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THE DIFFERENTIAL IMPACTS OF MARKETS FOR TECHNOLOGY ON THE VALUE OF TECHNOLOGICAL RESOURCES: AN APPLICATION OF GROUP-BASED TRAJECTORY MODELS

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Research summary*: This article uses Group-Based Trajectory (GBT) Models to advance strategic management research, focusing on demonstrating the differential impacts of markets for technology on the value of technological capabilities. Group Based Trajectory (GBT) models, a statistical technique based on finite mixture models, can be used to discern heterogeneity based on an attribute of interest, especially when the heterogeneity changes or evolves over time, and when there is a lack of theoretical guidance to discern the basis of heterogeneity. We illustrate these advantages of GBT models in our study of how the moderating effect of markets for technology on the value of technological capability is itself moderated by firm types. We conclude with a discussion of potential uses of the method in strategic management research.*

Managerial summary*: This article illustrates the use of Group-Based Trajectory Models in discerning heterogeneity in an attribute of interest, including firm resources, capabilities, strategies, and performance, especially when such heterogeneity changes or evolves over time. We illustrate these advantages of GBT models in an analysis of how the moderating effect of markets for technology on the value of technological capability is itself moderated by firm types. Specifically, we find that the performance of firms, whose strategic position is based on technological competence, is negatively impacted when MFT are extensive, whereas that of firms whose strategic position is also based on other complementary capabilities is relatively unaffected.*

INTRODUCTION

This study introduces group-based trajectory (GBT) models as a powerful statistical technique that addresses a fundamental problem in strategic management—the classification of a heterogeneous set of firms into "strategic groups" or "firm types" based on commonality in their endowments, including resources and capabilities, or strategies that leverage these endowments. Regression analyses are well suited to causally identifying the mean impact of firm endowments and strategies while controlling for unobserved firm types in the data. However, in the absence of theoretical guidance on proxies for heterogeneous firm types, regressions may be limited in informing theory about how diverse firm types moderate outcomes of interest. This is because regressions do not identify unobserved firm types in the data in a parsimonious way. The alternative of constructing firm types through arbitrary partitions of the data such as median splits may be uninformative if the splits mask true firm types that exist within each

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subsample. Yet, the accurate identification of firm types and their moderating effects on outcomes of interest has significant managerial implications since one strategy prescription may not apply to all firms.

Researchers often rely on data-reduction techniques such as cluster analysis to discern unobserved firm types. This data-driven approach is a powerful method to empirically explore heterogeneity. However, cluster analysis not be appropriate in research that uses longitudinal data in which the theorized organizational attribute(s) used to cluster firms evolves over time. Indeed, researchers have emphasized the method's limitations in testing the consistency of links between cluster membership and outcomes over time and the allied difficulty in testing hypotheses, especially with panel data (see Barney and Hoskisson, 1990; Dranove, Peteraf, and Shanley, 1998; Meyer, 1991; Ramanujam and Varadarajan, 1989; Thomas and Venkatraman, 1988).

GBT models are an effective method to identify firm heterogeneity that addresses the above limitations of cluster analyses. Specifically, GBT models identify unobserved firm types based on how the variable of interest evolves over time. As a result, GBT models can be a powerful alternative to cluster analysis, especially, when the resource, capability, or strategy of interest evolves over time. Further, GBT models are semiparametric and based on finite mixture models that form the basis of many maximum likelihood methods, such as Tobit regressions (Nagin, 2005). Thus, relative to cluster analyses, parameter estimates in GBT models are more precise and use more of the information present in the data.

We illustrate the benefits of GBT models by applying them to the study of the relation between firms' technological capabilities and performance. We are particularly interested in exploring how markets for technolgy (MFT), or the opportunities to trade and exchange technologies, moderate the relationship between technological capabilities and performance. Toward this objective, we first use GBT models to categorize firms in the data into technological capability types based on the relative levels of these capabilities as well as how they accumulate over time. Subsequently, we assess how the moderating effect of MFT on the performance impact of technological capability varies by capability type. We do so by regressing Tobin's Q on technological capability types and the interaction between each capability type and MFT. Based on prior research (e.g., Zahra and Covin, 1993) that emphasizes the fit between business strategy and the acquisition and deployment of technological capabilities, our theoretical explanation of these differential effects of MFT by technological capability type is informed by the strategic position underlying each capability type. Such strategic position of firms is defined in terms of their source of competitive advantage and competitive scope (Porter, 1980).

We find that the performance impact of technological capability is unaffected for firms, whose competitive advantage emanates from holding complementary marketing capabilities, either exclusively or in combination with technological capabilities. However, such performance impact is muted for firms that rely exclusively on technological expertise for competitive advantage. The contingent resource-based view (RBV) of the firm suggests that the extent to which a valuable, rare, inimitable, and nonsubstitutable (VRIN) resource is a source of competitive advantage is contingent on the environment that the firm operates in (Barney, 2001). Our results suggest that the contingency's influence on the competitive value of a VRIN resource may itself be contingent on the strategic position of firms.

In order to distinguish GBT models from other methods commonly used to discern heterogeneous firm types or classify firms as such, we compare the above results with those that emanate from identifying technological capability types using median splits and cluster analysis. The latter analyses find that the performance impact of technological capability for firm types, whose underlying strategic position is neither based on technological competence nor complementary capabilities, is unaffected by MFT. Further, the performance impact of technological capability is muted for firms whose strategic position is based on both technological competence and complementary capabilities. We conclude that GBT models, because they take into consideration both the level of the variable and how it evolves over time, offer richer, nuanced, and theoretically meaningful insights.

Below, we begin with an introduction to GBT models, including their statistical basis and properties. We then apply GBT models to the study of the performance impact of technological capabilities. We conclude with a discussion of the implications of our results to theory as well as other important applications of GBT models in strategy research.

