1.00	0.073	1.084	0.00	1.00	0.051	0.208	0.00	1.00
INTMKT	0.583	0.493	0	1	0.818	0.386	0	1	0.143	0.35	0	1	0.691	0.462	0	1
NATMKT	0.679	0.467	0	1	0.930	0.256	0	1	0.197	0.398	0	1	0.812	0.391	0	1
IPF	1.000	1.185	0	4	1.248	1.186	0	4	0.717	1.212	0	4	0.868	1.031	0	4
IPNF	0.987	1.110	0	3	1.051	1.154	0	3	0.686	0.946	0	3	1.264	1.129	0	3
OBSFIN	0.377	0.485	0	1	0.412	0.492	0	1	0.313	0.464	0	1	0.390	0.488	0	1
OBSKNOW	0.152	0.359	0	1	0.190	0.393	0	1	0.131	0.337	0	1	0.099	0.299	0	1
OBSMKT	0.232	0.422	0	1	0.290	0.454	0	1	0.208	0.406	0	1	0.145	0.352	0	1
MAKEONLY	0.139	0.346	0	1	0.196	0.397	0	1	0.102	0.303	0	1	0.071	0.257	0	1
BUYONLY	0.167	0.373	0	1	0.137	0.344	0	1	0.213	0.409	0	1	0.165	0.371	0	1
MAKEBUY	0.645	0.478	0	1	0.645	0.478	0	1	0.630	0.483	0	1	0.666	0.472	0	1
LOGEMP	4.646	1.517	1.61	12.97	4.835	1.413	1.61	11.38	4.442	1.433	1.61	10.09	4.527	1.772	1.61	12.97
STARTUP	0.014	0.119	0	1	0.009	0.094	0	1	0.025	0.155	0	1	0.012	0.109	0	1

Table X1: Regression of sales share of innovation new to the world (INNOWORLD, N=7,481)

	(1)	(2)	(3)	(4)	(5)	(6)
BREADTH	0.111** (0.053)	0.149*** (0.053)			0.122** (0.058)	0.138** (0.057)
BREADTH2	-0.003 (0.004)	-0.006 (0.004)			-0.004 (0.004)	-0.006 (0.004)
DEPTH	0.213*** (0.061)				0.180*** (0.061)	
DEPTH2	-0.027*** (0.009)				-0.019** (0.009)	
DEPTH×RD					0.360** (0.181)	
USER	0.219*** (0.079)	0.354*** (0.065)			0.219*** (0.080)	0.361*** (0.068)
COMPINFO			0.056* (0.034)		-0.140*** (0.042)	-0.111*** (0.040)
BASICINFO			0.243*** (0.066)		0.044 (0.075)	0.038 (0.075)
PUBINFO			0.016 (0.057)		-0.073 (0.063)	-0.063 (0.062)
COLLAB	0.592*** (0.068)				0.471*** (0.068)	
COLDEPTH		0.321*** (0.057)		0.225*** (0.021)		0.232*** (0.057)
COLDEPTH2		-0.026** (0.011)				-0.017 (0.011)
COLDEPTH×RD				0.311** (0.134)		0.288** (0.144)
RD	1.342*** (0.252)	1.328*** (0.252)	0.969*** (0.211)	0.633** (0.255)	0.574 (0.394)	0.750** (0.327)
INTMKT	0.602*** (0.092)	0.616*** (0.092)	0.531*** (0.092)	0.684*** (0.092)	0.446*** (0.091)	0.458*** (0.091)
NATMKT	0.210** (0.103)	0.187* (0.103)	0.167 (0.103)	0.211** (0.103)	0.125 (0.102)	0.114 (0.102)
OBSFIN			-0.053 (0.066)		-0.094 (0.065)	-0.097 (0.065)
OBSKNOW			0.087 (0.087)		0.066 (0.086)	0.065 (0.086)
OBSMKT			-0.213*** (0.076)		-0.226*** (0.075)	-0.218*** (0.075)
MAKEONLY			0.806*** (0.181)		0.689*** (0.181)	0.728*** (0.181)
BUYONLY			-0.319* (0.181)		-0.439** (0.182)	-0.391** (0.181)
MAKEBUY			1.277*** (0.167)		0.988*** (0.169)	1.042*** (0.169)
LOGEMP	0.045** (0.022)	0.041* (0.022)	0.059*** (0.022)	0.070*** (0.022)	0.014 (0.023)	0.009 (0.023)
STARTUP	0.191 (0.271)	0.208 (0.270)			0.280 (0.265)	0.248 (0.278)
STARTUP×RD	-2.070* (1.161)	-2.008* (1.092)			-2.416** (0.995)	-1.481 (1.617)
CONSTANT	-2.748*** (0.226)	-2.592*** (0.226)	-2.628*** (0.225)	-1.924*** (0.171)	-2.742*** (0.256)	-2.635*** (0.256)
Sector controls	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11,013.000	-11,011.120	-10,954.240	-11,055.390	-10,881.500	-10,881.000
Wald Test	725.867*** (df = 24)	733.225*** (df = 23)	807.243*** (df = 25)	657.695*** (df = 18)	934.458*** (df = 34)	939.397*** (df = 33)

