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Technical newness: Putting a spotlight on its dynamic nature and effects

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ABSTRACT

Differentiating products by means of novel technical features is an accepted approach to achieving and retaining long-term success. So far, innovation research has treated technical newness as a static concept. In this paper, we introduce a dynamic perspective and enhance the technical newness concept in three ways. First, we acknowledge that customers become accustomed to a product and perceive it as less new as time goes by. Second, we consider product updates that introduce new features and functionalities across a product's life cycle. Third, we uncover how technical newness affects the sales performance of new products over time. We track 175 cars over their life cycle, and find that the effect of technical newness takes an inverted-U shape. Our results imply that a dynamic perspective is crucial both when assessing a product's technical newness and when analyzing its performance impact.

Keywords: Technology life cycle, Technological Change, Management of Technological Innovation

1. Introduction

In technology-based firms, managers continuously strive to improve their sales performance by launching new products that contain entirely new or improved technologies, technical modules, or components. Several frameworks, including the product life cycle, the technology life cycle, and the growth-share matrix, postulate the need to develop new technologies and launch new products that will generate future sales and prevent obsolescence of the firm's products (Chaney et al. 1991, Cooper 1987). However, prior research paints a rather ambiguous picture of the relationship between technical newness and market performance. Some studies indicate a positive relationship (e.g., Kleinschmidt and Cooper 1991, Gatignon et al. 2002, Simon et al. 2002, Zhou et al. 2005), whereas others report insignificant results (e.g., Danneels and Kleinschmidt 2001, Polk et al. 1996, Swink 2000).

The reasons for these mixed findings may be manifold, including that empirical studies (1) regularly employ a cross-sectional design in which both constructs are assessed at a single point in a product's life cycle, (2) mostly use surveys, in which respondents assess both constructs in retrospect, (3) neglect the dynamic nature of technical newness, and (4) apply an overall assessment of technical newness for complex, multi-component products.

A discussion of how existing results regarding the relationship between technical newness and performance may have been affected by the above-mentioned issues leads to the goal of this study: to refine the assessment of technical newness by introducing a dynamic perspective. We consider three approaches to capture the dynamics in the relationship between technical newness and sales performance. The first two relate to the measurement of technical newness, and the third concerns the specification of the relationship between technical newness and sales performance.

First, we consider the fact that so far, empirical studies in innovation research have assessed the degree of newness at a single time point. However, this practice ignores the fact that in most industries, the technological status quo is constantly changing. Products that are perceived as radically new upon market entry will lose their technological distinctiveness either when competing products catch up or when superior technologies are introduced. In addition, consumer behavior literature suggests that perceived newness decreases over time because of a familiarization process (Zaichowksy 1985). When customers become accustomed to a new technology, its arousal potential declines, and

customers are stimulated to a lesser degree (Steenkamp et al. 1996). Technical newness, conceptualized as a dynamic concept that diminishes over time, may thus affect sales performance differently than a static concept. To provide a better understanding of these differences, we compare the performance impact of a depreciated versus a static measure of technical newness.

Second, we argue that in many product categories, firms regularly use updates (both physical and software-based) to introduce new features and functionalities of a current product (Druehl et al. 2009). Over time, such updates may result in a slower depreciation or even an increase of technical newness. We question whether research captures such dynamics properly if technical newness is assessed on an overall product level, and propose that a component perspective may be better able to handle component-related changes over the course of a product's life cycle. Apple, for example, recently updated its MacBook with Retina Display, Force Touch Trackpad, and Core-M-Processors. The integration of novel components can cause a discontinuous leap in the perception of the product's technical newness. Researchers have often argued that a component perspective better represents today's mostly complex, multi-component products (e.g., Henderson and Clark 1990), but an empirical application is still lacking. By comparing the performance impact of an overall measure and a component measure, we also advance the current understanding of the overall versus component perspective of technical newness.

Third, we investigate how technical newness affects the sales performance of new products across their life cycle. In a longitudinal study, we track 175 new car models over time to explore potential impact changes throughout the life cycle. Past research has largely neglected the importance of understanding the pattern of such impact changes, although the rationale of the technology adoption and diffusion literature implies inter-temporal changes (e.g., Rogers 2003).