INTRODUCTION TO GBT MODELS

GBT models are a specialized application of mixture models that use longitudinal data comprising firm-year observations to identify heterogeneous unobserved firm types. These types are best represented by trajectories that reflect how the underlying variable of interest evolves over time (Nagin, 1999). GBT models conceive of the population of firms as consisting of a mixture of J distinct unobserved subpopulations or types. The unconditional distribution of the variable of interest is simply the aggregate of J conditional distributions. For example, in our empirical illustration, a parametric distribution of technological capabilities of firm i can be represented as $P(Y_i)$, where $Y_i = (y_{i1}, y_{i2}, y_{i3}, \ldots, y_{iT})$. Therefore, a vector of measurements of technological capabilities over T time periods is expressed as:

$$P\left(\boldsymbol{Y_i}\right) = \sum_{j=1}^{J} P\left(C_i = j\right) \mathrm{P}\left(\boldsymbol{Y_i} = \boldsymbol{y_i} | C_i = j\right)$$
$$= \sum_{j=1}^{J} \pi_j P^j\left(Y_i\right), \tag{1}$$

where $P(C_i = j)$ is the probability that firm i is of type j and $\mathrm{P}(\boldsymbol{Y_i} = \boldsymbol{y_i} | C_i = j)$ is the probability distribution of technological capability conditional on being of type j. Note that this structure assumes that for each firm i within a type j, the distribution of the outcome of interest, y_{it}, in any period t is independent of the realizations in the previous periods, conditional on being of a specific type (Nagin, 2005). The GBT technique models $P(C_i = j)$ as a generalized logistic function given by $P\left(C_i = j\right) = \frac{\exp\left(\theta_j\right)}{\sum_{l=1}^{J} \exp\left(\theta_l\right)}$.[1] As a result, the estimation procedure provides, for each firm in the sample, the probability that the firm is of a specific type. The firm is then assigned to a type based on the maximum value of these estimated probabilities.

We specify $P^j(Y_i)$ as a censored normal distribution. The likelihood function for the censored normal version of a GBT model is given by:

$$\mathrm{P}\left(\boldsymbol{Y_i} = \boldsymbol{y_i} | C_i = j\right) = \prod_{y_{it} = S_{min}} \Phi\left(\frac{S_{min} - \beta^j x_{it}}{\sigma}\right)$$
$$\times \prod_{S_{min} < y_{it} < S_{max}} \frac{1}{\sigma} \phi\left(\frac{y_{it} - \beta^j x_{it}}{\sigma}\right)$$
$$\times \prod_{y_{it} = S_{max}} \left(1 - \Phi\left(\frac{S_{max} - \beta^j x_{it}}{\sigma}\right)\right),$$

where ϕ and Φ are the density and cumulative distribution functions, respectively, of a normally distributed random variable with mean $\beta^j x_{it}$ and standard deviation σ. The terms S_{min} and S_{max} are the minimum and maximum values of the random variable.

Two important parameters have to be specified while estimating a GBT model: the number of types and, for each type j, the relation between the variable of interest y_{it} and time t. For instance, when we use a quadratic specification for technological capability type, we specify $y_{it}^j = \beta_0^j + \beta_1^j t + \beta_2^j t^2$, where β_0^j, β_1^j, and β_2^j are parameters to be estimated that specify how the technological capability for every firm in that type evolves as a quadratic function of time. Like regressions, GBT models facilitate the inclusion of both time varying and time-invariant controls. Time-invariant controls are modeled as factors that influence the probability of type membership ($P(C_i = j)$) whereas time varying covariates influence the shape of the type's trajectory or how the dependent variable evolves over time. In our empirical example, we showcase both the unconditional as well as the conditional model that includes a variety of controls.

Model fit in GBT, which estimates the appropriate number of types in the data and the shape or trajectory of each type (denoting its relation with time), is assessed using the maximal value of the Bayesian information criterion (BIC) scores that correspond to different specifications (Nagin, 2005). The BIC is estimated as 2 log(L) – k log(N), where L denotes the value of the maximized likelihood; N, the number of observations; and k, the number of parameters (Kass and Raftery,

[1] By convention, for $j = 1$, θ_1 is set to 0 to facilitate identification. See Nagin (2005): 41–42 for an example.

1995; Schwarz, 1978). The model with the highest BIC score is the one that best fits the data. Subsequently, researchers can assess the accuracy of type membership. In our empirical context, this refers to the probability that any given firm in the data belongs to a particular technological capability type.

Our intention in the following section is to use GBT models to demonstrate how the moderating effect of MFT on the performance impact of technological capability itself varies by technological capability type. The latter is defined by the magnitude of firms' technological capability as well as how such capability evolves over time. Given this motive, we first use GBT to identify technological capability types in the sample. To this end, we begin by using the quadratic specification outlined above for all types and progressively increasing the number of types until the BIC can no longer be improved. After identifying the number of types, for each type, we sequentially try the linear, cubic, quartic, and quintic specifications until the BIC can no longer be improved. This step yields the specification for each of the technological capability types that best fits the data. After the first and second steps, we can also calculate , BIC_{max}, which is the maximal BIC value that corresponds to different specifications and BIC_j,which is the BIC of the focal specification, and choose the specification with the highest value of p_j given by $p_j = \frac{e^{BIC_j - BIC_{max}}}{\sum_j e^{BIC_j - BIC_{max}}}$ to determine the one that best fits the data. Similar to other empirical techniques, we determine the accuracy of type membership using the standard errors of the group membership probabilities.

