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Product proliferation, complexity, and deterrence to imitation in differentiated-product oligopolies

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Research Summary: Game theory suggests that, in oligopolistic markets characterized by nonprice competition, dominant incumbents can use product proliferation to occupy a region of the product space (i.e., a subspace) and deter rivals from imitating their products. In part, this is because product proliferation makes the introduction of close substitutes comparatively less profitable; in part, it is because the strategy conveys a threat of retaliation to potential imitators. Yet this threat is only credible if the proliferator has high costs of exit from the occupied region of space. We hypothesize that complexity, as a property of product (sub)spaces, generates exit costs for the proliferator and increases the deterrent power of its strategy. We test this hypothesis by studying sequential product introductions in the U.S. recording industry, 2004–2014.

Managerial Summary: Differentiated-product markets are often concentrated in the hands of a few dominant organizations, which strive to keep on equal footing by offering similar products. In these markets, a product proliferation strategy can help one of the dominant incumbents claim a particular submarket as its territory. Investing heavily in that submarket communicates a threat that the proliferator will retaliate against invaders to protect these investments. However, this threat is not credible enough to deter rivals unless the occupied submarket is sufficiently complex in terms of product attributes, as precisely this kind of complexity makes it harder for proliferators to back down if challenged. We find evidence of this mechanism in an analysis of product competition among major record companies and discuss implications for strategic decision-making.
1 | INTRODUCTION

Product proliferation is the strategy whereby a firm extends its product offer in a market or submarket so as to saturate the product space and minimize unmet demand (Mainkar, Lubatkin, & Schulze, 2006). This is a common strategy in industries characterized by nonprice competition, where large incumbents often use it to maintain an oligopolistic market structure (Connor, 1981). Schmalensee (1978) reported an example from the U.S. breakfast cereal industry, where four conglomerates—Kellogg, General Foods, General Mills, and Quaker Oats—launched such a vast number of new products between 1950 and 1972 that they were brought to trial by the Federal Trade Commission. Shaw (1982) described a similar pattern in the U.K. chemical industry, where Fisons, Imperial Chemical Industries (ICI), and Shell virtually hijacked the fertilizer market during the years 1958–1978. In the wake of these reports, Brander and Eaton (1984), Judd (1985), and Wernerfelt (1986) delivered formal proofs that, when a market has the traits of a differentiated-product oligopoly, firms' sequential decisions about the attributes of products to be offered on the market can lead to subgame perfect equilibria where each competitor monopolizes a submarket via product proliferation. This is because firms tend to grow reliant on different pockets of demand and strive to minimize local competitive intensity: filling a region of the product space (i.e., a subspace) with own products helps toward this purpose by making it less profitable for rivals to introduce similar products (Barroso, Giarratana, Reis, & Sorenson, 2016) and conveying the threat of retaliation against those who invade the proliferator's “turf.”

This deterrent mechanism finds its natural justification in Eaton and Lipsey's (1979) theory of spatial preemption. Because of it, a product proliferation strategy can raise barriers to imitation that protect a firm against new entrants (Salop, 1979), nonoligopolist incumbents (Caves & Porter, 1977), and even other oligopolists, provided these sell products in multiple subspaces and the proliferator's threat is credible to them (Gilbert & Matutes, 1993). Our research note focuses precisely on deterrence among oligopolists who are active in multiple subspaces. We think this phenomenon deserves consideration because it is highly consistent with models of spatial competition (Lancaster, 1990) but enjoys little empirical support. In fact, previous tests are few and far between, and sometimes provide no evidence of deterrent effects (Bayus & Putsis, 1999). Rather than pointing to a failure of game theory, we believe previous tests suffered from three limitations: first, they looked for deterrence by estimating firms' pricing behavior instead of their probability to introduce imitative products; second, they viewed the market as a homogeneous space and did not consider that proliferators can target submarkets or subspaces; third, they ignored variance in product space complexity, which recent research on this journal showed to moderate product proliferation's effects (Barroso & Giarratana, 2013). Addressing these problems, we aim to provide a more direct and focused test of deterrence.

Following Barroso and Giarratana (2013), we define the complexity of a product (sub)space as a function of heterogeneity and interdependence in the attributes of products offered in this (sub)space.