In summary, this study contributes to innovation research in several ways. We add to construct refinement by introducing two dynamic perspectives of technical newness. In addition, we develop a conceptual model of the varying impact of technical newness on sales performance over the product life cycle. Finally, we provide an empirical validation of our refinements of the concept of technical newness and its impact on sales performance. We specify regression models that are more

comprehensive than those presented by existing studies. Apart from our focal variables, we control for product life cycle, price, media expenditures, and brand differences.

The remainder of this article is organized as follows. First, we review several literature streams from technology adoption and diffusion research as well as consumer behavior research to refine the conceptual understanding of technical newness and to develop a conceptual model of the varying impact of technical newness on sales performance over the product life cycle. After outlining the research design, we report the results of a series of multiple least-squares regressions. We conclude with a discussion of the study's findings, implications for managers and policy makers, and avenues for future research.

2. Refining the concept of technical newness

In innovation research, technical newness is mostly understood as the degree of change in technological features, principles, and performance compared to the technology status quo (e.g., Gatignon et al. 2002). This change can occur either when technology moves along the S-curve or when a new technological paradigm is introduced and a new S-curve begins (Foster 1986). Thus, new products with high technical newness often exhibit considerable technological performance enhancements (Green et al. 1995) and/or embody a technology that follows a new technological paradigm (Garcia and Calantone 2002). As a result, old technologies can be superseded.

2.1. Technical newness: considering a depreciation perspective

A review of current measurement approaches of technical newness reveals that technical newness is mostly assessed either at one point in the product's life cycle or without referring to a specific time point at all. In most studies, key informants respond in retrospect as to a product's degree of newness at the time of its market entry (e.g., Avlonitis et al. 2001, Cooper and Kleinschmidt 1993). A few recent studies use industry-specific classification schemes to distinguish radical from incremental innovations at market entry (Sorescu et al. 2003, Pauwels et al. 2004), but several studies do not specify any particular reference point in the product's life cycle (Green et al. 1995).

Such a practice seems to indicate that researchers assume technical newness to be a static, time-invariant phenomenon and suppose a dynamic perspective in assessing technical newness to be

irrelevant. These assumptions do not consider that the technology status of most industries is in a state of flux, changing with every new product introduction. According to the S-curve concept (Foster 1986), technology is continuously developing, either improving technological performance in established paradigms or moving to a new principle and starting a new S-curve. Certain technologies that were radically new at their market entry may be replaced by superior technologies (Christensen 1997). Technology disruption may thus rapidly decrease such technologies' impact on the technological state of the industry and reduce their chances of success. The electric typewriter with a preview display is a prominent example of a product that was quickly replaced by personal computer-based word processing.

Apart from the case of technology disruption, competitors may strive to imitate technological advancements and establish similar technologies in their products (Baldwin and Clark 2000). For example, the airbag, which was introduced to the Mercedes S-class in 1981, was a highly innovative component that diffused rapidly. In 1991, approximately 40% of all new cars in the US were equipped with an airbag; by 1997, the share had increased to more than 95% (Beise 2006). As diffusion in an industry increases, the perceived level of technical newness is likely to decrease because the technology becomes common. However, even if a technology is not imitated either because of intellectual property rights or because competitors deem it irrelevant or unsuitable for their products, customers are likely to become accustomed to it after some time and perceive it as less novel.

Consumer behavior literature supports the notion of a familiarization effect. When products are on the market for some time, the probability increases that customers with an interest in the category eventually learn about the technical innovation even if they do not own the product (Zaichowksy 1985). When novel products or product attributes are added to customers' knowledge structure and reinforced through repeated exposure, customers become increasingly familiar with them. Consequently, the product's ability to generate arousal decreases, leading to lower levels of stimulation and a less favorable product evaluation (Berlyne 1978, Steenkamp et al. 1996).

Overall, we expect technical newness to decrease over time. Thus, a product's level of technical newness should depend heavily on the point in time at which its newness is assessed. The assessment should adopt a depreciation perspective because that perspective reflects that a product's technical

newness is influenced by (1) new technological developments, (2) the diffusion of innovations in the market, and (3) customers' familiarization process. A dynamic depreciated measure of technical newness should better explain market performance than a static measure. Therefore, we formulate the following exploratory research proposition:

P1. The technical newness of a product is not a static phenomenon. Instead, the degree of technical newness will decrease over time. Thus, the assessment of a product's technical newness as a dynamic depreciated measure is better able to explain market performance than is a static measure of technical newness.

