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Abstract

How do firm-specific, demand-related factors influence the relationship between intra-industry diversification (IID) and performance? Recent findings regarding the performance effects of IID depict a complex picture with curvilinear relationships and several contingencies. However, firm-specific contingencies on the demand side have remained unexplored. We analyze how IID relates to firm performance (market share) in the German automotive industry using panel data between 1999 and 2008. We specifically focus on a firm's high-quality brand image as a demand-side contingency. We find support for our hypotheses of complex curvilinear relationships as well as for moderating effects of brand quality. Our results have significant theoretical implications for the IID literature.

KEYWORDS: Related diversification, Intra-industry diversification, Intra-industry diversification-performance relationship, Across-segment product proliferation, Within-segment product proliferation

Introduction

A central topic in strategy is the diversification-performance relationship (Ahuja and Novelli, 2017; Chatterjee and Wernerfelt, 1991). Scholars distinguish between related and unrelated diversification (Rumelt, 1974) and there is evidence that, on average, the former produces superior performance compared to the latter (Palich, Cardinal, and Miller, 2000). Consequently, firms have an incentive to experiment with different types of related diversification.

By consequence, there has been a spate of interest in intra-industry diversification (IID) where firms diversify their product portfolio within a given industry (Barroso and Giarratana, 2013; Hashai, 2015; Kekre and Srinivasan, 1990; Li and Greenwood 2004; Nobeoka and Cusumano, 1997; Sorenson, 2000; Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). Initial findings suggest that IID – although by definition related diversification – is not always associated with positive performance outcomes. Instead, a more complex picture has emerged in which IID relates differently to different performance measures, has both positive as well as negative effects, and where contingencies are important. For example, it has been argued that the performance effects of IID depend on market-related context factors such as the degree of market complexity (Barroso and Giarratana, 2013), the similarity of firms in the market (Li and Greenwood, 2004), and the level of competition (Sorenson, 2000).

However, there is a lack of attention on firm-specific moderators. This is surprising, since firm-specific resources and capabilities should influence the way how benefits and costs are realized during product differentiation (Palich et al., 2000). To our knowledge, only Zahavi and Lavie (2013) have studied firm-specific contingencies (i.e., previous experience and technological investments). While their findings illustrate that firm-specific moderators are important, demand-side contingencies, which should shape demand-side synergies (Fosfuri and Giarratana, 2007; Ye, Priem, and, Alshwer, 2012), have yet to be investigated.

We aim to close this theoretical and empirical gap by analyzing how IID relates to firm performance in the context of the German automotive industry between 1999 and 2008, using market share as our measure of performance. We chose the automotive industry as it is characterized by significant heterogeneity of firms' diversification strategies that include many competing brands, each of which offering a large variety of product models with different features (Barroso and Giarratana, 2013).

As only few prior studies (e.g., Stern and Henderson, 2004; Barroso and Giarratana, 2013), we employ a fine-grained approach to measuring IID. Specifically, following the terminology of Barroso and Giarratana (2013), we distinguish between within-segment product proliferation (WPP), where the firm augments the quantity of variants that it sells in a single submarket, and across-segment product proliferation (APP), where a firm is simultaneously active in various submarkets (Barroso and Giarratana, 2013; Eggers, 2012; Siggelkow, 2003). To illustrate, Volkswagen engages in WPP and APP with its extensive product line-up, whereas Land Rover rather pursues WPP with its focused market presence. Thus, we define a market as a cluster of products satisfying similar requirements and submarkets as segments within markets, which comprise subgroups of homogenous and tangible products (Klepper and Thompson, 2006; Sutton, 1998).

We use market share as our dependent variable as it is a good proxy of performance when industry demand and the cost of production are relatively stable, both of which are applicable for the German automotive market (Statista, 2018a; Statista 2018b). Furthermore, market share is a top priority for managers in mature industries, which are characterized by fierce competition (cf. Tanriverdi and Lee, 2008; Venkatraman and Prescott, 1990) and it fits our logic of focusing on demand-side contingencies.

We capture customer perceptions of brand quality as one of the most important firm-specific demand-side contingency. The brand and its quality associations represent a reputational asset (or liability) to the firm and it is an important proxy for customers when adding products to their consideration set (Siggelkow, 2003). Additionally, customers often treat products of the same brand as close substitutes (Hui, 2004).

Using panel data, we find support for our hypotheses of an inverted U-shaped relationship between WPP and performance and a U-shaped relationship with between APP and performance. Furthermore, we find support for a moderating effect of brand-specific reputational assets. This effect is consistent for WPP and APP in the sense that a higher-quality reputation of the brand makes both curves more pronounced (i.e. more convex or concave).

Our contributions are twofold. First, we add to the literature investigating IID and performance effects (Hashai, 2015; Li and Greenwood, 2004; Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). We support previous findings that the relationship between IID, albeit by definition a type of related diversification, and performance is not unanimously positive (Zahavi and Lavie, 2013; Barroso and Giarratana, 2013). The performance effects depend on the type and degree of IID. Specialization within a given segment (WPP) leads to performance increases up to a certain point, only to become negative as diversification efforts continue. The effect is opposite when firms increase the breadth of their offering (APP). To this end, we extend previous research, particularly those of Barroso and Giarratana, 2013), by showing support for the idea that the APP and WPP effects are similar when market share is focused upon.

Second, we add to the literature that considers contingencies in the context of diversification-performance relationships. Here, we extend previous literature that has focused predominantly on market or environmental characteristics with firm-specific contingencies

(Zahavi and Lavie, 2013). Our findings show that brand quality is an important asset (liability) that moderates both APP and WPP effects in similar ways. Thus, we conclude that both external but also internal contingencies relating to the resources and capabilities of the firm, specifically those that are important on the demand-side, determine the success of IID decisions.

Theory and hypotheses

One key driver of firm diversification is the generation of economic benefits (Montgomery, 1994; Prahalad and Bettis, 1986). That is, firms often have an incentive to diversify excessive firm-specific and potentially synergistic resources (Barney, 1991; Penrose, 1959). However, diversification does not automatically yield a positive impact on corporate performance. In fact, none or even negative effects may materialize from diversification. Consequently, due to its practical significance, scholars have analyzed the diversification and performance linkage extensively to derive superior strategies and degrees of diversification (Weiss, 2016). Palich et al. (2000), in an extensive meta-analysis of 55 published studies, found that moderate levels of diversification produce the best performance outcome. Their findings provide support for a curvilinear relationship, in which performance increases as firms shift from single businesses to related diversification, but decreases as firms change from related diversification to unrelated diversification. Their study confirms that a certain degree of relatedness is required to profit from resource sharing and transfer (Barney, 1991; Lubatkin and Chatterjee, 1994; Wan, Hoskisson, Short, and Yiu 2011; Weiss, 2016; Wernerfelt, 1984). Relatedness, in this context, refers to the exploitable overlap of the firms' resources across their businesses with regards to skills (Robins and Wiersema, 1995; Rumelt, 1974, 1982; Tanriverdi and Venkatraman, 2005), common technologies, and customers (Pitts and Hopkins, 1982). Such overlap allows firms to share their resources across businesses, generating economies of scale where they are able to produce more of the same products, and economies of scope when they are able to use similar inputs to build a greater variety of different products (Hill, Hitt, and Hoskisson, 1992; Markides and Williamson, 1994). Contrarily, with unrelated diversification firms explore unfamiliar territories possessing only limited understanding of operations, customers and competition, thereby potentially impacting performance in a negative way (Kogut and Zander, 1992; Hoskisson and Johnson, 1992). Unsurprisingly, firms most commonly engage in IID, by definition related diversification. In such a setup, firms offer their products or services in multiple submarkets or product lines in the same segment, all focused on a single industry[1] (Li and Greenwood, 2004; Stern and Henderson, 2004). In fact, this type of diversification is not only more common than inter-industry diversification, but also a natural precursor to it.