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This is a game where firms' payoffs depend on the attributes of products they decide to offer on the market, the distribution of demand, and the product-attribute decisions of few rivals (Mazzeo, 2002).
We adopt the authors’ approach to measuring complexity by way of heterogeneity, while interdependence is held constant throughout the study period. We argue that greater product-attribute heterogeneity generates coordination costs that proliferators tend to offset by developing more intricate organizational structures (Zhou & Wan, 2017). These intricacies, in turn, give rise to exit costs by impeding later structural modifications (Hannan, Pólos, & Carroll, 2003a, 2003b), and because of costly exit, a proliferator’s threat of retaliation appears more credible to rivals (cf. Eaton & Lipsey, 1980). Hence, we posit that proliferating products in a more complex subspace have a stronger deterrent effect. Our findings contribute to strategic management theory by extending Barroso and Giarratana’s (2013) arguments on the moderating role of product space complexity and examining its influence on rivals’ product launch decisions. In addition, they point to promising but unexplored connections between studies on deterrence in industrial organization and the strategy literature on imitation (Ethiraj, Levinthal, & Roy, 2008).

2 | THEORY AND HYPOTHESES

Before explaining how product space complexity affects the relationship between product proliferation and deterrence, it is useful to provide an informal account of why deterrence is expected in the first place.\(^2\) We begin by characterizing the market as a multidimensional space where each axis represents a product attribute (Lancaster, 1990). In this abstract variant of Hotelling’s (1929) locational model, demand is represented by a set of points that correspond to consumers’ ideal product specifications. Firms, instead, are represented by sets of points that correspond to the products they currently offer on the market. Competition takes the form of a sequential game that revolves around location choice (Bonanno, 1987). The proportion of demand captured by a firm at any given time (i.e., its payoff) depends on the distance between its products and consumers. Over time, both consumers and firms can alter their locations in the product space: in the one case, this is because consumer preferences are inherently dynamic (Barroso et al., 2016); in the other, it is because a firm can introduce new products to keep up with shifting preferences or respond to rival firms’ behavior (Sorenson, 2000). It is generally advantageous for firms to occupy new locations in the product space if this enables them to steal demand from rivals, or if it prevents rivals from capturing demand that they intend to meet in the future.

Deterrence involves altering the payoffs of other firms in such a way that hostile decisions appear less attractive (Schelling, 1956). There are two reasons why this can be achieved by a product proliferation strategy.\(^3\) One reason is that this strategy allows a firm to tighten extant gaps within its product offer in a particular submarket, leaving smaller demand available to rivals’ products (Lanzillotti, 1954).\(^4\) The other reason, arguably more fascinating to game theorists, involves considerations about

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\(^2\)For a formal account, we refer the reader to game-theoretic literature (Gilbert & Matutes, 1993).

\(^3\)Barroso and Giarratana (2013) distinguish at least two kinds of product proliferation, depending on whether the proliferator’s products are brand new or they are merely new versions of existing products. Our analysis applies to the case where products are brand new. In case of versioning (see Giarratana & Fosfuri, 2007), additional factors can have a bearing on deterrence that we do not consider here, such as brand reputation (Choi & Scarpa, 1992). In our empirical study, we strictly consider original products.

\(^4\)For completeness, we should note that smaller demand remains available for the proliferator’s own products as well, an effect that Lanzillotti (1954) termed “self-competition.” Barroso and Giarratana (2013) refer to this as a form of cannibalization, and list it as a possible adverse effect of product proliferation when this strategy takes the guise of versioning. We assume that cannibalization is of little concern to firms in our analysis: we find this reasonable theoretically because we do not consider versioning (see Footnote 3), and empirically because we analyze an industry where product life cycle is notoriously short.
threats and commitments (Eaton & Lipsey, 1980). By sinking its investments in a product subspace, a proliferator threatens its potential imitators with an escalation of competitive intensity, which can be achieved via price competition, if this is allowed, or more simply via relentless advertising (Roberts & Samuelson, 1988). If the proliferator's costs of exit from the occupied subspace are substantial enough to make the realization of this threat not only possible but rational, that is, if the proliferator is committed, then its threat is credible and effectively keeps competitors in check (Judd, 1985). As a result, a product proliferation strategy can lead to a subgame perfect Nash equilibrium (Gilbert & Matutes, 1993).