2.2. Technical newness: considering a component perspective

Typically, the degree of technical newness is determined on the product level. For example, since 1963, *R&D Magazine* has used expert assessment to identify the 100 most technologically significant new products of the year for its well recognized R&D 100 Award. The journal editors and outside judges look for products with a so-called "Wow! factor": "products that leapfrog current technology, that provide simple, elegant solutions to complex or long-standing technical or practical problems – products that are so interesting, unusual, or clearly superior to existing technology that they make you say 'Wow!'" Although *R&D Magazine* recognizes that the competing products vary in their technical complexity, the assessment of technical newness relates to the overall product level. This practice is also common in empirical research (for an overview, see Garcia and Calantone 2002). However, most of today's products are conglomerates of components that can have significantly different levels of newness.

This fact is acknowledged by a considerable body of literature with an innovation focus (e.g., Clark 1985, Henderson and Clark 1990, Baldwin and Clark 2000, Schilling 2000). In concepts such as architectural innovation (Henderson and Clark 1990) and product modularity (Furlan et al. 2014, Gershenson et al. 2003, Ethiraj et al. 2008, Schilling 2000), products are described as consisting of multiple components or modules. Following this view, most "new" products are a combination of existing products with innovative components, rather than being radically new in the sense that they cause discontinuity on a macro level (Rothwell and Gardiner 1988, Garcia and Calantone 2002,

Kleinschmidt and Cooper 1991). They may introduce new materials or integrate new sub-systems or new technical components (Rothwell and Gardiner 1988). However, if most new products comprise a combination of existing products with innovative components, a component-based assessment may be a better method of determining the technical newness of a product relative to that of its competitors.

In addition, in many product categories, products are updated over the course of their life cycle. Automobiles, for instance, are regularly equipped with new technical components, and software updates can bestow new functionalities on consumer electronics such as mobile phones, tablets, and TV sets. For assembled products of this kind, the use of a component approach could provide a more precise way to capture the degree of technical newness when products are updated during their life cycle.

Information processing and product evaluation theories in the consumer-behavior literature also support the notion that a product's technical newness should be assessed on the basis of individual components. These theories assume that in consumers' minds, products are represented by a set of product attributes. For example, the schema pointer plus tag framework predicts that consumers memorize and recall unique ("tagged") attributes, such as an outstanding innovative technological component, more vividly than attributes that are common for the product. Therefore products with unique attributes are more present in the consumer's mind and stand out compared to competing products (Desai and Keller 2002, Graesser et al. 1979, Lee et al. 1996). The inclusion of new attributes has been found to affect overall product evaluation positively (Meyers-Levy et al. 1989, Nowlis et al. 1996), and also to lead to higher levels of arousal and pleasure (Lee et al. 2011) as well as and higher choice probability (Nowlis et al. 1996). When evaluating products as a whole, the weighted additive strategy suggests that consumers focus on a set of individual product attributes and give each attribute a subjective utility score that reflects its relative importance for the overall product. By summing the individual scores, consumers arrive at an overall utility score for the product (e.g., Bettman et al. 1998). Numerous other product-evaluation strategies, such as the lexicographic heuristic or the frequency of good and bad features heuristic, are also based on product attributes (for an overview, see Bettman et al. 1998). Overall, these theories imply that when assessing a product's level of newness, consumers are likely to focus on a set of individual technical components. That is, consumers are likely to pay

particular attention to unique technical components, to recall them more easily, and to focus on them when judging a product's technical newness.

So far, only three studies have built on the idea of a component-based approach when assessing a product's technical newness. Gatignon et al. (2002) evaluate the technological radicalness of an innovation from a component perspective, but they rate only the most and least innovative components in a firm's portfolio. Hong and Hartley (2011) rate the percentage of new technologies in a component but restrict their analysis to two components per product. To our knowledge, only Talke et al. (2009) follow a comprehensive component approach. They analyze the effect of technical newness by composing a measure based on the innovativeness of individual components.