Subsequent to identifying the capability types, we test how the moderating influence of MFT on the performance impact of technological capability varies by capability type. We do so by regressing Tobin's Q on the different capability types as well as the interaction between MFT and capability types. We also report results of regression and cluster analyses of the data to highlight the differences between these techniques in identifying technological capability types and their impact on performance. An analysis of the business strategy underlying the technological capability types informs our theoretical explanation of the differential effects of MFT by capability type.

EMPIRICAL ILLUSTRATION: DIFFERENTIAL MODERATING EFFECTS OF MFT ON THE PERFORMANCE IMPACT OF TECHNOLOGICAL CAPABILITIES

Motivation, data, and measures

The resource-based view of the firm argues that firm resources that are VRIN are important sources of competitive advantage (e.g., Barney, 1991; Wernerfelt, 1984). In line with this view, a rich body of work concludes that a firm's technological capability contributes to competitive advantage (e.g., Arora *et al.*, 2009; Henderson and Cockburn, 1996). Assuming that a firm's technological capability is embodied in its innovative efficiency, prior research (e.g., Hall, Jaffe, and Trajtenberg, 2005) has tested the relation between a firm's innovative efficiency, proxied by its patent stock per R&D dollar invested or patent stock per unit of assets, and its market value, proxied by its Tobin's Q. This body of work largely concludes that innovative efficiency of a firm positively influences its performance.

The contingent RBV argues that whether a capability is VRIN, and in turn, a source of competitive advantage, is contingent on the environment in which the firm operates (Barney, 2001). In line with this view, prior work examines MFT, or opportunities to trade technologies, as a contingency that alters the performance impact of a firm's technological capability. This literature largely notes that MFT mutes the relative competitive value of internal technological capability (Arora and Nandkumar, 2011). Stated otherwise, when externally sourced technology acts as a substitute for internal technological capability, MFT may diminish the value of the latter for performance.[2] Our goal is to explore how this average moderating effect of MFT documented in the literature varies by firm types and the underlying strategic position of firms.

[2] A competing hypothesis is that firms can synergistically combine technology sourced from the market with internally generated technology to enhance the value of the latter. For instance, to the extent that internal technological capability provides absorptive or integration capability (Ceccagnoli and Jiang, 2013), MFT development can increase the value of internal technological capability. But the literature shows that on average, technology that is available from the market acts as a substitute for internal technological capability.

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Following Zahra and Covin (1993), we identify four dimensions of strategic positioning—breadth of product markets, marketing intensity, and relative cost efficiency—that are particularly relevant to a firm's technology strategy and its acquisition of technological capabilities. These fundamental strategic choices are meaningful in diverse environmental settings and map to two indicators of strategic positioning—*competitive advantage* and *competitive scope*—that are widely acknowledged in the strategy literature (e.g., Miller, 1986; Porter, 1980). We draw on this rich body of prior work to theorize about the strategic role and impact of technological capabilities by capability type.

The data for our study comprise 1,059 firms within the intersection of the Compustat, National Bureau of Economic Research patent data, and Google patent assignment databases (available at http://www.google.com/googlebooks/uspto-patents-assignments.html [last accessed on August 2, 2015]). Our data span the years 1982–2006, and our unit of observation is the firm-year. We use Tobin's Q (*TQ* henceforth), which is the ratio of the market value of a firm's assets to their replacement cost, as a measure of performance. Following prior research (Griliches, 1981), we use the natural log of the firm's annual patent stock divided by R&D expenditure in millions as a measure of its technological capability (*patents per R&D dollar* henceforth). Finally, following Serrano (2010), we use patent reassignments to measure the extent of MFT in an industry. Although the number of reassignments in an industry varies by year, we construct a dummy variable, *high assignment*, that equals one if the mean proportion of patent reassignments—the total number of reassignments in a two-digit Standard Industrial Classification (SIC) code divided by the total number of patents in that SIC code—is greater than the median proportion of reassignments in the sample and zero otherwise (*low assignment*). We control for industry affiliation using industry dummies, *market concentration* using the Hershman Herfindahl Index (HHI) based on sales, *patent concentration* using the HHI based on patent stock, *size* using total sales of a firm, and *market share* using sales of the focal firm divided by industry sales (the total sales of all firms in a two-digit SIC in Compustat in a year) while estimating the market value of technological capabilities. Table 1 details the above measures of performance, technological capabilities, dimensions of business strategy, and controls used in our analyses. Table 1 also provides descriptive statistics for the data.

ANALYSIS AND RESULTS

Our analysis of technological capability types in the data, including an understanding of how the moderating effects of MFT on the performance impact of technological capabilities varies by technological capability type, proceeds in three stages. First, given the absence of theoretical guidance in constructing proxies for firm types, we discern technological capability types in the data using GBT models. We contrast these capability types with those obtained through median splits of the data and cluster analyses. Specifically, we show that the identified capability types are sensitive to the method adopted to create these types and that GBT presents important advantages over the other two methods. Second, for each technological capability type created by the GBT model, assuming that each technological capability type embodies an underlying strategic position that informs the acquisition of technological capabilities, we characterize each type based on the strategic position of firms. Finally, we regress *TQ* on the capability types and their respective interactions with MFT to demonstrate how capability types moderate the effect of MFT on the performance impact of technological capabilities.

Identification of technological capability types using GBT models

We begin by using GBT models to classify firms into technological capability types based on *patents per R&D dollar*. We fit a censored normal specification of the GBT model and evaluate model fit by choosing the specification with the maximum BIC value. The results are shown in Figure 1 and Table 2. In Table 2, we present the results of three specifications. In specification 1, we estimate an unconditional GBT model that does not include any controls.[3] In specification 2, we include industry-level controls, notably, the two-digit SIC code of the firm, industry averages of *patent concentration* and *market concentration*, and the

[3] We use the stata module traj for estimation.