We are interested in evaluating this game-theoretic argument in the context of nonprice competition among rival oligopolists who keep a foothold in multiple submarkets. Natividad and Sorenson (2015) highlighted some of the destructive implications a local increase in competitive intensity can have in this situation: studying U.S. film distributors during the period 1985–2009, the authors found that companies reacted to tighter competition in the submarket for theatrical releases by diverting resources away from the submarket for home videos, leading to a decrease in their home video sales. Thus, a threat that was originally localized to one submarket spiraled into market-wide disruption. Karnani and Wernerfelt's (1985) theory of multiple-point competition provides a general rationale for this dynamic: a local conflict can turn into a war that leaves participants vulnerable in other regions of the product space where they are active. Because firms are aware that imitating a proliferator's products can trigger such an escalation, their optimal strategy can be not to imitate, that is, to differentiate their products from the proliferator's. A literal application of Karnani and Wernerfelt's (1985) theory would require both the proliferator and its would-be imitator to be active in the same regions or subspaces, but in fact, it suffices for the latter to be active in at least one subspace other than the one targeted by the former. This is enough for the imitator to incur vulnerabilities that competitors can exploit, as in the case detailed by Natividad and Sorenson (2015). Hence, we hypothesize:

**Hypothesis 1 (H1) (Baseline)** If an oligopolist introduces a greater number of new products in a subspace, then the probability of new product introductions in this subspace by rival oligopolists who are active in at least one other subspace decreases.

Through the deterrence implied by Hypothesis 1, product proliferation can generate quasi-rents that improve the proliferator's competitive performance. However, much like the other effects of product proliferation on performance (see Barroso & Giarratana, 2013), deterrence can be moderated by product space complexity. Strategy scholars generally argue that interdependence, one of the two components of complexity, prevents imitation by inducing causal ambiguity (Reed & DeFillippi, 1990). As a result, complex strategies are hard to copy (Rivkin, 2000), complex information is resistant to transfer (Sorenson, Rivkin, & Fleming, 2006) and complex products are difficult to retro-engineer (Pil & Cohen, 2006). But product space complexity can also deter imitation through its other component, that is, heterogeneity. This is because sinking one's investments in a region of the market where product attributes are more heterogeneous can create coordination problems in manufacturing (MacDuffie, Sethuraman, & Fisher, 1996), distribution (Zhou & Wan, 2017) and relations with external partners (Mol & Wijnberg, 2007). Firms tend to address these problems by setting up ad hoc routines (Gupta & Srinivasan, 1998) and decentralizing their decisions (Siggelkow & Rivkin, 2005): in this sense, the complexity of a product subspace engenders complexity in organizational structures. Once in place, a complex structure makes the firm averse to change, to the point that even small modifications can have disastrous repercussions (Hannan et al., 2003a). This creates exit costs from the occupied subspace, especially in terms of opportunity (Hannan et al., 2003b).
As noted by Judd (1985), it is exactly in the presence of high exit costs that product proliferation makes a credible deterrent (cf. Thomas, 1996). If a firm deploys this strategy in a less complex subspace, it encounters fewer coordination problems and can maintain a more versatile structure, so that in the presence of an imitator it will be less motivated to put up a fight. Its rational course of action in this case could be to pivot to another region of the market. Rivals would be aware of this because they can also observe complexity or the lack thereof, experiencing its effects on their internal operations. If complexity is low, they can conclude that the proliferator is not committed to its threat. If complexity is high, however, the proliferator normally has to adapt its structure, and because it faces greater exit costs, it can no longer shy away from fighting—this option comes to dominate retreat (Eaton & Lipsey, 1980). Insofar as rivals are aware of this, the threat of retaliation appears credible to them. For this reason, we expect product proliferation to more strongly deter the introduction of imitative products in more complex subspaces. Hence:

**Hypothesis 2 (H2) (Moderation)**

If an oligopolist introduces a greater number of new products in a more complex subspace, then the probability of new product introductions in this subspace by rival oligopolists who are active in at least one other subspace decreases more.