We investigate how a component-based measure of technical newness affects market performance compared to an overall measure. A measure that is based on technical component ratings should better (1) capture changes in technical newness that occur over the course of a product's life cycle, (2) represent today's mostly multi-component products, (3) reflect differences in the technological states of products, and (4) describe consumers' multi-attribute choice processes. We therefore formulate the following exploratory research proposition:

P2. Products are composed of multiple components, which may differ largely in their individual newness levels. The assessment of a product's technical newness as an aggregate measure of component newness is better able to explain market performance than is an overall measure of technical newness.

3. Market performance effects of technical newness over the product life cycle

In our research, we intend to shed light on the question of whether the influence of technical newness on sales performance remains stable over the product life cycle or changes in terms of its strength and direction. Although several researchers recognize that assessing this relationship at different time points may yield different results (e.g., Montoya-Weiss and Calantone 1994), comprehensive conceptual thinking and empirical evidence are still lacking. We first review the theoretical expectations of the performance effects of technical newness over the product life cycle, and then focus on the empirical outcomes of earlier studies.

Our rationale is guided by product life cycle concepts and diffusion theory (Rogers 2003, Vernon 1966). Both theories describe demand growth and saturation processes as innovations spread among a population of adopters. Diffusion theory posits that adopters have different levels of readiness to adopt new products (Rogers 2003). In addition to adopters' characteristics, such as innovators' novelty-seeking tendency, innovation specifics and contextual factors also affect the decision to adopt.

The usual shape of both the product life cycle and the diffusion curve (Vernon 1966, Rogers 1965, Bass 1969) predicts that most products will experience a period of slow sales growth directly following market entry. For products of high technical newness, this period is likely to take longer. Large deviations from the technological status quo are likely not only to lead to high levels of initial innovation resistance (Talke and Heidenreich 2014) but also to affect customers' perception of product complexity and the functional and financial risks associated with the product (Rogers 2003). Customers tend to experience increased difficulty understanding new features and functions and their use case (Engel et al. 2005). Very innovative products are often difficult to assess not only as to whether the introductory price is reasonable but also whether other profit- or cost-related benefits will manifest (Golder and Tellis 1997). Less venturesome customers may thus postpone their purchase decision to avoid making a "bad deal" (Thaler 1985). Initial sales of products of high technical newness can also be slow if the product environment needs to be adapted, as such adaptations often take time. New interfaces may require changes in complementary products, and novel configurations may require changes in the product infrastructure or new types of legal contracts with customers or other partners (Kohli et al. 1999). To summarize the foregoing, we expect a weak sales response to products of high technical newness early in the product life cycle.

After the launch, product life cycle and diffusion concepts predict a phase of demand growth during which the speed of sales accelerates. For products with high technical newness, demand growth may be slower and sales may peak later. Communicating and demonstrating the benefits of truly novel features and functions is more difficult (Lee and O'Connor 2003). In particular, less venturesome customers tend to be unwilling to invest resources into understanding these features and functions, so they take longer to become accustomed to very new products (Bagozzi and Lee 1999, Kohli et al. 1999).

However, we argue that highly innovative products sell better as soon as initial adoption resistance has been overcome. In several cases, significant performance improvements accompany large technology jumps, which can be a strong argument for adoption (Schilling 2003). When new products containing very innovative technologies do not initially sell as well, fewer competitors may be attracted to the market. If these products are also technically more complex, they may be more difficult to imitate and therefore maintain their monopoly position longer and profit more from the resulting returns. Consequently, we hypothesize a stronger sales response when the new product is in the maturity phase of the product life cycle.

Following the sales peak, product life-cycle and diffusion concepts predict a phase of market saturation, marked by progressively declining sales. Products with greater technical newness should be more likely than incremental innovations to experience demand saturation and degeneration both later and to a lesser degree. If these products embody larger technology jumps and more significant performance improvements, competition is likely to need more time to develop and introduce superior products. Factors such as the magnitude of R&D investments, greater technological significance, and increased functional performance can explain why some technology-based products survive longer in the market (Åstebro and Michela 2005). Similarly, products containing novel technologies have a persistent, more sustainable impact on adoption decisions over time (Talke et al. 2009). Technical newness is thus expected to have a delaying effect on demand decline, and we hypothesize its performance effect in the decline phase to be positive, but smaller than during the maturity phase of the product life cycle.