Table 1. Descriptive statistics

Variable	Measure	Description	Source of variation	Mean	Std. dev.
Performance	*TQ*	Measured using Tobin's Q, the ratio of the market value of a firm's assets to the replacement cost of the assets for each firm-year, in log	Firm, year	1.41	0.84
Technological capability	*Patents per R&D dollar*	0.01+ natural log of yearly patent stock divided by R&D expenditure in millions of U.S. dollars	Firm, year	1.28	2.61
Markets for technology	*High assignment dummy*	= 1 if the number of patent reassignments in the focal industry exceeds the sample median number of reassignments	Industry, year	0.51	0.49
R&D investments	*R&D*	R&D investments of a firm in a year	Firm, year	71.21	387.09
Size	*Log sales*	Total sales of a firm in millions of U.S. dollars in natural log	Firm, year	6.60	1.89
Market share	*Market share*	Sales of the focal firm divided by industry sales—the total sales of all firms in a two-digit SIC in Compustat in a year	Firm, year	0.06	0.15
Patent concentration	*Patent HHI*	Herfindahl-Hirschman index of patent holding in an industry	Industry, year	0.21	0.18
Market concentration	*Sales HHI*	Herfindahl-Hirschman index of revenues in an industry	Industry, year	0.05	0.08
Marketing intensity	*Marketing divided by sales*	Sales, marketing, and advertising expenses of a firm divided by sales (both in millions of U.S. dollars)	Firm, year	0.02	0.04
Relative cost efficiency	*Efficiency dummy*	= 1 if the income per employee of a firm is higher than industry average	Firm, year	0.51	0.49
Product scope	*No. of product markets*	Number of four-digit SIC codes that a firm is in in a given year	Firm, year	4.01	2.46
Industry dummies		43 industry dummies based on the firm's primary two-digit SIC code	Industry		
Year dummies		24 year dummies, one for each year of observation	Year		

This table presents descriptive statistics for the main variables in our final estimation sample. The unit of observation is firm-year. The means of all variables are based on 26,475 observations that are composed of 1,059 firms that belonged to the following SIC codes: 10, 13–17, 20–39, 48–51, 53–54, 57, 59–61, 65, 67, 72–73, 78–80, 87, and 89.

high assignment dummy that proxies for the extent of MFT.[4] In specification 3, we also include mean firm values of *market share* and *sales* as controls. We rely on the results of this fully specified model (specification 3) for further analysis. The results of specification 1 suggest that the standard errors associated with the probability of type membership are low and that the type membership probabilities for each capability type are accurately estimated. Specifications 2 and 3 suggest that the inclusion of industry and firm controls do not significantly alter our estimates. Figure 1 and Table 2 point to three technology capability types estimated by the GBT model: Type 1, Type 2, and Type 3, which constitute 6, 32, and 62 percent of the sample, respectively.

Prior research (e.g., Hambrick and Lei, 1985; Zahra and Covin, 1993) finds that the acquisition of technological capabilities must fit or be compatible with the business strategy of the firm. Therefore, in order to improve our theoretical understanding of the technological capability types, including differences in their strategic role and performance impact, we profile three dimensions of strategic

[4] We prefer to use industry and firm averages instead of including them as time-varying controls. Including these as time-varying controls would imply that we would have to estimate about 24 additional coefficients per control, which would be computationally very costly simply because we would have to estimate 144 additional coefficients. We state this as a limitation of the method in our concluding remarks.

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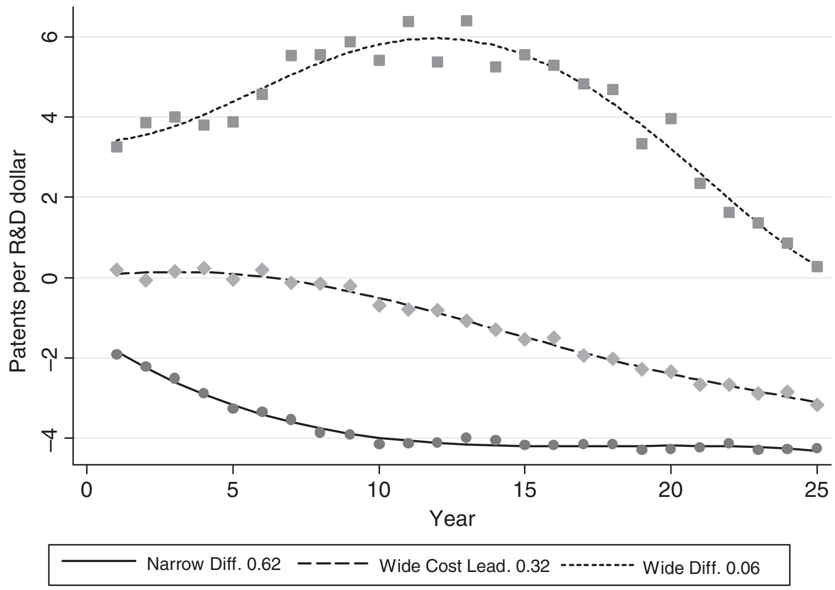

Figure 1. Shapes of technological capability types. This figure shows the shape of each technological capability type as estimated by GBT using specification 3 of Table 2. The proportion of the sample that is included in each type is shown below the figure against the respective type. The X-axis denotes time elapsed since 1982 in years. The Y-axis denotes *patents per R&D dollar* which is estimated as 0.01+ natural log of yearly patent stock divided by R&D expenditure in millions of U.S. dollars.