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively. Six industry dummies, Coefficients of Tobit regressions, standard errors in parentheses. Underlining indicates that variables loose or gain significance depending on the other variables in the model.

Table X2: Regression of sales share of innovation new to the firm (INNOFIRM, N=7,384)

	(1)	(2)	(3)	(4)	(5)	(6)
BREADTH	0.328*** (0.050)	0.352*** (0.050)			0.235*** (0.055)	0.251*** (0.055)
BREADTH2	-0.019*** (0.004)	-0.022*** (0.004)			-0.015*** (0.004)	-0.017*** (0.004)
DEPTH	0.129** (0.056)				0.074 (0.056)	
DEPTH2	-0.012 (0.009)				-0.009 (0.009)	
DEPTH×RD					-0.003 (0.043)	
USER	0.167** (0.074)	0.271*** (0.061)			0.110 (0.075)	0.148** (0.064)
COMPINFO			0.278*** (0.031)		0.156*** (0.039)	0.165*** (0.038)
BASICINFO			0.028 (0.062)		-0.057 (0.071)	-0.082 (0.071)
PUBINFO			0.105** (0.054)		-0.001 (0.059)	0.001 (0.059)
COLLAB	0.376*** (0.063)				0.341*** (0.064)	
COLDEPTH		0.196*** (0.053)		0.196*** (0.020)		0.172*** (0.053)
COLDEPTH2		-0.010 (0.011)				-0.007 (0.011)
COLDEPTH×RD				-0.140 (0.132)		-0.019 (0.044)
RD	-0.089 (0.066)	-0.091 (0.068)	-0.063 (0.047)	0.109 (0.139)	-0.079 (0.177)	-0.044 (0.094)
INTMKT	0.337*** (0.088)	0.345*** (0.087)	0.307*** (0.088)	0.411*** (0.088)	0.265*** (0.088)	0.272*** (0.087)
NATMKT	0.170* (0.097)	0.150 (0.097)	0.153 (0.097)	0.182* (0.098)	0.128 (0.097)	0.107 (0.097)
OBSFIN			-0.078 (0.061)		-0.098 (0.061)	-0.108* (0.061)
OBSKNOW			-0.093 (0.081)		-0.098 (0.081)	-0.106 (0.081)
OBSMKT			0.247*** (0.070)		0.233*** (0.070)	0.236*** (0.069)
MAKEONLY			0.541*** (0.171)		0.429** (0.171)	0.447*** (0.171)
BUYONLY			0.130 (0.169)		0.00001 (0.170)	0.014 (0.169)
MAKEBUY			0.953*** (0.158)		0.723*** (0.160)	0.729*** (0.159)
LOGEMP	-0.024 (0.021)	-0.029 (0.021)	-0.023 (0.021)	-0.004 (0.021)	-0.046** (0.021)	-0.053** (0.021)
STARTUP	0.090 (0.242)	0.106 (0.242)			0.131 (0.240)	0.141 (0.240)
STARTUP×RD	0.895* (0.472)	0.910* (0.472)			0.924** (0.469)	0.885* (0.473)
CONSTANT	-1.467*** (0.211)	-1.347*** (0.211)	-1.103*** (0.210)	-0.144 (0.158)	-1.538*** (0.243)	-1.437*** (0.243)
Sector controls	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11,425.600	-11,418.490	-11,408.430	-11,481.520	-11,371.030	-11,361.140
Wald Test	436.529*** (df = 24)	451.310*** (df = 23)	472.346*** (df = 25)	334.754*** (df = 18)	539.124*** (df = 34)	559.107*** (df = 33)

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively. Six industry dummies, Coefficients of Tobit regressions, standard errors in parentheses. Underlining indicates that variables loose or gain significance depending on the other variables in the model.