However, contrary to its high importance for managers and widespread prevalence in practice, scholars have devoted only limited attention to IID (Zahavi and Lavie, 2013). Consequently, very few studies have investigated the relationship between IID and performance. Due to its inherently high degree of relatedness, one could assume a similar and consistent positive diversification-performance relationship as for related diversification in general (Tanriverdi and Lee, 2008). Since the study of the IID-performance relationship has not reached maturity yet, the evidence gathered is quite ambiguous (Hashai, 2015; Palich et al., 2000; Zahavi and Lavie, 2013). The scarce research on the effects of IID on performance reports heterogenous findings: Some authors indicate a positive effect (Kekre and Srinivasan, 1990; Nobeoka and Cusumano, 1997), others report varying results depending on the type of IID (Tanriverdi and Lee, 2008), the degree of IID (Hashai, 2015; Zahavi and Lavie, 2013) as well as several market-specific contingencies (Barroso and Giarratana, 2013; Li and Greenwood, 2004; Sorenson, 2000; Stern and Henderson, 2004). Others find a negative effect (Cottrell and Nault, 2004). Given the

[1] Contrary to inter-industry diversification, which refers to the expansion of firms into novel businesses (Chandler, 1962).

diverging results, a nuanced, potentially curvilinear relationship is most likely. In sum, the evidence on the IID and firm performance relationship is lacking consistency and research has not exhaustively explained positive and negative implications. We propose two key reasons for these inconsistencies.

First, research on IID is either not fine-grained enough or does not use consistent definitions of the phenomenon. Previous literature has lumped different forms of within-industry diversification together or looked at one particular type of diversification exclusively, without differentiating between the depth and breadth of a firm's offering. Generally, a market is defined as a cluster of products satisfying similar requirements. Within a market, submarkets exist, which are comprised of subgroups of products characterized as homogenous and tangible (Klepper and Thompson, 2006; Sutton, 1998). On the one hand, some firms increase the submarkets they serve, thereby increasing the breath of its product offering (Stern and Henderson, 2004). On the other hand, some firms increase the quantity of different variants in a given submarket, which involves an increase in depth (Li and Greenwood, 2004). Without specifying the type of diversification firms engage in, research could produce measurement errors and thus misleading results (Barroso and Giarratana, 2013; Dowell, 2006; Eggers, 2012; Ramdas, 2003; Sorenson, 2000; Zahavi and Lavie, 2013). Consequently, a more granular perspective, considering across-segment as well as within-segment diversification separately, is better suited to calibrate performance implications

Second, few studies have included contingency effects that impact and moderate the diversification-performance relationship. Such contingencies arise through competitive interplay (Stern and Henderson, 2004), but can also be related to demand factors such as customer consideration sets (Siggelkow, 2003). While the research efforts regarding market-specific moderators has seen some development, there is an eminent paucity of research on moderators specific to the firm. Zahavi and Lavie (2013) are the first to demonstrate the influence of such moderators on the IID performance relationship, thereby highlighting their importance. They find that technology investment pronounces the effect of IID, whereas prior diversification experience attenuates it. While the two authors have produced valuable insights related to firm-specific contingencies, there are many other moderators that need to be considered, particularly from a demand-side perspective, which has equally significant impact on a customer's buying decision and, hence, the success of diversification. Consequently, accounting for such demand-side context factors could help further clarify the complex nature of the IID and the performance relationship.

Intra-industry diversification and performance

Diversification in general has been associated with both positive and negative effects on performance. The mechanisms that drive a positive relationship are market power advantages, internal market efficiencies, and exploitation of excess firm-specific assets, whereas cannibalization, cost of control and coordination drive negative performance implications (cf. Palich et al., 2000). While similar arguments hold true for IID, they become slightly finer grained. Additionally, expanding the product line-up within an industry comes with unique benefits and liabilities when compared to diversification into distinguishable industries (Zahavi and Lavie, 2013) due to novel challenges in unfamiliar segments and a larger scope as well as greater degrees of complexity. Consequently, merely highlighting the positive and negative effects of IID neglects an important characteristic of the performance relationship. As we face arguments for both positive and negative impact, we need to be aware that the initial conditions of the firm play an important role in the manifestation of performance effects. In fact, they might lead to a non-linear relationship with performance (Barroso and Giarratana, 2013).

Within-segment product proliferation (WPP)

WPP might contribute positively to performance through a number of mechanisms. From a resource-based perspective, WPP enables a firm to benefit from operational and management synergies in the form of economies of scale through expanding into new products in the same submarkets of their industry (Barroso and Giarratana, 2013). Even without prior experience in these submarkets, firms can thus realize cost reductions (Paine and Anderson, 1983; Siggelkow, 2003), which increases financial performance or frees cash to invest into innovation, marketing, or advertising. Furthermore, if a company conducts WPP and introduces new products in a segment it already serves, learning-by-doing effects drive an increase in operational and management efficiencies due to already existing experience (Kessler, Bierly, and Gopalakrishnan, 2000; Kim and Kogut, 1996; Kogut and Zander, 1992; Smith, Collins, and Clark, 2005). Similarly, prior experience in a segment increases the quality of new products introduced in WPP and enables firms to exploit firm-specific assets such as technology and brand names (Eggers, 2012; Li and Greenwood, 2004), which may boost market share and or financial performance.

From a market-based perspective, WPP indicates a continuous product refinement process. As a result, firms that engage in WPP should better meet the needs of the more heterogeneous customer preferences of submarket loyalists (Eggers, 2012; Shapiro and Varian, 1998). As an example from the car industry, a customer might prefer[2] the segment of upper middle class cars, a segment in which products such as the Audi A6, Mercedes E class, or the BMW 5 series are competing. When BMW complemented their offering of a traditional 5 series sedan with an estate, a coupe, and a convertible, which all belong to the segment of upper middle class cars, it

2 This preference might result from the customer's individual preferences, but it might also be caused by company car policies, which require from their employees to select a product from a given range. Our example of the upper middle class is a typical class of company cars for the senior/top Management level in Germany.

allowed them to respond to quite heterogeneous needs within this submarket. Consequently, a segment focus strengthens a firm's identity and its bond with a particular customer group (Hsu, Hannan, and Kocak, 2009). Such attention to consumers is likely helping firms to grow (Penrose, 1959).

However, increasing WPP often also increases costs. In fact, previous research (Dowell, 2006) argued that WPP may lead to increased inventory costs (Kekre and Srinivasan, 1990), higher design costs (Bayus and Putsis, 1999), as well as higher manufacturing costs (Anderson, 1995; Mac Duffie, Sethuraman, and Fisher, 1996) due to increased complexity and more variants. In addition, there may often be negative learning effects in the form of learning traps. With limited knowledge and experience in diversification, there is a probability of misinterpretation and faulty conclusions (Zahavi and Lavie, 2013). Continuing our example from the car industry, a brand might overlook that consumers interested in convertibles might have very different preferences than those that interested in a sedan. From a market perspective, liabilities can stem from cannibalization effects (Barroso and Giarratana, 2013).

So far, we have outlined reasons why there may be positive and negative effects on performance when firms increase WPP. In the following, we argue that the WPP-performance relationship is non-linear as the effect depends on the level of WPP itself. First, many of the positive effects of WPP exert a greater influence at higher levels of WPP. The benefits that result from operational and management synergies are limited at low levels of diversification, but they grow as the level of diversification increases (Jones and Hill, 1988; Stern and Henderson, 2004; Zahavi and Lavie, 2013). However, at higher levels, the marginal benefits of those synergies decrease, comparable to the logic of the experience curve (Henderson, 1984). The learning-by-doing effects are negligible at low levels of diversification, as prior knowledge and experiences in new product variants or categories are still limited. As the level of WPP increases, knowledge and experience grow, leading to higher benefits from learning-by-doing effects. To conclude, the resource-based benefits of WPP might manifest in full force only at higher levels of diversification. Likewise, the market-based benefits are greater at higher levels of WPP. With a narrow product offering, there might still be some unmet customer needs. As the level of WPP increases, the product offering meets a broader range of submarket loyalists' preferences (Lancaster, 1990).