So far, performance effects of technical newness over the life cycle have not been thoroughly discussed in the empirical literature. Although several researchers have addressed the performance effects of technical newness, most articles either do not state the time at which new product performance was assessed or analyze product performance at the beginning of the life cycle.

Overall, we observe that empirical evidence for the relationship between technical newness and market performance is ambiguous. Some studies provide evidence for a positive effect of technical newness on market performance (e.g., Gatignon et al. 2002, Molina-Castillo and Munuera-Alemán 2009, Simon et al. 2002, Talke et al. 2009, Talke et al. 2011, Zhou et al. 2005, Sorescu et al. 2003), and

most researchers argue that technical newness affects a wide array of benefits associated with new products. A product with new technical performance features should be better able to meet the latent needs of potential customers (Veryzer 1998). High relative advantage often has the strongest effect on product adoption (Rogers 2003), and the degree of a product's technological sophistication is a strong predictor of innovation success (Henard and Szymanski 2001). A novel technology can also serve as an effective argument for product positioning and differentiation from competitors (Lynn et al. 1996) and allow for the realization of temporary monopoly returns (Min et al. 2006). However, a number of articles also report an insignificant relationship of novel technology with market performance (e.g., Danneels and Kleinschmidt 2001, Polk et al. 1996, Swink 2000). With respect to the aforementioned discussion, these mixed effects may partially result from the cross-sectional measurement approach, in which technical newness is assessed at only one time point in the product's life cycle. Indeed, most studies that assess market performance at later stages of the life cycle find positive performance effects (Gatignon et al. 2002, Simon et al. 2002, Molina-Castillo and Munuera-Alemán 2009, Zhou et al. 2005).

In this article, we focus on the effect of technical newness on product sales, which is a classical measure of market performance. Both our theoretical reasoning and most of the empirical evidence emphasize positive sales effects, so that we generally expect a positive relationship between technical newness and product sales. In addition, we follow the rationale of diffusion theory and propose that the performance effect of technical newness will change in strength over a product's life cycle. In the first phase after the product launch, technical newness will have a dampening effect on sales. However, the effect of newness will become significantly positive during later phases of the product life cycle, and it will decrease toward the end of the life cycle. H1 summarizes our expectations:

H1. The effect of technical newness on the product's market performance exhibits an inverted U-shaped relationship over the product life cycle.

4. Methods

4.1. Sample

We consider a sample of 175 new car models introduced in the German market between 1978 and 2006. We chose the automotive industry as the field of investigation because of the important

strategic role of product innovations in that industry (Pauwels et al. 2004). In addition, cars represent complex products consisting of several distinct components, and thus the use of the automotive industry enables a decomposed assessment of technical newness. Because cars are high-involvement products, several industry publications target end customers. Some of these magazines have existed for more than 50 years, offering a variety of publicly available data on new product launches and their technical specifications over time. In addition, model-specific sales figures are publicly available because every new car sold in Germany must be registered with the German vehicle registration office (Kraftfahrt-Bundesamt). These conditions allow the construction of a data set reflecting reduced concerns about both common-source and retrospective bias.

Germany is the largest European market for cars and is known for its high level of competitiveness. Many models from international original equipment manufacturers (OEMs) are present across all major segments. In building our sample, we concentrate on the six main car segments: micro, small, lower midsize, midsize, upper midsize, and luxury.¹ The models in these segments account for more than 70% of the overall car sales in 2006. To secure sufficient variance in our sample, we include models from both German and international OEMs, and models with both strong and limited market share. We also asked five industry experts to identify car brands that follow different product/market strategies. On the basis of their classification, we chose models from brands that attempt to achieve competitive advantage through differentiation (e.g., BMW) and from brands that strive for cost leadership (e.g., Skoda). Overall, the sample contains fourteen brands.

Since the focus of this research is on providing more precise measurements of a product's technical newness, we needed a sample covering all of the major technological innovations in the automotive industry. Because of the speed of change in that industry, and because of sample size requirements for robust statistical analyses, we include new cars launched between 1978 and 2006 in our sample. By analyzing a time span of 29 years, we can capture major innovations such as ABS (launched in 1978), the aluminum chassis (1994), and daylight or rain sensors (1995).