Table Y1: Model averaging results – sales share of innovations new to the world (INNOWORLD)

Variables	(1) Posterior inclusion probability (PIP)	(2) Posterior mean conditional on inclusion	(3) Sign certainty probability	(4) Fraction of regressions with p<10%
BREADTH	0.025	0.024	1.000	0.475
BREADTH2	0.000	0.002	0.973	0.973
BREADTH×RD	0.037	0.066	1.000	0.054
DEPTH	0.001	0.051	0.999	0.978
DEPTH2	0.000	-	-	-
DEPTH×RD	0.015	0.058	0.946	0.033
USER	**0.989**	**0.264**	**1.000**	**1.000**
COMPINFO	0.089	-0.078	0.000	1.000
BASICINFO	0.009	0.058	1.000	0.000
PUBINFO	0.006	-0.001	0.423	0.000
COLLAB	**0.705**	**0.334**	**1.000**	**1.000**
COLDEPTH	0.316	0.103	1.000	1.000
COLDEPTH2	0.044	0.000	0.691	1.000
COLDEPTH×RD	**1.000**	**0.443**	**1.000**	**0.999**
RD	0.006	0.342	1.000	0.000
RD2	0.006	-0.004	0.010	0.990
INTMKT	**1.000**	**0.386**	**1.000**	**1.000**
NATMKT	0.022	0.148	1.000	0.001
IPF	**1.000**	**0.227**	**1.000**	**1.000**
IPNF	**1.000**	**0.368**	**1.000**	**1.000**
OBSFIN	0.039	-0.114	0.000	0.739
OBSKNOW	0.007	0.021	0.556	0.000
OBSMKT	**0.526**	**-0.216**	**0.000**	**1.000**
MAKEONLY	**1.000**	**0.954**	**1.000**	**1.000**
BUYONLY	0.043	-0.322	0.000	0.631
MAKEBUY	**1.000**	**1.142**	**1.000**	**1.000**
LOGEMP	0.122	-0.051	0.000	1.000
STARTUP	0.010	0.234	1.000	0.000
STARTUP*RD	0.015	-0.591	0.000	0.151

Note: Analysis based on 600,000 MCMC iterations which includes 300,000 burn-in iterations. CorrPMP = 0.998. Sector controls and country controls are always part of the models. The parameters base on the 1.000 best models. Variables with a PIP > 0.500 are in bold.

Table Y2: Model averaging results – sales share of innovations new to the firm (INNOFIRM)

Variables	(1) Posterior inclusion probability (PIP)	(2) Posterior mean conditional on inclusion	(3) Sign certainty probability	(4) Fraction of regressions with p<10%
BREADTH	**1.000**	**0.267**	**1.000**	**1.000**
BREADTH2	**1.000**	**-0.019**	**0.000**	**1.000**
BREADTH×RD	0.000	-0.018	0.000	0.211
DEPTH	0.000	0.065	1.000	1.000
DEPTH2	0.000	-	-	-
DEPTH×RD	0.049	0.022	0.333	0.667
USER	0.017	0.161	1.000	1.000
COMPINFO	**1.000**	**0.195**	**1.000**	**1.000**
BASICINFO	0.000	-0.028	0.000	0.000
PUBINFO	0.000	-0.025	0.001	0.000
COLLAB	0.000	0.346	1.000	1.000
COLDEPTH	**0.997**	**0.133**	**1.000**	**1.000**
COLDEPTH2	0.003	0.024	1.000	1.000
COLDEPTH×RD	0.325	-0.054	0.000	0.116
RD	0.000	-0.243	0.000	0.000
RD2	0.000	-0.089	0.000	0.005
INTMKT	0.215	0.291	1.000	1.000
NATMKT	0.000	0.227	1.000	0.707
IPF	0.350	0.075	1.000	1.000
IPNF	0.003	0.062	1.000	1.000
OBSFIN	0.000	-0.075	0.000	0.000
OBSKNOW	0.000	-0.092	0.000	0.000
OBSMKT	**0.682**	**0.210**	**1.000**	**1.000**
MAKEONLY	**1.000**	**0.471**	**1.000**	**1.000**
BUYONLY	0.000	-0.232	0.293	0.707
MAKEBUY	**1.000**	**0.737**	**1.000**	**1.000**
LOGEMP	0.010	-0.050	0.000	0.906
STARTUP	0.000	0.266	1.000	0.000
STARTUP×RD	0.009	0.916	1.000	1.000