Table 2. GBT estimates of technological capability types

	Spec. 1 Unconditional	Spec. 2 Industry controls	Spec. 3 Industry and firm controls
Type 1 (wide differentiation)	0.05 (0.01)***	0.05 (0.01)***	0.06 (0.01)***
Type 2 (wide cost leadership)	0.32 (0.02)***	0.32 (0.01)***	0.32 (0.01)***
Type 3 (narrow differentiation)	0.63 (0.02)***	0.63 (0.02)***	0.62 (0.02)***
σ	2.78 (0.01)***	2.79 (0.01)***	2.79 (0.01)***
LL	−65486.85	−65357.18	−65356.36
BIC	−65563.23	−65337.22	−65346.58
N	26,875	26,875	26,875

This table uses GBT mdoels to classify firms into technological capability types based on *patents per R&D dollar*. The unit of observation is firm-year. Spec. 1 uses GBT without controls. Spec. 2 uses industry controls, including 13 two-digit SIC code dummies that constitute 76 percent of the sample, *mean patent concentration, mean market concentration*, and *high assignment dummy*. The 13 two-digit dummies correspond to the following SIC codes: 20, 26, 28, 33–39, 49, 67, and 73. Spec. 3 additionally uses firm controls, including average *market share* of the firm and average *log sales* of the firm. Standard errors within parentheses. Number of firms is 1,059. The trajectories for these types are shown in Figure 1. ***Significant at 1%. **Significant at 5%. *Significant at 10%.

position—marketing intensity, relative cost efficiency, and product scope or breadth of product markets—across each of the three capability types. As noted earlier, these dimensions map to two widely acknowledged dimensions of strategic positioning—source of competitive advantage and competitive scope. The operationalization of these constructs is detailed in Table 1. Panel A in Table 3 presents the mean estimates for the dimensions of business strategy across the three capability types. In the following paragraphs, we use the results of specification 3 of Tables 2 and 3 to define and interpret the three trajectories of technological capabilities. Specifically, we define each trajectory on the basis of only those variables that exhibit differences in the mean estimates at the 10 percent level.

Type 1: Wide differentiation

Figure 1 and Table 2 together suggest that a small minority of firms that constitute about six percent

Table 3. Descriptive statistics by technological capability types

Panel A: Descriptive statistics based on GBTs[a]

Variable	Narrow differentiation	Wide cost leadership	Wide differentiation
Marketing intensity	0.02 (0.00)	0.01 (0.00)	0.03 (0.00)
Relative cost efficiency	0.45 (0.01)	0.55 (0.01)	0.51 (0.01)
Product scope	3.56 (0.03)	4.44 (0.02)	4.65 (0.07)
Technological capability	0.58 (0.03)	1.16 (0.03)	3.90 (0.06)
Sample proportion	0.62	0.32	0.06

Panel B: Descriptive statistics based on cluster analyses[b]

Variable	Cluster 1	Cluster 2
Marketing intensity	0.01 (0.00)	0.02 (0.00)
Relative cost efficiency	0.58 (0.01)	0.71 (0.00)
Product scope	4.62 (0.03)	3.71 (0.02)
Technological capability	1.08 (0.05)	0.67 (0.04)
Sample proportion	0.24	0.76

Panel C: Descriptive statistics based on median splits[c]

Variable	High growth	Low growth
Marketing intensity	0.02 (0.00)	0.02 (0.00)
Relative cost efficiency	0.57 (0.01)	0.70 (0.00)
Product scope	4.61 (0.05)	3.90 (0.02)
Technological capability	1.11 (0.07)	0.71 (0.03)
Sample proportion	0.50	0.50

[a] This table provides descriptive statistics for each of the capability types estimated through GBT as per spec. 3 of Table 2. These statistics help us understand the strategy position of firms. The unit of observation is firm. Standard errors within parentheses. Number of firms are 1,059.
[b] This table provides the descriptive statistics for each of the types estimated through cluster analysis. These statistics help us understand the strategy position of firms. The unit of observation is firm. Standard errors within parentheses. Number of firms are 1,059.
[c] This table provides the descriptive statistics for each of the types estimated through median splits. These statistics help us understand the strategy position of firms. The unit of observation is firm. Standard errors within parentheses. Number of firms are 1,059.

of the sample are highly efficient in generating patents. Panel A in Table 3 reveals that the source of competitive advantage for these firms is differentiation, as evidenced by greater than mean levels of marketing intensity. These firms have wide competitive scope and include products across diverse product markets. Such firms are also moderately efficient, as evidenced by intermediate levels of operational efficiency. Thus, while the technological capability of these firms is critical to creating value in diverse product markets, equally critical is their complementary marketing capability that differentiates these innovations or increase their relative perceived utility to appropriate value.

A canonical example of a firm in this technological capability type is Coca-Cola. The firm produces and sells about 112 products, and it operated in about five different product markets (based on four-digit SIC codes) between 1982 and 2006. The firm is renowned for its technological capability, or ability to create new products for diverse markets, as well as for its marketing and branding prowess that play a critical role in differentiating its products and appropriating value in the market. Its marketing intensity averaged nine percent during the sample period.

Type 2: Wide cost leadership

Figure 1 and Table 2 also suggest that about 32 percent of the firms had moderate innovative efficiency, as evidenced by intermediate but decreasing levels of *patents per R&D dollar*. Panel A in Table 3 suggests that in contrast to the previous capability type, the source of competitive advantage for these firms is cost leadership, as evidenced by highest levels of relative cost efficiency and significantly lower levels of marketing intensity. However,

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similar to the previous capability type, the competitive scope of firms in this type extends to a large number of product markets. Therefore, the dominant role of technological capabilities in this type is efficient creation of innovative products for diverse markets. With little emphasis on marketing to differentiate the perceived value of these products, the technological innovation itself emerges as a source of competitive value.