However, with increasing levels of WPP, also the costs increase. Costs from adjustments (operational and organizational) and coordination increase with more diversification efforts, and even marginally increase (Barroso and Giarratana, 2013; Hashai, 2015). Contrarily, the potential of learning traps and negative learning effects is higher at low levels of diversification, whereas it is more likely to be avoided by experienced firms (Zahavi and Lavie, 2013). As for market-based liabilities of WPP, the cannibalization effects increase with the number of versions a company offers within the segment and is even stronger at higher levels of WPP (Garud and Kumaraswamy, 1993; Hui, 2004; Hsu, 2006). The broader a product offering, the more likely it is that, instead of generating additive demand from new customers, existing customers might simply substitute one of the company's products with another.

In sum, WPP comes with benefits and cost that vary with the level of WPP. All benefits and costs need to be jointly considered to understand the relationship with performance. As described above, most positive effects (i.e., benefits) of WPP increase linearly or in a marginally decreasing way. The negative effects (i.e., liabilities), however, seem to increase exponentially, mainly due to the more severe cost and cannibalization effects at higher levels of WPP. Hence, we propose that that the additive combination of the mechanisms results in an expected inverted U-shaped performance effect of WPP (see Table 1 and 2 for a summary):

Hypothesis 1: *Firm performance exhibits an inverted U-shaped association with WPP, so that performance will initially increase, then decrease with the extent of such diversification.*

Across-segment product proliferation (APP)

APP benefits from the same resource-based factors as WPP. Through offering products in different submarkets of the industry, the firm should be able to realize operational and management synergies since there might be some overlaps in production. APP also benefits firms through prior experience and learning-by-doing effects. However, those resource-based benefits appear lower for APP, because WPP offers more relatedness (i.e., similarity) between the products than APP (Stern and Henderson, 2004).

From a market-based perspective, APP can create one-stop shopping solutions that are especially valuable for brand loyalists[3].Thereby, it helps to meet brand loyalists' heterogeneous needs better and it might allow firms to increase sales and prices (Moorthy, 1984; Perloff and Salop, 1985; Pigou, 1920; Salop, 1979; Sappington and Wernerfelt, 1985). APP can also lead to a higher willingness to pay and increased consumption habits (Barroso and Giarratana, 2013) as well as to a compromise in overall demand requirements and specifications due to the one-stop shopping opportunity it provides (Siggelkow, 2003). Prior research has in fact provided evidence in favor of such a positive relationship between product line breadth and market share (Kekre and Srinivasan, 1990; Robinson and Fornell, 1985). Lastly, firms that engage in extensive APP could reduce competition through mutual forbearance when they have a similar portfolio as their

[3] Please note that the brand loyalist is different from a submarket loyalist. While a submarket loyalist stays loyal to a product segment (e.g., compact-sized cars), a brand loyalist stays loyal to a brand (e.g., BMW), even across different product segments. Hence, the focus on brand loyalists is only relevant as an effect of APP. By definition, submarket loyalist remain within their product segment and are not (primarily) attracted by (additional) offers in different product segments.

competitors (Li and Greenwood, 2004) and by preempting new market entrants (Fosfuri and Giarratana, 2007; Ye et al., 2012).

APP also faces the similar resource-based liabilities as WPP. APP incurs the liabilities from increased costs (i.e., coordination and adjustment, inventory, and manufacturing costs), and from the negative transfer of knowledge and the resulting learning impediments (Levitt and March, 1988). However, following the same relatedness-based argumentation from above, those resource-based liabilities appear higher for APP than for WPP.

From a market perspective, there is a risk of identity loss, which affects the relationship with submarket loyalists[4]. Firms with strong ties to a specific submarket usually profit from a superior image and reputation in these particular markets (Anderson and Spellman, 1995; Posavac, Sanbonmatsu, and Fazio, 1997). An extension of the product offering beyond the limits of these submarkets might weaken the ties to the respective customers (Keller and Aaker, 1992; Loken and John, 1993). As a result, associations with multiple categories or segments might make companies – or their brands – eventually lose their identity (Dobrev, Kim, and Carroll, 2003).

As for WPP, we argue that the APP-performance relationship is non-linear because the effect depends on the level of APP itself. The benefits of APP – unlike in the case of WPP – manifest in full force only at higher levels of APP. For example, the benefits of forbearance are likely higher when firms meet in many markets with a similar product portfolio; consequently, their full potential unfolds at a high degree of APP (Li and Greenwood, 2004). In addition, as the level of APP increases, brand loyalists are given more opportunities to purchase within a specific brand's offering. This, in turn, reduces their search cost and potentially leads to higher demand for all products of the brand.

4 The risk of identity loss with submarket loyalists might also play a role in the case of WPP (Garud and Kumaraswamy, 1993). However, as this only appears relevant at very high levels of WPP (Negro, Hannan, and Rao, 2010), we only consider this effect for APP.

The resource-based liabilities of APP are higher at high levels of APP[5]. While these effects are similar to WPP, the magnitude is expected to be higher due to the lower degree of relatedness of APP compared to WPP. As for market-based liabilities, the potential loss of identity is more likely to occur at companies that specialize in a particular segment, have built a strong identity and association with that segment, and do not engage in extensive APP. For example, the German car manufacturer Porsche has a historically strong identity as a sports car manufacturer (i.e., a specific product segment and, thus, a submarket). Expanding their product offering into mass markets, Porsche may alienate and jeopardize their existing customer base. When Porsche introduced their first SUV, the Porsche Cayenne, they faced a controversy whether this move would dilute their highly specialized and exclusive brand image. If a company is already present in various segments such as, for example, Toyota, i.e. it has a very high level of APP, the benefits from a strong identity that is linked to a specific segment are lower, as are the cost of identity loss. Consequently, the potential loss of identity is higher at low levels of APP. The more submarket loyalists associate a brand with a specific submarket and the more the brand relies on such loyalists, the greater the loss that APP can cause (Keller and Aaker, 1992; Loken and John, 1993).

In sum, as for WPP, we need to jointly consider the different effects of APP to understand the relationship with performance. As described above, the most important positive effects of APP (e.g., one-stop shopping and mutual forbearance) increase exponentially. Thus, they are likely to outweigh the only linear or marginally decreasing resource-based benefits. At the same time, the crucial negative effect of losing the identity with sub-market loyalists is negative, which means this primarily occurs at low levels of APP and is likely to disappear at higher

5 Please note that we consider the marginally increasing costs to have a stronger effect on the overall resource-based liabilities than the negative effect of the learning traps, as they appear more direct and tangible.

levels. Hence, we propose that that the additive combination of the mechanisms results in an expected U-shaped performance effect of APP:

> ***Hypothesis 2:*** *Firm performance exhibits a U-shaped association with APP, so that performance will initially decrease, then increase with the extent of such diversification*

For a better overview of the different mechanisms described above and to comprehend the varying effects, Table 1 compares the respective resource-based and market-based benefits and liabilities for WPP and APP. Furthermore, Table 2 integrates all suggested performance effects for WPP and APP to illustrate the proposed shapes of the respective performance relationships.

Table 1 and 2 about here

Contingency effects

As discussed above, research on the diversification-performance relationship within-industries has produced inconsistent findings. A new stream of research tries to reconcile one potential reason for this issue by considering that the relationship is moderated by the presence of other factors (Ahuja and Novelli, 2017; Zahavi and Lavie, 2013). Different types of contingencies have been identified so far such as *industry contingencies*. The environmental context matters a great deal in diversification efforts. Research has, for example, found that performance effects depend on the changing level of diversification in the industry a firm operates in (Stern and Henderson, 2004) and the total number of competing products (Sorenson, 2000). Additionally, the complexity of the product space impacts the performance effects of IID (Barroso and Giarratana 2013), as well as the degree of overlap with rivals (Dowell, 2006; Li and Greenwood, 2004). Authors have also looked into *firm characteristics*: for example, the type and degree of diversification are relevant since they impact how a firm can employ resources across related products. Tanriverdi and Lee (2008) find a positive performance effect from combining platform and product market relatedness while an independent application leads to adverse results. Dowell (2006) finds that firms with moderately complex product line-ups perform worse than their simple and highly complex counterparts. The performance effect is also moderated by the previous diversification experience and the technology investment of the firm. Higher technology investment intensity pronounces the performance effect, whereas more previous experience attenuates it (Zahavi and Lavie, 2013). Finally, the speed of IID negatively moderates performance (Hashai, 2015).