¹ This definition of segments follows the German vehicle registration office's official classification, which is primarily based on size and engine-power criteria.

4.2. Measures

To test our propositions, we compile four measures of technical newness and compare how well they predict sales over the product life cycle (e.g., Steenkamp and Baumgartner 1995, Peter 1981). As measures of technical newness, we consider (1) an overall, non-depreciated, (2) a component-based, non-depreciated, (3) an overall, depreciated, and (4) a component-based, depreciated measure. Below, we first explain how we obtained the scores for the overall measure and the component-based measure of technical newness, and then describe how we operationalized depreciation of both measures.

4.2.1. Technical newness: assessment from an overall perspective and from a component perspective

4.2.1.1. Overall perspective

To assess technical newness from an overall perspective, we turned to relevant industry publications for an in-depth document analysis. The leading German automotive journal (*Auto-Motor-Sport*) was used as the main document source. At the time of its launch, each new car model is featured in a three- to four-page article authored by expert journalists. These articles are content-rich, contain information about the brand, the model line, and its history, and regularly emphasize the model's technological specifics. For a content analysis, we had three independent researchers search for phrases that indicate the model's overall technical newness. Following previous measurement approaches to technical newness (e.g., Danneels and Kleinschmidt 2001, Salomo et al. 2007, Kock et al. 2011), the researchers assessed whether and to what degree the car (1) was perceived as containing new components, modules, and materials, (2) was making old technologies obsolete, and (3) was realizing significant technological performance enhancements. Researchers were asked to mark explicit phrases in the test reports that indicated the degree of technical newness in the three categories. Additionally, they were asked to look for summary statements describing how the journalist perceived the car's overall technical newness. Using this information, the researchers then rated each car model's overall technical newness on a 7-point-scale. Using the three ratings for the overall technical newness of each car model, we calculated the single-item intraclass correlation coefficient (ICC: .66; $p < 0.001$). The ICC indicates moderate-to-good agreement that allows us to calculate a mean score of technical newness for each car model.

4.2.1.2. Component perspective

The assessment of technical newness from a component perspective is based on the architectural innovation concept (Henderson and Clark 1990), which defines technical newness as the accumulated technical change in substantial product components relative to the technical state of the art in the industry. To apply this concept to measurement practice, we closely follow the procedure described by Talke et al. (2009).

In a first step, we turned to industry publications and identified technical component innovations in the primary automotive domains—the chassis, interior, power train, and electronics—introduced between 1978 and 2006. For verification and completion, we then presented the list of component innovations to 12 industry experts from different technology fields who were working at OEMs and first-tier suppliers. The experts also rated the newness level of each of the 23 components when it first appeared on the market (e.g., ABS in 1979). The experts used a 7-point scale to assess the degree to which the component (1) was perceived as a new technical principle, (2) made old technologies obsolete, (3) achieved a performance leap, and (4) induced a technological change in the car. Intraclass correlation coefficients indicated high levels of agreement among the experts (ICCs ranged from .68 to .93), and a mean score of technical newness was calculated for each component. We then had to determine which set of component innovations was built into the car models of our sample at the time of market entry. As a source for an in-depth document analysis, we selected the leading German automotive journal (*Auto-Motor-Sport*). For each model, we reviewed at least two test reports, which include lists of all technological specifics built into the cars.

However, at its market entry, a car model usually does not contain all of the component innovations that are offered at the end of its life cycle. In the automobile industry, new technical components are regularly introduced to existing models. Some components may be fully marketable only after the car's market entry, or after component innovations from a different car model are integrated into models that use the same platform. Thus, a measure of technical newness that describes the car's technical state only at the time of market entry would not include ongoing changes. To reflect each car's technical newness at each life-cycle stage, we determined the change of component innovations over time on a yearly basis. Overall, more than 1,000 different documents were needed for

this task.

Finally, we assigned a single technical-newness score to each car model. We calculated the technical newness of each car as the sum of the individual newness scores of all of the integrated component innovations. For an overview, please see Table 1.