A classic example of a firm in this technological capability type is 3M. The company is a diversified firm that operates in markets ranging from adhesives to dental and orthodontic products to electronic materials and circuits. It operated in about seven different product markets based on a count of four-digit SIC codes between 1982 and 2006. Further, while the firm has spearheaded many innovations in these markets, including Scotch™ tape, audio tapes, and Post-it® notes, it incurs limited marketing expenditure in differentiating these products and their perceived value—its marketing intensity averaged only three percent during the sample period.

Type 3: Narrow differentiation

Figure 1 and Table 2 show that about 62 percent of the firms have low levels of innovative efficiency and focus on narrow product markets. Panel A in Table 3 suggests these firms are relatively inefficient, but have above average levels of marketing intensity. In brief, they pursue a Narrow Differentiation strategy. In turn, the strategic role of technological capability is limited in these firms that appear to rely more on marketing abilities such as branding and distribution for their success.

Our results for the three capability types are also consistent with prior research in strategy (Miller, 1986; Porter, 1980), which finds that when firms utilize neither cost leadership nor differentiation strategies, their profitability is muted relative to firms that pursue one of these strategies. Indeed, we find that profit margins of Type 3 is the lowest amongst the three capability types.

Identification of technological capability types using cluster analyses

We contrast the technological capability types obtained through GBT models with those identified through cluster analyses. We largely follow recommendations for cluster analyses offered by Bensaou and Venkatraman (1995), including use of the squared Euclidian distance as a similarity measure and Ward's minimum variance method as the method for cluster formation. We use the variance ratio criterion (VRC) index proposed by Caliński and Harabasz (1974) to determine the number of clusters in our data.

The VRC index indicates that there are two clusters in the data, descriptive statistics for which are shown in Panel B of Table 3. About 24 percent of the sample firms fit into cluster 1, which displays relatively higher levels of *patents per R&D dollar* (1.08), while the rest fit into cluster 2, which displays relatively lower levels of *patents per R&D dollar* (0.67). The results in Panel B of Table 3 also suggest that the competitive scope of firms in cluster 2 is narrower than that of firms in cluster 1 (3.71 versus 4.62). More interestingly, firms in cluster 2 seem to pursue both differentiation and cost leadership toward creating competitive value, as reflected in their relatively higher levels of relative cost efficiency (0.71 versus 0.58) as well as marketing intensity (0.02 versus 0.01). In brief, firms in cluster 2 seem to be characterized by a *Narrow Differentiation and Cost Leadership* strategy. The firms in cluster 1 emphasize differentiation over cost leadership and seem to be characterized by a *Wide Differentiation* strategy. Prior research in strategy (Porter, 1980; Porter and Siggelkow, 2008) finds that a firm's activity systems need to be fundamentally different to create low-cost versus differentiated products so that the pursuit of both strategies simultaneously results in "strategic mediocrity and below-average performance" (Porter, 1980). Not surprisingly, cluster 2 is characterized by significantly higher profit margins than cluster 1.

Identification of technological capability types based on median splits of patents per R&D dollar

As a final step, we create technological capability types using median splits of the data. Specifically, we partition our sample into firms that display above median levels of growth in *patents per R&D dollar* versus those that display below median levels of year-on-year growth in *patents per R&D dollar* (*high-growth* and *low-growth* firms). Note that Since the GBT is also based on how *patents per R&D dollar* evolve over time, we classify firms into types based on *growth in patents per R&D dollar* rather than on absolute values of *patents per R&D*

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dollar. About 50 percent of our sample comprises *high-growth* firms (*patents per R&D dollar* of 1.11), while the rest comprises *low-growth* firms (*patents per R&D dollar* of 0.71). The results in Panel C of Table 3 suggest that both categories of firms have similar marketing intensity (0.02 each); however, the low-growth firms additionally emphasize cost leadership, as evidenced by their greater efficiency of operations (0.70 versus 0.57), and operate in a narrower set of product markets (3.90 versus 4.61). Thus, the business strategies of these two groups mirror those of the clusters—as in the case of cluster 2, the low-growth firms pursue a *Narrow Differentiation and Wide Cost Leadership* strategy while the high-growth firms, as in the case of cluster 1, pursue a *Wide Differentiation* strategy. As might be expected, the high-growth firms are characterized by greater profit margins than low-growth firms.

The results suggest that the types created by GBT models take into account both the level and the evolution of *patents per R&D dollar* over time. In turn, the capability types differ from those created by median splits of the data and cluster analyses. Notably, GBT models create an intermediate type that is masked by the capability types in cluster analyses. In what follows, we explore if these differences matter not only for the impact of technological capability on performance, but also for variance in the moderating effect of MFT on the performance impact of technological capability by capability type.

Regression analyses of technological capability types

Table 4 reports results for the performance impact of technological capability, the moderating effect of MFT on this relation, and variation in the moderating effect of MFT by capability type. Following prior literature (e.g., Griliches, 1981; Hall, 1993), we start with the regression of *TQ* on technological capability along with controls. Specifically, we use a linear specification in which we include size, market share, market concentration, and patent concentration along with 24 year dummies and 43 two-digit SIC code dummies as controls. This baseline specification, reported in specification 1, does not distinguish between technological capability types. We estimate the relationship between technological capability and MFT using the interaction between our measures of technological capability and MFT, that is, interaction between *patents per R&D dollar* and *high assignment dummy.* The results of specification 1 suggest that higher technological capability is associated with superior firm performance. Also when MFT is low, a 10 percent increase in technological capability increases TQ by about 0.2 percent. However, when MFT is high, an equivalent increase in technological capability increases TQ by a statistically insignificant 0.1 percent (std. err. is 0.01; $p-$value is 0.29). These results are in line with the literature, which suggests that while superior technological capability improves performance, the advent of MFT mutes this importance of technological capability for performance (Arora and Nandkumar, 2012).