Yet, what has been missing is the consideration of *demand-side effects*, which are highly significant for customer buying decisions and, hence, the success of firm diversification. For expensive customer buying decisions, the perceived quality of the brand is of high importance. In turn, the perceived brand quality is influenced both by firm characteristics as well as demand-side considerations. Hence, we aim at extending the emerging literature on contingencies that moderate IID by adding brand-related assets to the equation. More specifically, we study how a high-quality image of the brand moderates the diversification-performance relationship. The quality of a brand is a perceptual measure of the extent to which the brand is perceived as high quality and highly reliable from the perspective of consumers. Brand image is an important factor in customer buying decisions. It acts as a screening device, especially in complex product environments, as well as a common anchor to simplify buying decisions (Gilbride and Allenby, 2004; Hauser, Toubia, Evgeniou, Rene, and Dzybura, 2010; Lapersonne, Laurent, and Le Goff, 1995). Additionally, in an environment with many products and potential purchasing choices – as is the case with extensive IID – the brand influences what purchasing options customers add to their consideration set (Siggelkow, 2003) as customers see multiple products of one brand as close substitutes (Hui, 2004). Firms can benefit from this, since IID allows them to exploit brand-specific assets such as the brand image (Eggers, 2012; Li and Greenwood, 2004) which could trigger customer-based synergies (Ye et al., 2012).

However, we argue that the brand image can have both positive and negative effects depending on the type and degree of IID. Higher-quality brands generally enjoy a higher degree of trust from customers. The higher the quality, the more pronounced is the positive effect on the influence of brand expansion success (Aaker, 1990; Smith and Park, 1992; Völckner and Sattler, 2006; 2007). However, negative effects may be even more noticeable the higher the brand quality. Consequently, we have to explore the effects of higher-quality brands on WPP and APP at low and high levels on their respective benefits and liabilities. In the following, we will start our discussion with APP, as APP can also be viewed as the brand extension across product segments, where the impact of the specific brand assets might be more obvious.

For a brand that starts to engage in APP, we suggest that the higher the brand quality, the more pronounced the initial negative effect. When a higher-quality brand in a given segment starts to diversify across segments, the brand-submarket association is even more at risk of disruption and, depending on the new segment, the image may suffer significantly. To illustrate, following our example from above, when Porsche moved into the SUV segment with its Porsche Cayenne, representing an increased APP at low levels, this was already considered to negatively affect the submarket loyalists[6], as this could hurt Porsche's image as a sports car specialist, thereby decreasing the overall performance. However, given Porsche's high-quality brand, this effect was amplified, as the customers' association with the Porsche brand was particularly strong. The impact is depicted in Figure 1. Nonetheless, once the higher-quality brand has

6 In fact, a heavy debate arose in Germany before the product launch, where the public questioned why a sports car manufacturer should also offer a SUV, portraying a rather skeptical public perception (Gerster, 2017; "Porsche Cayenne", 2019)

successfully diversified into other segments, the benefits such as the one-stop solution for brand loyalists are more readily realized and improve the positive performance effect. The high-quality image from a particular segment can diffuse into new segments and can quickly find adoption. For example, BMW was already well established in terms of APP with its 3 series, 5 series, and 7 series, and also managed to establish a high-quality brand. When they successfully expanded across more product segments into SUVs with their X series as well as into compact cars with their 1 series. However, their high-quality brand allowed them to benefit from increased APP to a large extent. They successfully leveraged their strong brand providing a wide-ranging yet credible one-stop solution for their brand loyalists. Additionally, once submarket loyalists notice that diversification into a new niche has no negative impact on the old niche, the sentiment might improve again. Consequently, we hypothesize that the higher the quality of a brand, the more pronounced the initial negative effects at low levels of APP and the more pronounced the more beneficial effects at high levels of APP, leading to a steepened relationship between APP and performance.

Similarly, once firms start to diversify their higher-quality brand via WPP, they will likely enjoy even greater benefits, since the reputation within their segment benefits such endeavors. Those brands will not only manage to better meet the submarket loyalists' needs, they can also leverage their strong brand perception into the new products within this segment. However, at the same time, higher quality is usually associated with a more restrained product offering, focusing on quality over quantity. Consequently, there might be a risk that extended diversification disrupts the brand-submarket association and customers perceive a poorer fit with market segment schemas. Furthermore, the negative effect from cannibalization is also intensified, as customers see multiple products of strong brand as even closer substitutes (Hui, 2004). As a result, the negative effects amplify as diversification via WPP continues.

Consequently, as shown in Figure 2, we hypothesize[7] that the higher the quality of a brand, the more pronounced the initial positive effects at low levels of WPP and the more pronounced the negative effects at high levels of WPP, leading to a steepened relationship between WPP and performance.

Hypothesis 3a: *The association between firm performance and WPP will be strengthened by a firm's high-quality brand image, leading to a steepening of the curve.*

Hypothesis 3b: *The association between firm performance and APP will be strengthened by a firm's high-quality brand image, leading to a steepening of the curve.*

Figures 1 and 2 about here

Data and methods

Empirical context

We base our study in the German automotive industry, the fourth largest automotive market by new car registrations (GAD, 2018). This market is well suited for the study of IID for several reasons. First, it is a mature industry and characterized by fierce competition for market share. Second, there is a high number of competing brands with multiple products catering to different segments (Barroso and Giarratana, 2013) and most firms diversify. Third, it closely mirrors a population to which the central research question and conclusions are relevant (Short, Ketchen, and Palmer; 2002). Fourth, the automotive sector is quite transparent providing highly reliable data on sales in an officially established rosters for market segmentation. These fine-grained and consistent data allow a more nuanced analysis of IID.

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7 Please note that we while we changed the order of our argumentation (because of the closer relationship between brand assets and APP), we kept the order of WPP and APP in our Hypotheses 3a and 3b according to our Hypotheses 1 and 2.

Our data contains the number of cars sold in all market segments per brand and model during the 10-year period from 1999-2008. We stop with 2008 since the financial crisis led to the introduction of a scrapping bonus for older cars, incentivizing new car purchases, thereby potentially leading to market distortions. Such policy has not been employed at earlier crises.

We define cars as all motor-driven vehicles with the primary purpose of transporting people with more than three wheels and up to eight seats. (i.e. pick-up trucks do not belong in there as they are predominantly commercial vehicles and, generally, have very low sales volume in Germany). Based on this distinction, we use IHS data for all sales of cars in Germany. In total, the dataset includes 27 automotive groups, 51 brands, 548 models and amounts to a total of 511 brand-years observations. We exclude models with missing data and removed duplicates from follow-up models (e.g., Hyundai Elantra became Hyundai i30). Additionally, we exclude outlier brands with sales of less than 1,000 units per year with affiliated group (e.g., General Motors' Cadillac). Thus, our final sample consists of 35 brands.

Dependent variable

Several performance measures have been used to study the impact of IID. Some authors have focused on firm survival (Dobrev, Kim, and Hannan, 2001; Hsu, 2006), product quality (Eggers, 2012), sales growth (Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013), rate of return (Li and Greenwood, 2004) or profitability (Barroso and Giarratana, 2013). Our study is conducted on a brand-level, using a market share measure as a practically important and empirically established indicator of performance. A prerequisite for our measures is a detailed segmentation of the automotive market. We apply the official segmentation of the German Federal Motor Transport Authority (Kraftfahrtbundesamt), which is based on body style and vehicle size. The segmentation is objective and generally recognized within the automotive industry. A combination of 8 body styles and 10 vehicle sizes defines a segment. It is important to note that SUVs and MPV (multi person vehicle or "Vans") are considered as body styles, but are also often referred to as a vehicle size. In total, 80 theoretical segments exist, of which 59 are occupied with models in the automotive market. All 10 vehicle sizes together with the two body styles SUV and MPV are grouped into nine segment groups.