### 3 | METHODOLOGY

We test our hypotheses by analyzing patterns of sequential product introductions in the U.S. recording industry, 2004–2014. This is an ideal setting because products’ prices are conventionally fixed for particular formats (such as singles), there is a short product life cycle, and the costs of new product introductions for established incumbents are relatively low (Benner & Waldfogel, 2016). Much like in related industries (e.g., Berry & Waldfogel, 2001), these conditions motivate the firms to introduce marginally different products in order to deter their rivals. The U.S. recording industry is also a good setting because there is a well-defined and close-knit group of oligopolists, that is, the major record companies, who carefully monitor each other’s strategies and use them as a basis for their own decisions (Huygens, van den Bosch, Volberda, & Baden-Fuller, 2001). As these firms imitate each other by default (cf. Kennedy, 2002), changes in their pattern of behavior are easier to observe empirically. Finally, this setting suits our purpose because the various regions or subspaces whereby the market for recorded music is partitioned—that is, genres and subgenres—can differ greatly in complexity (Percino, Klimek, & Thurner, 2014).

We collect product and firm-level data from several online sources, including Billboard, Discogs, and MusicBrainz. Data on product attributes are obtained from AcousticBrainz, a platform that creates acoustic fingerprints of songs using machine-learning algorithms (Porter, Bogdanov, & Serra, 2016). Our dataset consists of 8,263 original singles released during our study period, of which 416 were released directly or indirectly (i.e., through subsidiaries or imprints) by one of four majors: Sony, Universal, Warner, and Electric and Musical Industries (EMI). Original release dates in the U.S. are obtained from MusicBrainz. The submarkets to which singles belong are determined by genre and subgenre (or “style”) tags retrieved from Discogs. To minimize the chance of error, our dataset includes only singles for which MusicBrainz provides an exact cross-reference to Discogs. The singles are distributed across 14 genres and 221 styles: both levels of classification serve to

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5See Askin and Mauskapf (2017) for a study of product differentiation based on similar acoustic data.
divide the product space into submarkets in the eyes of record companies (Montauti & Wezel, 2016; Phillips & Kim, 2009), but we focus on styles because Discogs genres can be very broad (e.g., “pop,” “rock,” “jazz”), and at this level of analysis deterrent effects could be very difficult to identify. In addition, partitioning the market into styles affords a greater number of firm-submarket spells, thereby increasing the statistical power of our test. Because EMI exited the industry at the end of 2011, we tally 9,061 major-style-year combinations, which constitute observations in our preliminary sample. Our choice of yearly spells agrees with previous research on product strategies in differentiated-product markets (Giachetti & Dagnino, 2014).

Our dependent variable is the number of singles released by a major in a given style-year (OwnSingles). Because this is a count variable that violates assumptions of equivariance (Cameron & Trivedi, 1990), we estimate it using a quasi-Poisson generalized linear model. To capture the effect of product proliferation, we compute the maximum number of singles released by a rival major in the focal style-year (Proliferation). A higher value of this variable indicates that one of the rivals is pursuing a product proliferation strategy. The degree of heterogeneity in product attributes within a subspace, which corresponds to the subspace's level of complexity when interdependence is fixed (Barroso & Giarratana, 2013), is computed on the basis of nine audio properties that AcousticBrainz showcases to summarize the fingerprint of songs, including track length, primary key, scale and frequency of the primary key, most frequent key of the chord progression, scale of the most frequent chord progression key, “dance-ability” (see Streich & Herrera, 2005), average number of beats per minute, and total count of beats. With these dimensions in hand, we define a product space based on a Mahalanobis metric (see also Liu, Montauti, & Piazzai, 2018), which accounts for interdependence by learning it from the covariance of spatial coordinates (Xiang, Nie, & Zhang, 2008). We then calculate the centroid of each style during each year of observation and compute the Mahalanobis distance of each product in the style-year from this centroid. The mean distance increases with the degree of heterogeneity in product attributes and constitutes our measure of complexity (Complexity).

We control for the total number of products introduced within the style-year by all the major (MajorSingles) and nonmajor record companies (IndieSingles). We also control for the total number of products released by the focal major in any style during the current year (PortfolioSize). To account for variance in majors' performance, we compute a score based on the ranking of the major's singles on the Billboard Hot 100. This chart is universally considered an indicator of competitive success in the recording business (Anand & Peterson, 2000): it ranks singles on a weekly basis using Nielsen SoundScan data on physical and digital sales, downloads, and streaming. We use this information to compute a weighted score (Performance) for each major-style-year according to the formula: $\sum_{s \in S} \sum_{i=1}^{W_s} \left( \frac{(101 - r_{si})}{100} \right)$, where $S$ is the set of singles released by the major in the style-year, $W_s$ is the number of weeks that single $s$ was on the chart, and $r_{si}$ is the rank achieved by single $s$ in week $i$, from highest ($r_{si} = 1$) to lowest ($r_{si} = 100$). In addition, we control for majors' level of diversification by calculating the yearly concentration of their products across styles through a Herfindahl–Hirschman index (Diversification). Finally, we account for variance in demand through a weighted score (Demand) analogous to the one used for Performance except that $S$ in this case represents the set of products released by any major or nonmajor within the style-year. Therefore, a greater value of this variable indicates that products in a given style-year sold more copies on the U.S. market.