In specification 2, as an alternative to the interaction between *technological capability* and *MFT*, we create discrete firm types using median splits of the data to explore if the moderating impact of technological capability on performance varies by firm types. Note that the *high-* and *low-growth* types are created based on growth of *patents per R&D dollar*, so they reflect differences in how efficiently firms generate patents. We find that the results are qualitatively similar to those in specification 1. The *high-growth* type performs better than *low growth* type only when MFT is low (*high assignment = 0)* with the *TQ* of *high-growth* firms about four percent higher. However, when MFT is high, the *TQ* of the *high-growth* type is about the same as that of the *low-growth* type (net effect is 0.01, std. err. is 0.01; $p-$value is 0.36).

In specification 3, we explore how the moderating influence of MFT on the performance impact of technological capabilities varies by the clusters created by cluster analysis. To this end, we interact the *cluster 2* dummy (equal to 1 if a firm fits into cluster 2) with the *high assignment* dummy. The coefficient for the *cluster 2* dummy is negative and significant. Recall that firms in cluster 2 are less efficient in generating patents. As such, this result suggests that firms that are relatively inefficient in generating patents also perform worse on average. The results of specification 3 suggest that the *TQ* of firms in cluster 2 is about four percent lower when MFT is low. Thus, these results also suggest that firms that are more efficient in generating patents perform especially better when MFT is low. However, when MFT is high, the performance differential between technologically superior and inferior firms is lower. Firms in cluster 2 perform only two percent worse than those in cluster 1 when

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Table 4. Regressions of the influence of patents and MFT on performance

	OLS Spec. 1	Median split Spec. 2	Cluster analysis Spec. 3	GBT Spec. 4
Market concentration	0.02	0.01	0.00	0.01
	(0.03)	(0.04)	(0.03)	(0.04)
Market share	0.15***	0.12***	0.12***	0.09***
	(0.03)	(0.04)	(0.04)	(0.03)
Technological capability	0.02***			
	(0.00)			
Size	−0.02***	−0.01**	−0.01**	−0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Patent concentration	−0.02 *	−0.05**	−0.05**	−0.05**
	(0.01)	(0.02)	(0.02)	(0.02)
High growth		0.04***		
		(0.01)		
Markets for technology (MFT)	−0.05***	−0.01	−0.06**	0.00
	(0.01)	(0.01)	(0.03)	(0.01)
Tech. capability × MFT	−0.01***			
	(0.00)			
Cluster 2 dummy			−0.04***	
			(0.01)	
Wide cost leadership				0.07***
				(0.01)
Wide differentiation				0.17***
				(0.02)
MFT × *high growth*		−0.03***		
		(0.01)		
MFT × *cluster 2 dummy*			0.02***	
			(0.00)	
MFT × *wide cost leadership*				−0.04***
				(0.01)
MFT × *wide differentiation*				−0.01
				(0.02)
Constant	0.18	0.22	0.16	0.16
	(0.17)	(0.15)	(0.15)	(0.15)
R^2	0.48	0.47	0.46	0.47
Year dummies	24	24	24	24
N	26,475	26,475	26,475	26,475
Firms	1,059	1,059	1,059	1,059

This table reports OLS estimates of regressions of TQ to understand how the performance of firms varies by technological capability and MFT. Spec. 1 is a baseline specification that explores how MFT moderates the performance impact of technological capability. Spec. 2 uses technological capability types created using median splits of the data to understand how the performance impact of technological capability varies by capability type. Spec. 3 uses capability types created using cluster analysis to understand how the performance impact of technological capability varies by capability type. Spec. 4 uses capability types created using GBT to understand how the performance impact of technological capability varies by capability type. Standard errors within parentheses.
***Significant at 1%; **significant at 5%; *significant at 10%.

the *high-assignment* dummy = *1* (net effect is 0.02, std. err. is 0.01; p−value is 0.09).

Finally, in specification 4, we explore how the moderating influence of MFT on the performance impact of a firm's technological capability varies by the technology types created by GBT models. To this end, we use two capability type dummies—*Wide Cost Leadership* and *Wide Differentiation*—as well as their interactions with MFT. The results of specification 4 suggest that the set of firms that have the highest number of *patents per R&D dollar* or the *Wide Differentiation* type perform the best amongst all capability types. Their TQ is about 17 percent higher than that of *Narrow Differentiation* type, which is the excluded or baseline category. Firms that have an intermediate number of patents per R&D dollar or the *Wide Cost Leadership* type also perform better than the *Narrow Differentiation* type, but only seven percent better. Recall from Table 3 that, while *Narrow Diferentiation* has the lowest amount of patent stock, the *Wide Differentiation* type has an intermediate stock of patents. *Wide Cost Leadership* type has the highest patent stock. Thus, these results suggest that the efficiency with which a firm generates its patents matters more for performance than its patent stock. To the extent that superior technological capability implies lower cost of R&D per patent, these results are consistent with prior literature, which suggests that technological capability positively impacts performance. Further, note that these conclusions are not as explicit for our results for capability types obtained through median splits or cluster analysis in which firms that generate higher numbers of patents per R&D dollar also hold more patents.

Specification 4 also suggests that the evolution of MFT does not affect the *Narrow Differentiation* and *Wide Differentiation* categories whereas it affects the *Wide Cost Leadership* type the most—the coefficient of the interaction between the *Wide Differentiation* type and MFT (*high assignment* dummy) is a statistically insignificant -0.01, which suggests that the evolution of MFT has no effect on the *Wide Differentiation* type. Similarly, MFT has no effect on the *Narrow Differentiation* type either as evidenced by the statistical insignificance of the coefficient of MFT (0.00; std. err – 0.01). However, the interaction between MFT and *Wide Cost Leadership* is a statistically significant -0.04, suggesting that TQ declines by four percent for this type with the advent of MFT (net effect is 0.03; std. err. 0.02; *p*-value 0.07). These results are consistent with the strategic position underlying the capability types—for the *Wide Cost Leadership* type, the pace of technological innovation for diverse markets is a dominant source of competitive value, while in the other two categories, complementary capabilities, specifically marketing capabilities that appropriate the value created through technological innovation, are a distinctive source of competitive advantage. Not surprisingly, MFT has a less adverse impact in the latter two types.