We use market share of the brand as a proxy for performance (Venkatraman and Ramanujam, 1986), as it is a stable predictor of firm performance in the absence of profitability data for individual brands and models (cf. Tanriverdi and Lee, 2008; Venkatraman and Prescott, 1990) and as it has been used before in IID studies (e.g. Tanriverdi and Lee, 2008). Market share is a particularly good proxy of performance when industry demand and the cost of production are relatively stable, which is the case in the German automotive market (Statista, 2018a; Statista 2018b). Market share is also a top priority for managers in mature industries characterized by fierce competition (cf. Tanriverdi and Lee, 2008; Venkatraman and Prescott, 1990) – a description that fits the automotive industry in Germany.

The (weighted) market share is the sum over all product markets, of the sales-weighted shares of each product market.

$$(Weighted)\ Market\ Share = \sum_{j=1}^{m} \left(\frac{s_i^j}{\sum_{i=1}^{n} s_i^j} \right) \times \left(\frac{s_i^j}{\sum_{j=1}^{n} s_i^j} \right)$$

where s_i^j gives the number of sales of brand *i* in of segment *j*, while *m* represents the number of segments of brand *i* and *n* represents the number of brands with sales in segment *j*. In other words, the market share of a brand is the sum of each segment's market share weighted with the share of the segment's sales compared to total sales, reflecting the importance of the segment for the brand.

Independent variables

The focal independent variables are the types of intra-industry diversification (IID), the degree of within-segment product proliferation (WPP) and the degree of across-segment product proliferation (APP). The extension of a brand's offering within one segment group (via different body styles) is defined as WPP; the extension beyond one segment group is defined as APP. A prerequisite to measure WPP and APP is a detailed segmentation of the automotive market. Using the segmentation outlined above, we can measure our independent variables in the following way: To measure WPP, we count the sales-weighted number of models that a brand is selling in the product line with the highest density of product models for that same brand (Barroso and Giarratana, 2013; Dowell, 2006). To measure APP, we calculate as follows:

$$APP = \sum_{j=1}^{m} p^j \times \ln(\frac{1}{p^j})$$

where p^j denotes the share of the product line *j* in the total sales of the brand and *m* represents the number of product lines of the brand (Stern and Henderson, 2004).

Moderating variables

Additionally, to test Hypotheses 3a and 3b, we include the quality rating of the brand for its moderating effect on the IID performance relationship. Both ratings are based on yearly customer ratings from the most important German automotive magazine *Auto Motor Sport*. The magazine collects input from close to 100,000 automotive enthusiasts on an annual basis to ask for the evaluation of automotive brands in several survey points. The ratings are time variant and on a scale from 0-100. For the operationalization of *quality*, we use subjective quality as this is more appropriate in our context than objective quality since the subjective measure more accurately predicts the customers buying intentions. The variable is determined by averaging the survey points "high reliability" and "good built quality", since they are key factors that constitute a subjective quality measurement (Gavin, 1987). The moderating effect of *quality* is calculated as interaction term between the degree of diversification and quality.

Control Variables

To preclude alternative explanations for our findings, we introduce several controls that are likely to impact market share at different aggregate levels. All control variables are lagged by one year to reduce endogeneity concerns related to reverse causality.

Industry-level controls. First, we control for competitive conditions on an industry-level in Germany. As Barroso and Giarratana (2013) find, the complexity of the product space impacts the performance effects of IID. Taking this into account, we looked at the *brand density* in the industry. By capturing how many brands operate in one market, we control for market complexity and rivalry. Additionally, we look at the *number of new segments* from one year to the next to control for the development of market place complexity. In the same vein, we control for contingency factors in the competitive landscape that influence the diversification-performance relationship (Stern and Henderson, 2004). Competitive intensity could potentially force companies to diversify into less competitive market segments. To cover competitive intensity in the market we look at *the number of new model introductions by competitors* as well as the *level of competition*. We follow the approach by Barroso and Giarratana (2013) to calculate the *level of competition.* It represents the segment's canonical Berry Index, which we base on the weighted average of the Berry indices computed by compiling market shares in the different segments a brand competes in. The importance of a segment is defined as the brand's proportion of total revenue earned in that segment. Consequently, we capture in which segments a brand is active, how important the segment is for the brand as well as the competitive level in each.

Group-level controls. To accommodate structural differences between the companies, we control for size effects and effects related to intangible assets and innovativeness. A larger capital stock might enable firms to invest more heavily into product line or brand extension and therefor capture higher market share. To control for scale economies, we employ the *total assets* (in EUR) of a group as a control variable. Market segments differ regarding their margins. Additionally, varying profitability can influence the ability to diversify. We employ *return on sales (in EUR)* to control for this effect. Lastly, firms differ historically regarding their stock of intangible assets and innovativeness, both factors that could influence diversification performance. To control for this effect on performance we include *R&D expenses (in EUR)*.

Brand-level controls. Advertising and marketing efforts can impact sales of products. Additionally, in a distinct market, sales of local competitors potentially benefit from their location advantage. Especially in the automotive industry, advertising plays an important role to improve the image and create concrete purchase intentions through an increase in perception. Thus, the effect of advertising needs to be considered. Consequently, we control for *advertising spend* by brand which can be used as an indicator for local adaptations as well as internationalization effects. We use gross advertising expenditures (in EUR) of the brands, comprising classic above-the-line advertising in general-interest magazines, newspapers, trade journals, television, radio, posters, and online. The data source used in this study is the annual study *Autofahren in Deutschland*, which refers in its representations to data of the Nielsen Media Research GmbH.

Analysis

In our baseline estimations, we run random effects panel regressions. We include lagged control variables to account for the time lags between strategic decisions and outcome and to reduce potential endogeneity from reverse causality. We also include group fixed effects for brands of the same group and the lagged dependent variable (i.e. weighted market share) to reduce autocorrelation issues. We perform a series of robustness tests and describe how we assess and treat endogeneity concerns in our results section.

Results

The correlations of our variables are depicted in Table 3. Table 4 summarizes the descriptive statistics of the data in our sample.

Table 3 and 4 about here

The results from our panel regression analyses are included in Table 5. Model 1 is the control model only containing the control variables. Models 2-5 add the variables of interest. In Model 2, we exclusively add WPP, in Model 3, we remove WPP and exclusively add APP. With Model 4, in which we include both WPP and APP as the two separate forms of intra-industry diversification strategies, we test Hypothesis 1 and Hypothesis 2. With Model 5, we test Hypothesis 3a and 3b.

Table 5 about here

We find support for Hypothesis 1 and the hypothesized inverted U-shape effect of WPP on market share (p=0.005). At 3.19, the inflection point is squarely in the middle of our observed range of [1.00-6.00]. Hypothesis 2 regarding the U-shaped effect of APP on performance is also supported (p=0.022). Firms benefit either from focus (i.e. low APP) or higher levels of APP. The inflection point occurs at 1.59, which lies again within the range of observed values [0.00-1.73]. Lastly, we find support for Hypotheses 3a and 3b (p=0.019, p=0.001). The higher the quality image of the brand moderates the performance relationship in the expected direction both for WPP and APP. As hypothesized, our results suggest that there are different performance implications depending on the type and degree of diversification, as well as that the performance relationship is moderated by brand reputational assets.

Robustness checks

We ran two sets of robustness checks, for which the results are shown in Tables 6 and 7. First, we run generalized linear models (GLM) including year fixed effects in addition to group fixed effects and the lagged dependent variable. We use a logit link and robust standard errors to account for the skewed and truncated shape of our dependent variable (between 0 and 1). Second, we fit population-averaged generalized linear panel models (XTGEE) with group fixed effects and the lagged dependent variable. We use within group correlation and an identity link exchangeable. This produces an equal-correlation linear regression estimator equivalent to the weighted-GLS (STATA, 2018).