Every predictor is lagged by 1 year so that the value of OwnSingles at year $t$ is estimated as a function of independent variables at $t - 1$. This causes the loss of 884 observations relative to 2004.

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6 We subtract the value of Proliferation when computing MajorSingles to prevent collinearity.

7 See Piazzai and Wijnberg (2017) for another use of the same score in a study of firm performance.
We specify fixed effects for majors, years, and genres. To control for possible feedback effects, we include a lagged value of the dependent variable in the list of predictors. We note that many styles on Discogs are peripheral to the recording industry and witness no releases during some years of observations, which impedes the computation of Complexity. Wherever possible, we fill in the missing values by looking to the previous style-years and allowing the last known value of Complexity to carry over. As a result, our final sample includes 6,069 major-style-years with complete data. Postestimation diagnostics suggest that none of them has excessive leverage (Cook's $D > 1$).

## RESULTS

Table 1 reports the descriptive statistics and pairwise correlations of the variables involved in our regression models. Most predictors are significantly correlated with the dependent variable, and some of them are strongly correlated with each other, but collinearity is not of concern as the conditioning number of the data matrix (6.12, further reduced to 3.77 after mean-centering) is well below the threshold 30 recommended by Belsley, Kuh, and Welsch (1980). We standardize all the independent variables before regression to facilitate comparison of effect sizes in our table of estimates (Table 2). We begin our analysis with a specification that includes only control variables (Model 1), then we add Proliferation (Model 2), Complexity (Model 3), and finally their interaction (Model 4). The coefficients in Table 2 represent additive effects on the logarithm of the expected count of new releases by the focal major. To compute effects on the probability of a release, the coefficients should be exponentiated to obtain incidence risk ratios (IRRs). For example, a coefficient of 0.50 corresponds to an IRR of $e^{0.50} = 1.65$, which implies that a 1-unit increase in the predictor—or a one-SD increase, if the predictor is standardized—leads to a 65% greater probability of new product introduction. In presenting marginal effects below, we rescale the coefficients from Table 2 so that they can be interpreted as effects of 1 unit increases on the original (i.e., nonstandardized) scale of the independent variables. We automatically convert these into IRRs and report 95% confidence intervals (CIs).

Our estimates are stable throughout hierarchical models, and tests of deviance show that each additional predictor significantly adds to model fit. For brevity, we only describe the results from Model 4. We find that all predictors except Diversification (IRR = 1.26, CI = [0.63, 2.53]) and MajorSingles (IRR = 0.98, CI = [0.89, 1.08]) lead to significant changes in the value of the dependent variable: more specifically, we find positive effects for lagged OwnSingles (IRR = 1.32, CI = [1.24, 1.40]), which suggests that majors tend to replicate their previous launch decisions; for Demand (IRR = 1.01, CI = [1.01, 1.01]), which indicates that majors tend to target subspaces where consumer preferences are concentrated; and for IndieSingles (IRR = 1.06, CI = [1.04, 1.08]), which suggests that greater activity by independent record companies prompts majors to release products of their own. We find a negative effect for PortfolioSize (IRR = 0.95, CI = [0.92, 0.97]), which is likely to be a consequence of resource constraints (cf. Natividad & Sorenson, 2015), and Performance (IRR = 0.99, CI = [0.98, 1.00]), which indicates that greater sales for products in a particular subspace induce majors to abstain from further product introductions. This could be because successful singles continue to sell into the following year, and the majors do not need to release additional products to defend their current position in the subspace.

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8We specify genre- instead of style-fixed effects to avoid overparametrization. Using styles for this purpose would require the inclusion of 220 binary variables instead of 13.