Note: Analysis based on 600,000 MCMC iterations which includes 300,000 burn-in iterations. CorrPMP = 0.998. Sector controls and country controls are always part of the models. The parameters base on the 1.000 best models. Variables with a PIP > 0.500 are in bold.

Appendix

Table A1: Correlation

	BREADTH	DEPTH	USER	COMPINFO	BASICI~O	PUBINFO	COLLAB
DEPTH	0.373	1.000					
USER	0.251	0.568	1.000				
COMPINFO	0.527	0.475	0.375	1.000			
BASICINFO	0.497	0.184	-0.009	0.069	1.000		
PUBINFO	0.445	0.144	-0.011	0.088	0.444	1.000	
COLLAB	0.252	0.203	0.107	0.092	0.277	0.119	1.000
COLDEPTH	0.345	0.250	0.141	0.152	0.333	0.148	0.764
RD	0.021	0.022	0.011	0.012	0.020	0.002	0.030
INTMKT	0.053	0.047	0.009	-0.022	0.156	0.123	0.207
NATMKT	-0.015	0.010	-0.035	-0.065	0.122	0.099	0.154
IPF	0.198	0.187	0.095	0.122	0.169	0.121	0.212
IPNF	0.241	0.213	0.124	0.104	0.197	0.141	0.238
OBSFIN	0.035	0.079	0.022	0.039	0.057	0.053	0.042
OBSKNOW	-0.002	0.033	0.016	0.012	0.007	0.005	0.017
OBSMKT	0.063	0.080	0.034	0.077	0.045	0.059	0.041
MAKEONL	-0.173	-0.088	-0.028	-0.082	-0.086	-0.034	-0.121
BUYONLY	-0.151	-0.103	-0.105	-0.078	-0.129	-0.085	-0.152
MAKEBUY	0.318	0.192	0.124	0.158	0.204	0.130	0.265
LOGEMP	0.275	0.161	0.083	0.141	0.207	0.086	0.260
STARTUP	0.031	0.035	0.023	0.025	-0.014	0.000	-0.004

	COLDEPT	RDINT	INTMKT	NATMKT	IPF	IPNF	OBSFIN
RD	0.025	1.000					
INTMKT	0.150	0.002	1.000				
NATMKT	0.106	0.016	0.652	1.000			
IPF	0.239	0.022	0.255	0.191	1.000		
IPNF	0.249	0.021	0.242	0.182	0.340	1.000	
OBSFIN	0.058	0.025	0.030	0.084	0.003	0.051	1.000
OBSKNOW	0.022	-0.008	0.022	0.040	-0.008	0.032	0.134
OBSMKT	0.043	-0.009	0.028	0.046	0.020	0.018	0.203
MAKEONL	-0.143	-0.007	0.038	0.050	-0.061	-0.102	0.018
BUYONLY	-0.155	-0.018	-0.204	-0.140	-0.197	-0.197	-0.024
MAKEBUY	0.276	0.023	0.179	0.115	0.245	0.276	0.014
LOGEMP	0.289	-0.009	0.253	0.135	0.341	0.203	-0.098
STARTUP	-0.001	-0.001	-0.054	-0.038	-0.033	-0.011	0.010

	OBSKNOW	OBSMK	MAKEONL	BUYONLY	MAKEBUY	LOGEMP	STARTUP
OBSMKT	0.184	1.000					
MAKEONL	0.023	0.029	1.000				
BUYONLY	-0.027	-0.043	-0.180	1.000			
MAKEBUY	0.018	0.022	-0.542	-0.604	1.000		
LOGEMP	-0.061	-0.009	-0.113	-0.141	0.242	1.000	
STARTUP	-0.024	-0.001	-0.002	0.012	-0.016	-0.021	1.000

Note: Correlations larger than 0.022 are significant at the 5% level.