Our findings are mostly robust across the different specifications of the models. Nonetheless, it is important to note that our Hypothesis 1 and Hypothesis 3a are not significant in the XTGEE model (Models 8 and 9) and Hypothesis 3b is not significant in the GLM model (Model 7). However, since these variables are significant in all other models and the directions of the effects are consistent in all models, we are confident that our data provide support for all our hypotheses.

Tables 6 and 7 about here

Endogeneity

Studies focusing on the causal relationship between diversification and firm performance are plagued by concerns of endogeneity. Diversification can be both a cause of and a consequence for superior performance. In our hypotheses development, we have provided sound theoretical arguments to support our direction of causality, following the suggestion of Reeb, Sakakibara, and Mahmood (2012). Empirically, lagging of our independent variables, the use of theoretically important controls and including group fixed effects in our panel estimations can alleviate some potential sources of endogeneity.

Ideally, researchers would address endogeneity by using more sophisticated econometric methods that better approximate randomized controlled experiments such as Matching and Propensity Score Models and/or Instrumental Variable Regressions (Reeb et al., 2012). However, the use of instrumental regressions in our setting has two major caveats: First, quadratic and polynomial models require strong instruments not only for the polynomial term, but also for each individual effect and their interactions with each other. Since the 2SLS bias *"tends to get worse as we add more (weak) instruments"* (Pischke, 2018), the econometric literature is skeptical about the use of instrumental regressions for three-way interactions (Greene, 2018; Kennedy, 2008; Wooldridge, 2010). Second, instrumental regressions require large sample sizes to yield better estimates than OLS. In an ideal scenario in which all IV assumptions hold, the threshold sample size at which IV regression provides superior estimates than OLS is between 6,000 and 29,000 observations (Boef, Dekkers, Vandenbroucke, le Cessie, 2014:1260). Applied to samples of our size, IV estimates tend to have inflated standard errors, biased coefficient estimates and the possibility of small sample bias.

As a result, in small sample studies like ours, it is widely recommended to perform a sensitivity analysis of the results (e.g. impact threshold of confounding variables), rather than performing biased IV analysis. We follow this recommendation using three different approaches. First, we follow Davidson and MacKinnon (1993) to conduct a Durbin–Wu–Hausman test (augmented regression test) for endogeneity of our diversification variables. We find no significant evidence for endogeneity of our direct effect.

Second, we calculate the magnitude of potential bias using the ITCV methodology (Frank Maroulis, Duong, and Kelcey, 2013; Busenbark, Gamache, Yoon, Certo, and Withers, 2019). In sum, ITCV indicates that an omitted variable would require a surprisingly high correlation with our DV and diversification measures to create a spurious finding. For the most problematic direct effect, to sustain inference, 46% of the estimated effect would have to be due to bias (the other diversification measures achieved much higher thresholds). The lowest threshold for an omitted confounding variable is a correlation of -0.24 with our dependent variable and the regressor. Comparing this with the correlations in our data (excluding lagged variables), this correlation is abnormally high.

Third, we follow Lyngsie and Foss (2017) and conduct simple mean comparisons based on above/below median and mean values of past performance. We split the sample in two groups based on their performance in 1999. Collapsing group-level data and using diversification at the end of our observation period (2008), we test if initially high performing firms have higher degrees of intra-industry diversification in later years. This simple test indicates no significant differences between the two groups regarding later within-product proliferation (WPP) ($p=0.3550$) and across-product proliferation (APP) ($p= 0.6836$). The same insignificant difference in means applies to the squared terms of WPP and APP.

Despite these econometric strategies to estimate and address endogeneity, we concede possible endogeneity in our models. Nonetheless, our sensitivity analyses following different approaches indicate that we do not face a significant bias from endogeneity and that we are better off with our suggested estimations compared to performing a biased IV analysis.

Finally, to test for potential reverse causality, we flip the panel regression specification and the lag structure. More specifically, we regress our measures of diversification as dependent variables on lagged firm performance and the entire set of lagged controls. This multivariate test indicates that past performance is not significantly related to subsequent within-product proliferation (WPP) ($p=0.698$) and across-product proliferation (APP) ($p= 0.347$). The same is true for the squared terms and their interactions with brand image. In addition, these reversed models have significantly poorer model fit (Wald chi2 WPP^2 model = 17.27; APP^2 model =

62.83) compared to our original models (Wald chi2 WPP^2 model= 335.85; APP^2 model = 188.26). Thus, controlling for covariates, the reverse effect of firm performance on the different diversification measures disappears (or becomes insignificant). This indicates that reverse causality does not drive our results to a significant degree.

Discussion

For our study, we examined the nature of the relationship between intra-industry diversification and firm performance. We extend the scarce, specialized literature by finding support for our hypothesized non-linear effects as well as for our novel demand-side and firm-specific contingency that relate to consumers' brand perceptions.

Our study uses the context of the German automotive market between 1999 and 2008. The context is uniquely suited to study intra-industry diversification with multiple groups and brands competing across segments.

Our contributions to the strategy literature are twofold. First, our study contributes to the emerging stream of research on within-industry diversification and performance effects, an important but understudied phenomenon (Hashai, 2015; Li and Greenwood, 2004; Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). Contrary to its high importance for managers and widespread prevalence in practice, few studies have investigated the relationship between intra-industry product diversification and performance (Zahavi and Lavie, 2013). In sum, the study of the diversification-performance relationship has not reached a consensus yet (Palich et al., 2000) and the few studies that have tackled the topic have produced inconsistent findings. We find support for opposing curvilinear effects of APP and WPP on brands' market share, albeit by definition both types of related diversification. We add to this stream and from most extant research by showing that performance effects depend on the type and degree of

IID. We achieve greater clarity in this regard by distinguishing interrelated, but conceptually different facets of intra-industry diversification. More concretely, instead of investigating an aggregate measure of intra-industry diversification, we distinguish APP and WPP. Our findings indicate that increasing the quantity of different variants in each submarket is very different from expanding the product offering over several market segments. Transferring this insight into a different industry like the fashion industry (e.g. Inditex). Introducing several items in a summer product line in the Zara brand has a different effect on the market share than doing the same across several product lines, each with very different styles, quality, price points, and associated value chains. The findings are consistent with our hypotheses. While both APP and WPP are characterized by a curvilinear relationship with performance, their impact has very different properties. In that sense, our results for Hypothesis 1 and 2 extend the findings of Barroso and Giarratana (2013).

However, while these scholars focused more narrowly on profit margin by using a simulation implied equilibrium price for profit maximization, our results using a weighted market share provide similar results, thereby strengthening and clarifying our understanding of the implications of intra-industry diversification. We find an inverted U-shape for WPP and performance and a U-shaped relationship between APP and performance, respectively. At medium degree of APP firms incur increased coordination costs as well as weaken the link with submarket loyalists, without profiting fully from economies of scale at higher levels of diversification. Regarding WPP, when starting to diversify within a given segment, firms benefit from their experience, product relatedness and loyal customers. However, learning effects decrease at higher levels. Cannibalization and the chances of an identity loss increase. As a result, at a certain point of WPP, we observe diminishing returns of diversification. Accordingly, the net effect of intra-industry diversification ranges from positive to neutral and negative, depending on the dominance of either

WPP or APP. As such, the distinction of intra-industry diversification in APP and WPP provides a possible explanation for the diverging results from past studies and ideas for further refinement.