9Regression with non-standardized independent variables produces qualitatively identical results.
### TABLE 1 Descriptive statistics and pairwise correlations

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>OwnSingles</td>
<td>0.10</td>
<td>0.50</td>
<td>0</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>OwnSingles(_t)</td>
<td>0.10</td>
<td>0.51</td>
<td>0</td>
<td>10</td>
<td>0.61 (0.000)</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>PortfolioSize(_t)</td>
<td>10.75</td>
<td>7.95</td>
<td>0</td>
<td>35</td>
<td>0.12 (0.000)</td>
<td>0.14 (0.000)</td>
</tr>
<tr>
<td>4</td>
<td>Performance(_t)</td>
<td>0.36</td>
<td>3.41</td>
<td>0</td>
<td>88.08</td>
<td>0.38 (0.000)</td>
<td>0.60 (0.000)</td>
</tr>
<tr>
<td>5</td>
<td>Diversification(_t)</td>
<td>0.14</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
<td>-0.01 (0.356)</td>
<td>-0.04 (0.001)</td>
</tr>
<tr>
<td>6</td>
<td>Demand(_t)</td>
<td>5.03</td>
<td>20.17</td>
<td>0</td>
<td>203.39</td>
<td>0.45 (0.000)</td>
<td>0.52 (0.000)</td>
</tr>
<tr>
<td>7</td>
<td>IndieSingles(_t)</td>
<td>1.05</td>
<td>2.82</td>
<td>0</td>
<td>32</td>
<td>0.47 (0.000)</td>
<td>0.50 (0.000)</td>
</tr>
<tr>
<td>8</td>
<td>MajorSingles(_t)</td>
<td>0.08</td>
<td>0.49</td>
<td>0</td>
<td>8</td>
<td>0.41 (0.000)</td>
<td>0.39 (0.000)</td>
</tr>
<tr>
<td>9</td>
<td>Proliferation(_t)</td>
<td>0.26</td>
<td>0.88</td>
<td>0</td>
<td>11</td>
<td>0.42 (0.000)</td>
<td>0.44 (0.000)</td>
</tr>
<tr>
<td>10</td>
<td>Complexity(_t)</td>
<td>2.01</td>
<td>2.20</td>
<td>0</td>
<td>11.15</td>
<td>0.22 (0.000)</td>
<td>0.22 (0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
</tbody>
</table>

Note: *p*-values in parentheses.
With regard to our predictors of theoretical interest, we find Proliferation to be associated with a greater probability of new product introduction by the focal firm (IRR = 1.65, CI = [1.27, 2.14]). If the maximum number of products introduced by a rival is 1-unit higher, ceteris paribus, then the focal firm's probability to release a similar product increases by 65%. Consistently with previous research (Huygens et al., 2001), this is indicative of strong imitative tendencies among the major record companies, which just like oligopolists in other creative industries (Kennedy, 2002) tend to replicate each other's product launch decisions. All else being equal, product proliferation seems to trigger a reaction that prevents one of the majors from taking over a subspace. It remains to be assessed whether this relationship is moderated by complexity. In and of itself, Complexity is associated with a greater probability of new product introduction (IRR = 1.38, CI = [1.29, 1.47]), which makes sense because our measure of complexity is driven by heterogeneity and more heterogeneous subspaces allow for greater differentiation.

However, Complexity also changes the effect of Proliferation. The interaction between these variables is negative ($p = 0.005$) and the size of the coefficients points to a complete reversal of Proliferation's effect as Complexity increases. Indeed, if Complexity is 1 unit above its mean, then a 1-unit increase in Proliferation leads to a 44% increase in the focal major's probability to introduce a similar product (IRR = 1.44, CI = [1.11, 1.87]). This is still a positive effect, but smaller than what we have at mean Complexity. If Complexity is 2 units above the mean, instead, then the positive effect disappears (IRR = 0.96, CI = [0.74, 1.25]). But there is no evidence of deterrence yet: this emerges only if the value of the moderator increases further. If Complexity is set to the observed maximum, then a 1-unit increase in the value of Proliferation leads to a 63% decrease in the probability of imitation (IRR = 0.37, CI = [0.28, 0.48]). This effect is just as strong as what we have at mean Complexity but goes in the opposite direction. In such an extremely