To conclude, the results of the analysis that use GBT suggests that the performance of firms, whose strategic position is based on technological competence, is negatively impacted when MFT are extensive, whereas that of firms whose strategic position is also based on other complementary capabilities is relatively unaffected. In contrast, results that use the types produced by cluster analysis and median splits suggest that the performance impact of technological capability for firm types, whose underlying strategic position is neither based on technological competence nor on complementary capabilities, is unaffected by MFT, whereas the performance impact of technological capability is muted for firms, whose strategic position is based on both technological and complementary capabilities.

DISCUSSION

The broad focus of strategy research is to understand which firm resources, capabilities, firm attributes, and environmental conditions drive superior performance. This study introduces GBT models as a powerful technique to identify heterogeneity in the above-mentioned parameters, especially when researchers cannot develop suitable proxies for such heterogeneity. GBT models, an application of finite mixture models, offer a powerful alternative to existing data driven methods such as cluster analysis to facilitate robust identification of heterogeneous firm types along an attribute of interest. In contrast to extant methods, GBT models consider both the magnitude or levels of an attribute and how it accumulates over time to empirically identify firm types in the data.

We apply GBT models to study how the moderating effect of MFT on the performance impact of a firm's technological capability varies by technology capability types that are *ex-ante* unobserved by the researcher. In order to illustrate the properties of GBT models, we compare the insights obtained from analyses of technological capability types identified through GBT models with analyses of the capability types identified through other techniques commonly used by strategy researchers, namely, median splits and cluster analysis. We find that GBT models offer new insights on how the moderating effect of MFT varies by firm types. Our results indicate that the performance of firms whose strategic position is based on technological competence is negatively impacted when MFT are extensive, whereas that of firms whose strategic position is also based on other complementary capabilities is relatively unaffected. In contrast, results of regressions that use the types engendered through cluster analysis and median splits suggest that the performance impact of technological capability for firm types whose underlying strategic position is neither based on technological competence nor on complementary capabilities is unaffected by MFT.

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Further, the performance impact of technological capability is muted for firms whose strategic position is based on both technological competence and complementary capabilities.

Our study, therefore, emphasizes many advantages of GBT models over traditional empirical approaches, such as regression and cluster analyses. While standard panel data regression methods such as fixed effects are not parsimonious enough to enable *ex-post* theorization of the role of heterogeneity, other techniques such as median splits or cluster analysis may not be appropriate when the variable of interest evolves over time. Given GBT models use both the level of the variable of interest as well as how it evolves over time to group firms into types, they are suited to analyzing a wide array of topics in strategic management. For example, while the literature suggests that firms learn from export participation, it is unclear which firms, notably technologically sophisticated versus unsophisticated firms, benefit from export participation. One view is that the extent of gains from export participation is higher for technologically superior firms relative to technologically inferior firms due to the former class of firms being endowed with higher amounts of absorptive capacity (Aw, Roberts, and Winston, 2007; Salomon and Jin, 2010). Another view is that superior firms that are closer to the technological frontier may learn less from exporting relative to inferior firms that are farther away from the frontier (Greenaway and Kneller, 2007). GBT models can be used to discern different types of firms based on their *ex-ante* productivity, and for each of these types, can discern the impact of entry into export markets on their productivity.

As another instance, prior research (e.g., Moeller, Schlingemann, and Stulz, 2005) finds that mergers and acquisitions, on average, destroy shareholder wealth in acquiring companies. However, there is also evidence that this outcome may vary by firm type. For example, Moeller, Schlingemann, and Stulz (2004) show that the documented post-acquisition loss in shareholder value is an outcome of the significant shareholder loss experienced in large firms; acquisitions by smaller firms create value for shareholders. However, the identification of bases for heterogeneity in post-acquisition returns such as size may be difficult to identify a priori. In such cases, the researcher can use GBT models to estimate performance types based on post-acquisition returns and then profile each performance type using observed parameters, including resources and capabilities of constituent firms, to understand the bases of heterogeneity. Such analyses can help the researcher infer capabilities that drive performance differences amongst acquirers.

Like most methods, GBT models suffer from certain limitations. First, since GBT models use longitudinal sequences of observations to discern unobserved firm types, they are not very useful for the analysis of cross-sectional data. In such cases, cluster analysis may be a useful alternative. Second, as we noted earlier, unobserved firm types are estimated along with the relation between firm behavior/actions and performance. While we control for a set of factors that may also determine the unobserved types, that GBT models use maximum likelihood implies that controlling for several time-varying or time-invariant exogenous factors renders the method computationally intensive. Linear regressions, such as ordinary least squares, are better suited to control for a variety of exogenous factors. Finally, other disadvantages of the maximum likelihood technique apply to GBT models as well, the most prominent being that the method can be biased in small samples, and in many cases, may not converge to a global maximum.

Despite these limitations, we believe that GBT models have significant potential to help strategic management researchers discern unobserved heterogeneous firm types. An understanding of the strategic dissimilarities between firms that contribute to persistent performance differences is fundamental to strategy research. GBT models provide a rigorous statistical basis for identifying unobserved types in populations based on an organizational attribute, and in turn, inferring the underlying effect of certain strategies. We hope this article encourages more researchers to both use this method and develop novel extensions that would strengthen its applicability to strategic management research.

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