Second, we add to the growing body of literature that considers contextual contingencies to the diversification-performance relationship. Specifically, we consider a firm-specific moderator and their effect on the performance relationship. Here, we extend the current perspective on moderators that relies mainly on external contingencies or financial metrics. We follow Zahavi and Lavie's (2013) suggestion to test the moderating effect of company internal resources and capabilities or, more specifically, branding aspects. We hypothesize that brand value moderates the IID – performance relationship since it helps a firm to create a differentiated market presence to attract and retain customers. When a brand differentiates, the current image projects onto the new products. To stay with our fashion example of Inditex, if their casual-clothing brand Pull and Bear introduced an expensive high-end fashion product line, customer brand associations would still be based on the old lower-value brand image. Consequently, the performance effect of diversification is affected by the brand value. Our findings support that brand reputational assets, such as a high-quality image, moderate the effect of diversification by increasing its strength. We show that a higher-quality brand amplifies the performance effect of intra-industry diversification and greater total benefits materialize. However, the benefits erode more quickly as diversification continues, since the brand-submarket association erodes. Consequently, a loss of identity might follow as customers perceive poorer fit with market segment schemas. Hence, brand quality is both an important asset and a potential liability that moderates the effect of APP and WPP on firm performance. Most broadly, internal contingencies – such as firm-level contingencies related to commercialization of products across segments – may affect the diversification-performance relationship and the optimal strategies for companies.

From a managerial perspective, our study indicates that managers should be wary that intra-industry diversification, the most common diversification strategy and a natural precursor to inter-industry diversification, comes with nuanced implications. More concretely, our results carry two implications for managers. First, due to its high degree of relatedness, it is tempting to assume a similar and consistent positive diversification-performance relationship as for related diversification in general (Palich et al., 2000; Tanriverdi and Lee, 2008). However, we provide evidence that an extension of this argument to intra-industry diversification may be premature, falsely assuming linearity and ignoring important firm-level contingencies. With beneficial performance outcomes in mind, our findings can guide practitioners on the type and extent of diversification, depending on the initial situation and context of the firm. It is crucial to recognize the curvilinear properties of the relationship and acknowledge that diversification does not necessarily yield positive results. Second, our findings create awareness that other factors have the potential to influence the performance relationship, or more concretely, strengthen or attenuate it. In our study, we highlight the need for managers to carefully think about brand positioning in the context of diversification.

Our study, as any other study, has limitations that need to be acknowledged. First, the industry-specific empirical context of automotive industry comes with a potential limitation on generalization. However, while the empirical findings might not apply to all industries equally, we argue that the validity of our arguments likely holds in industries with similar characteristics such as high capital and labor intensity, as well as a high degree of market saturation. Second, weighted market share, our dependent variable, captures performance only indirectly. Nonetheless, market share has been found to be a good predictor of firm profitability (Venkatraman and Prescott, 1990) and it appears to be a variable of high managerial importance in saturated and oligopolistic markets. Third, we are only able to employ group-level controls due to limited data availability, however, measure performance on a brand-level. Fourth, lagged independent variables can only partially alleviate endogeneity. Future researchers should continue to study the relationship of intra-industry diversification on a more granular level, considering both APP and WPP. Additionally, they could extend the scope of their study by considering mixed effects of intra- and inter-industry diversification. Equally important, they could further investigate firm-specific moderators such as other brand-specific characteristics of the firm and their effect on the diversification-performance relationship. Lastly, scholars could adopt different and more direct measures of performance, also considering a cost perspective.

With our study on the IID and performance relationship, we attend both to the quest for a more nuanced investigation and the inclusion of contingencies, thereby amending inconsistent findings over the years. More specifically, we confirm findings of other scholars and extend this emerging stream of research by adding a new set of moderating variables. We hope that by untangling the complex phenomena and their contingencies we create greater clarity and understanding of this understudied phenomenon.

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Figures and tables

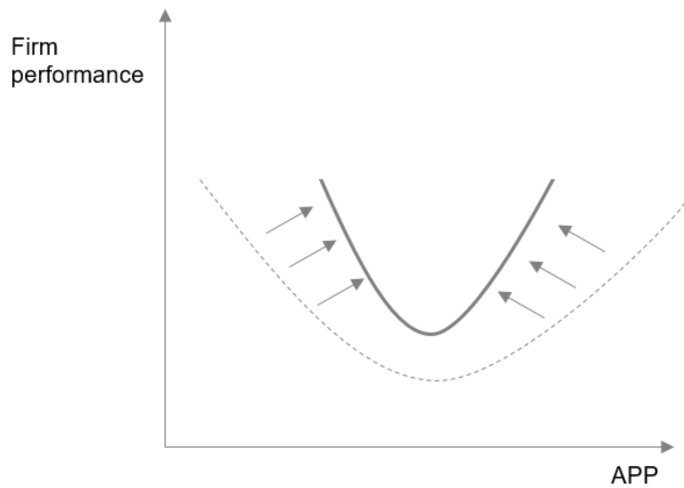

Figure 1. The hypothesized effect of higher-quality brand value on the association between firm performance and APP

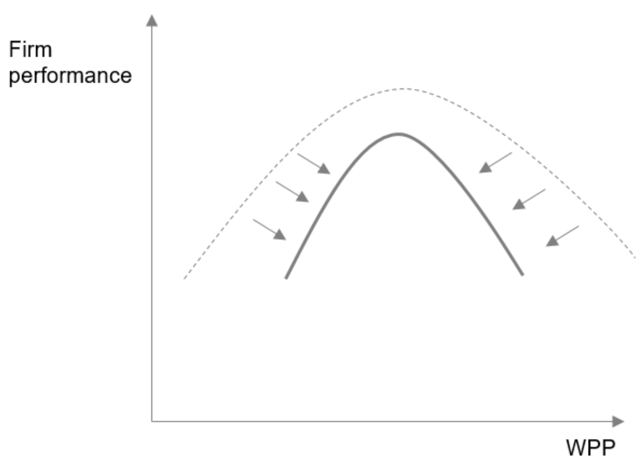

Figure 2. The hypothesized effect of higher-quality brand value on the association between firm performance and WPP

Category		Factor	Effect[1)] of an increase of WPP/APP on factor: WPP	APP	Comparison WPP and APP effect
Benefits	*Resource-based*	- Operational and management synergies	Positive (with decreasing marginal effect)	Positive (with decreasing marginal effect)	Stronger positive effects for WPP (because WPP exhibits higher relatedness than APP)
		- Prior experience and learning	Positive	Positive	
	Market-based	- Meeting needs of submarket loyalists	Positive	-	By definition, WPP only affects submarket loyalists, while APP only affects brand loyalists. Similarly, mutual forbearance appears only feasible with a coverage across submarkets (i.e., only via APP)
		- One-stop shop solution for brand loyalists	-	Positive (with strongly increasing marginal effect)	
		- Mutual forbearance to decrease competition	-	Positive (with strongly increasing marginal effect)	
Liabilities	*Resource-based*	- Costs of coordination, complexity etc.	Positive (with increasing marginal effect)	Positive (with increasing marginal effect)	Weaker negative effects for WPP (because WPP exhibits higher relatedness than APP); furthermore, we consider the cost effect more impactful than the learning traps
		- Learning traps	Negative	Negative	
	Market-based	- Cannibalization	Positive (with increasing marginal effect)	-	While cannibalization might play a role in the case of APP as might identity loss with submarket loyalists in the case of WPP, we consider them as rather negligible
		- Identity loss with submarket loyalists	-	Negative (with strongly decreasing marginal effect)	

1) Please note that a positive effect of an increase of WPP/APP on a factor from the category of liabilities results in a negative effect on performance (as the positive effect would lead to an increase in liabilities (cost)).