### TABLE 2 Quasi-Poisson generalized linear estimates

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−17.44 (0.978)</td>
<td>−17.49 (0.978)</td>
<td>−17.59 (0.978)</td>
<td>−17.49 (0.978)</td>
</tr>
<tr>
<td>OwnSingles$_{-1}$</td>
<td>0.16 (0.000)</td>
<td>0.16 (0.000)</td>
<td>0.14 (0.000)</td>
<td>0.14 (0.000)</td>
</tr>
<tr>
<td>PortfolioSize$_{-1}$</td>
<td>−0.44 (0.000)</td>
<td>−0.42 (0.000)</td>
<td>−0.41 (0.000)</td>
<td>−0.43 (0.000)</td>
</tr>
<tr>
<td>Performance$_{-1}$</td>
<td>−0.05 (0.000)</td>
<td>−0.04 (0.000)</td>
<td>−0.03 (0.011)</td>
<td>−0.04 (0.006)</td>
</tr>
<tr>
<td>Diversification$_{-1}$</td>
<td>0.02 (0.619)</td>
<td>0.03 (0.416)</td>
<td>0.03 (0.454)</td>
<td>0.02 (0.525)</td>
</tr>
<tr>
<td>Demand$_{-1}$</td>
<td>0.21 (0.000)</td>
<td>0.18 (0.000)</td>
<td>0.14 (0.000)</td>
<td>0.15 (0.000)</td>
</tr>
<tr>
<td>IndieSingles$_{-1}$</td>
<td>0.25 (0.000)</td>
<td>0.20 (0.000)</td>
<td>0.14 (0.000)</td>
<td>0.17 (0.000)</td>
</tr>
<tr>
<td>MajorSingles$_{-1}$</td>
<td>0.01 (0.531)</td>
<td>−0.02 (0.239)</td>
<td>−0.00 (0.959)</td>
<td>−0.01 (0.641)</td>
</tr>
<tr>
<td>Proliferation$_{-1}$</td>
<td>0.16 (0.000)</td>
<td>0.13 (0.000)</td>
<td>0.44 (0.000)</td>
<td>0.74 (0.000)</td>
</tr>
<tr>
<td>Complexity$_{-1}$</td>
<td></td>
<td>0.70 (0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proliferation$<em>{-1}$ × complexity$</em>{-1}$</td>
<td></td>
<td>−0.26 (0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dispersion parameter</td>
<td>0.95</td>
<td>0.93</td>
<td>0.99</td>
<td>1.03</td>
</tr>
<tr>
<td>Major effects</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Year effects</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Genre effects</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>No. major-style-years</td>
<td>6,069</td>
<td>6,069</td>
<td>6,069</td>
<td>6,069</td>
</tr>
<tr>
<td>Residual deviance</td>
<td>1921.0</td>
<td>1886.3</td>
<td>1,752.8</td>
<td>1,745.4</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>6,036</td>
<td>6,035</td>
<td>6,034</td>
<td>6,033</td>
</tr>
<tr>
<td>Deviance difference</td>
<td>34.72 (0.000)</td>
<td>133.51 (0.000)</td>
<td>7.35 (0.008)</td>
<td></td>
</tr>
</tbody>
</table>

Note: $p$-values in parentheses.
complex space, it takes as little as four releases by a rival to annihilate the focal major's tendency to follow suit (IRR = 0.02, CI = [0.01, 0.05]). Figure 1 visualizes this reversal: in this plot, the x-axis corresponds to the nonstandardized value of *Proliferation*, and the y-axis corresponds to the multiplicative effect on the probability of an imitative release by the focal major, and the color gradient represents *Complexity*.

To check the robustness of our estimates, we replicate our analysis after excluding from our sample major-style-years where the value of *Complexity* is more than two *SD* away from the mean. The results are qualitatively identical, suggesting that our findings are not driven by styles with an extreme level of complexity. Our estimates are also robust to the use of alternative regression models for overdispersed count data, such as the negative binomial. Based on these results, we reject Hypothesis 1: the negative effect of product proliferation we expected at mean complexity is not supported. On the contrary, we find that product proliferation provokes a reaction whereby rivals get back on equal footing. Nevertheless, a negative effect occurs if the proliferator targets a sufficiently complex subspace. In this case the strategy averts rival product introductions, and for this reason we accept Hypothesis 2. We conclude that spatial complexity does not simply weaken or strengthen the effect of product proliferation on the probability of imitation but determines the effect's direction. This is negative only if complexity is sufficiently high, which is consistent with our argument that complexity makes the threat of retaliation more credible to rivals.