Table 1. Comparison of APP and WPP effects

Level	Combined WPP effect on performance	Combined APP effect on performance
At low levels	While the positive effects (synergies, learning, meeting needs of submarket loyalists) already materialize, the negative effects (costs and cannibalization) are not yet effective; hence, an increase in ***WPP increases performance.***	The negative effect of losing the identity with submarket loyalists is crucial, while the positive effects (synergies, learning, one-stop shop, mutual forbearance) do not yet materialize; hence, an increase in ***APP decreases performance.***
At high levels	The positive effects (synergies, learning, meeting needs of submarket loyalists) stop growing, while the negative effects (costs and cannibalization) significantly increase; hence, an increase in ***WPP decreases performance*** .	While the negative effect of losing the identity with submarket loyalists disappears, the positive effects (synergies, learning) materialize, some even exponentially (one-stop shop, mutual forbearance); hence, an increase in ***APP increases performance.***

Table 2. Combined effects of APP and WPP on performance

		1	2	3	4	5	6	7	8	9	10	11	12
1	Market share (weighted)	1.00											
2	APP	-0.21	1.00										
3	WPP	0.24	0.15	1.00									
4	Quality	0.60	0.18	0.35	1.00								
5	Market share (lag)	0.25	0.47	0.43	0.57	1.00							
6	Advertising spend	0.00	0.15	0.18	0.26	0.54	1.00						
7	Total assets	-0.16	-0.16	-0.03	0.03	0.08	0.49	1.00					
8	Return on sales	0.17	0.08	-0.10	0.26	-0.02	-0.16	-0.29	1.00				
9	R&D spend	-0.08	-0.17	-0.03	0.16	0.08	0.31	0.83	-0.19	1.00			
10	Brands in market	-0.01	0.03	0.02	-0.04	-0.02	0.03	0.02	-0.03	-0.02	1.00		
11	New segments	0.02	0.20	0.10	0.09	0.09	0.12	0.05	-0.07	0.04	0.02	1.00	
12	New competitor models	0.01	-0.04	0.00	-0.01	-0.04	-0.03	-0.03	-0.02	0.02	0.23	-0.02	1.00
13	Competition	-0.57	0.49	0.09	-0.35	0.21	0.20	-0.02	-0.05	-0.06	0.05	0.07	-0.01

Table 3. Correlation Table

Variable	Obs	Mean	Std.Dev.	Min	Max
Market share (weighted)	460	0.17	0.18	0.00	0.91
APP	459	0.77	0.62	0.00	1.73
WPP	414	2.51	1.06	1.00	6.00
Quality	294	0.00	16.81	-10.48	65.52
Market share (lag)	414	0.02	0.04	0.00	0.19
Advertising spend	339	57.81	56.98	0.00	201.00
Total assets	413	132006	98967	1466	405663
Return on sales	421	0.04	0.04	-0.09	0.28
R&D spend	373	3867	2160	23	9135
Brands in market	459	46.00	1.57	44.00	49.00
New competitors	408	0.38	0.75	0.00	8.00
New competitor models	408	3.34	0.23	2.77	3.71
Competition	414	0.70	0.16	0.05	0.93

Table 4. Descriptive Statistics

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
WPP		0.0562		0.0952**	0.148***
		(1.85)		(3.01)	(4.03)
WPP^2		-0.00750		-0.0149**	-0.0218***
		(-1.52)		(-2.84)	(-3.67)
APP			-0.139***	-0.138***	0.0394
			(-3.77)	(-3.31)	(0.29)
APP^2			0.0437*	0.0562*	-0.0118
			(2.29)	(2.39)	(-0.21)
WPP_Quality					0.0117**
					(3.16)
WPP^2_Quality					-0.00182**
					(-3.27)
APP_Quality					0.0238
					(1.71)
APP^2_Quality					-0.0124*
					(-2.34)
Market share (lag)	1.151***	1.440***	1.415***	1.717***	1.754***
	(3.82)	(6.09)	(4.47)	(7.09)	(7.34)
Quality	0.000966	-0.00000714	0.00128*	0.0000574	-0.0288*
	(1.65)	(-0.01)	(2.22)	(0.13)	(-2.53)
Advertising spend	16.89	-29.52	5.439	-96.08	175.8
	(0.09)	(-0.14)	(0.03)	(-0.46)	(0.77)
Total assets	-0.00061	-0.0261	-0.0316	-0.0812	-0.0263
	(-0.07)	(-0.22)	(-0.37)	(-0.61)	(-0.17)
Return on sales	-0.0371	-0.0269	-0.0901	-0.0614	0.0719
	(-0.35)	(-0.19)	(-0.92)	(-0.38)	(0.38)
R&D spend	-0.958	-1.026	-1.509	-0.765	2.289
	(-0.28)	(-0.22)	(-0.46)	(-0.15)	(0.37)
Brands in market	0.000611	0.000858	0.00126	0.000725	0.00184
	(0.38)	(0.40)	(0.83)	(0.29)	(0.63)
New segments	-0.000609	-0.000695	-0.000571	0.00242	0.00643
	(-0.19)	(-0.16)	(-0.19)	(0.47)	(1.08)
New competitor models	-0.00365	-0.00391	-0.00363	-0.00433	-0.00160
	(-0.37)	(-0.29)	(-0.39)	(-0.28)	(-0.09)
Level of competition	-0.345***	-0.555***	-0.349***	-0.656***	-0.825***
	(-5.34)	(-8.77)	(-5.67)	(-10.60)	(-13.17)
Cons	0.393***	0.454***	0.410***	0.543***	0.415*
	(4.07)	(3.69)	(4.47)	(3.99)	(2.31)
Group Fixed Effects	YES	YES	YES	YES	YES
N	218	218	218	218	218
df_m	28	30	30	32	36

t statistics in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 5. Estimation results of random effects panel regressions

	Model (6)	Model (7)
WPP	2.372***	2.540***
	(7.33)	(8.02)
WPP^2	-0.358***	-0.376***
	(-7.06)	(-7.72)
APP	-1.376**	0.640
	(-2.77)	(0.70)
APP^2	0.669**	-0.0546
	(2.61)	(-0.14)
WPP_Quality		0.268**
		(2.80)
WPP^2_Quality		-0.129***
		(-3.64)
APP_Quality		0.0214
		(0.63)
APP^2_Quality		-0.00354
		(-0.72)
Market share (lag)	10.31***	9.468***
	(5.98)	(5.11)
Quality	-0.00579*	-0.170*
	(-2.52)	(-2.43)
Advertising spend	-953.8	1943.2
	(-0.56)	(1.20)
Total assets	-0.719	-0.419
	(-0.49)	(-0.30)
Return on sales	-1.237	-0.585
	(-0.71)	(-0.39)
R&D spend	29.10	53.86
	(0.61)	(1.31)
Brands in market	-0.383*	-0.312
	(-2.02)	(-1.80)
New segments	-0.0616	-0.0525
	(-1.10)	(-0.89)
New competitor models	-2.011	-1.724
	(-1.61)	(-1.48)
Level of competition	-5.051***	-5.961***
	(-9.81)	(-11.14)
Cons	23.49	18.12
	(1.82)	(1.52)
Group Fixed Effects	YES	YES
Year FE	YES	YES
N	218	218
aic	188.4	195.7
bic	317.1	337.9
df_m	37	41

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 6. Robustness tests (I): GLM

	Model (8)	Model (9)
WPP	0.0192	0.0329
	(0.87)	(1.13)
WPP^2	-0.00271	-0.00426
	(-0.77)	(-0.97)
APP	-0.172***	0.0238
	(-5.23)	(0.31)
APP^2	0.0601***	-0.0145
	(3.48)	(-0.46)
WPP_Quality		0.00372
		(1.18)
WPP^2_Quality		-0.000573
		(-1.31)
APP_Quality		0.0218**
		(2.67)
APP^2_Quality		-0.00833*
		(-2.56)
Market share (lag)	1.171***	0.970**
	(3.56)	(2.88)
Quality	0.00148**	-0.0184*
	(2.75)	(-2.30)
Advertising spend	-34.35	107.5
	(-0.24)	(0.66)
Total assets	-0.0221	0.0204
	(-0.32)	(0.29)
Return on sales	-0.0988	-0.0542
	(-1.24)	(-0.67)
R&D spend	-0.830	0.236
	(-0.31)	(0.09)
Brands in market	0.00121	0.000736
	(0.98)	(0.58)
New segments	-0.00180	-0.00124
	(-0.68)	(-0.46)
New competitor models	-0.00379	-0.00337
	(-0.51)	(-0.45)
Level of competition	-0.280***	-0.279***
	(-5.23)	(-5.20)
Cons	0.344***	0.216*
	(3.87)	(2.00)
Group Fixed Effects	YES	YES
N	218	218
df_m	32	36

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 7. Robustness tests (II): XTGEE