**FIGURE 1** The effect of product proliferation on the probability of imitation by oligopolistic rivals depends on the product subspace's level of complexity. At mean complexity (lighter edge) or lower, the effect is positive, meaning that product proliferation triggers imitation. As complexity increases, however, the effect becomes weaker, and at sufficiently high complexity it turns negative, which suggests that proliferation works as a deterrent. At maximum complexity (darker edge), the curve is so steep that a handful of products are already sufficient for the proliferator to wipe out the probability of imitation by its rivals.
DISCUSSION

Our results show that product proliferation strategies can prevent imitation under the conditions stipulated by our theoretical model; however, this effect may not be strong enough to stop rival oligopolists. If there are compelling reasons to imitate—such as fundamental uncertainty about market conditions (Lieberman & Asaba, 2006)—rivals are still likely to introduce similar products. The question a strategist should ask is then the following: Conditional on product proliferation occurring in a subspace, will this be enough to convince rivals that they should keep their distance? The answer to this question depends on the subspace's level of complexity, particularly on its degree of product-attribute heterogeneity. The higher its degree of heterogeneity (and thus its level of complexity), the lower the probability that rivals will encroach on the proliferator's territory. The opportunity then presents itself to the strategist of manipulating a subspace's level of complexity precisely through product proliferation. If a firm designs new products so as to increase the heterogeneity of product attributes within the targeted submarket, then product proliferation will not only lead to a more defensible positioning in product space, but it will also automatically generate commitment. Naturally, the strategist should take into account that manufacturing and distributing products with more heterogeneous attributes can require more complex organizational structures, which come with their own sets of benefits and problems (Zhou & Wan, 2017). Firms should be aware that, by espousing complexity, they are most likely sacrificing some of their mobility (Hannan et al., 2003a, 2003b).

Of course, no definitive answer to the strategist's question can be given without considering the firm's standing in the market. Our test considered oligopolistic competition, and specifically the situation where both the proliferator and its potential imitator are among the oligopolists. In this case, product proliferation works as a deterrent as long as rivals believe the proliferator is committed. Based on existing literature in industrial organization and management science, we may also expect the strategy to work against new entrants (see Mainkar et al., 2006) and smaller incumbents (see Caves & Porter, 1977), but the extent to which it has deterrent power when enacted by nonoligopolists remains in need of testing. Smaller firms are generally more vulnerable to change (Barron, West, & Hannan, 1994), and this makes commitment that much easier to achieve, but they are also better capable of repositioning in product space (Liu et al., 2018), and most importantly, they are unable to sustain vigorous competition against much larger firms. One could expect product proliferation to have deterrent power only vis-à-vis new entrants and small-sized incumbents in their case: it may not be sufficient to deter larger competitors.

This note contributes to the strategy literature by (a) extending previous results by Barroso and Giarratana (2013) on the moderating role of product space complexity, (b) clarifying that this can also be a property of subspaces or submarkets, (c) proposing an empirical approach to measure product space complexity based on heterogeneity rather than interdependence, and (d) using this approach to study effects of complexity on imitation that cannot be ascribed to interdependence. On a more general level, our note points to fruitful connections between game-theoretic research on deterrence in industrial organization, which does not consider complexity, and research on imitation in strategic management, which considers both complexity and deterrence (Ethiraj et al., 2008) but does not account for game-theoretic dynamics predicated on threats and commitments. Further efforts in this direction seem to be germane, especially in the study of imitation within highly concentrated product markets. Nonetheless, future research should be mindful of our note's limitations. We argued that proliferating products in a complex subspace causes an increase in organizational complexity, and that by affecting exit costs, this makes the proliferator's threat of retaliation appear more credible to rivals. Still, we did not measure organizational complexity: we only measured spatial complexity (as moderator), product proliferation (as main independent variable), and rival product introductions...
(as dependent variable). We felt justified in this approach because previous research already established that greater heterogeneity in the attributes of products offered by a firm generates complexity in organizational structures (Zhou & Wan, 2017), but a more explicit test of our mechanism would need to treat organizational complexity as a mediating variable.

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RESOURCES

This article has earned an Open Data badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. The data is available at https://github.com/piazzai/smj-18-19552. Learn more about the Open Practices badges from the Center for Open Science: https://osf.io/tvyxz/wiki.

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