Table 1: Overview of Components

Component	Introduction	Component	Introduction
anti-lock braking systems (ABS)	1979	seat belt tensioner	1981
adaptive cruise control	1999	head-up display	2003
Airbag	1981	hands-free remote central locking system	1999
active head restraint	1989	head/ torso side airbags	1994
aluminium chassis	1994	day light/ rain sensor	1995
traction control system	1987	multifunctional steering wheel	1994
tire pressure monitoring system	2000	night vision system	2005
emergency brake assistant	1997	lane departure warning system	2004
motor-adjustable steering column	1985	adjustable steering column	1972
parking sensors	1993	xenon headlights	1991
dynamic stability control	1995	remote central locking system	1984
dynamic seat	2002		

4.2.2. Technical newness: assessment as a non-depreciated and as a depreciated score

For the non-depreciated scores of technical newness, we used both the overall and the component assessments detailed above. For the depreciated scores of technical newness, we accounted for the decrease of any innovation's newness over time and depreciated each technical-newness measure.

However, determining a depreciation rate a priori is difficult given the absence of a conceptual rationale or empirical evidence that relates to the technical newness of products. In a search for analogies, we turned to the economics literature that addresses the endogenous estimation of a depreciation rate for technological knowledge, mostly operationalized by investments in R&D capital or patent renewal data. We summarize the most relevant characteristics of key studies in this area in Table 2. The average estimated depreciation rate of these studies is 14.2%. In reference to these results, many authors decided to use a deterministic depreciation rate of 15% (Belezon et al. 2013, Cincera et al. 2014, Grimpe et al. 2014, Huang 2013).

Table 2: Estimations of depreciation rates in the literature

Authors	Year	Dep. Rate	Note	Depreciated Variable	Construct
Bessen	2008	14.0%	US patent data (1985-1991)	patente value	n.a.
Bosworth	1978	13.1%	UK patent data (1934-1965)	patent renewal data	technical knowledge
Goto and Suzuki	1989	11.6%	Japanese R&D expenditures (1981)	R&D capital	stock of knowledge
Nadiri and Prucha	1996	12.0%	US total manufacturing data (1930-1988)	R&D capital	knowledge capital
Pakes and Schankerman	1984	25.0%	European patent data (1930-1939)	patent renewal fees	knowledge capital
Park et. al	2006	13.5%	US patent data (1975-1999)	life-time of reference	technological capital
Schott	1976	10.0%	UK R&D expenditures (1930-1984)	R&D capital	technological capital
Average		14.2%			

Although the methods for estimating a depreciation rate differ across the studies in Table 2, they are similar in the sense that depreciation rates reflect declining economic benefits over time, which are caused by the inability to further employ an innovation in an economic manner (Pakes and Schankerman 1984). This principle is also fundamental when selecting the appropriate depreciation method for intangible assets from an accounting perspective (IAS 38, § 97-106).

Following this notion, we decided to establish the depreciation rate empirically. An optimal depreciation rate would be one that maximizes the fit of a regression model that relates depreciated technical newness to sales—that is, a depreciation rate that performs best in explaining the economic performance of the car model on the basis of its technical newness.

To the overall measure of technical newness, this procedure is rather easily applied. We let $OverallTechNewness_{i,t_i^0}$ denote the designed newness score assigned to car i at its time of introduction, t_i^0 , and let the baseline regression model (Model 1, which we develop below) find the optimal depreciation rate $\delta_{Overall}$, which is the same for each car model. The depreciated newness score for car model i at time t is then computed as:

$$OverallTechNewness_{i,t}^{Dep} = (1 - \delta_{Overall})^{(t-t_i^0)} \times OverallTechNewness_{i,t_i^0} \quad (1)$$

For the component-based measure of technical newness, the procedure is somewhat more complex. For each component j , the experts determined $Component_{j,t_j^0}$, the component newness score

at t_j^0 , the time this component was first introduced in the market. We depreciate all component newness scores with depreciation rate δ_{Comp} over the “age” of the component—that is, the difference between the current year t and t_j^0 . Again, we use a model-generated optimal depreciation rate that is the same for all components and car models. The depreciated component-based technical newness score for each car model i is then calculated as the sum of the depreciated newness score of all components that are built in that car model:

$$ComponentTechNewness_{i,t}^{Dep} = \sum_{\substack{\text{Components in} \\ \text{car model } i}} (1 - \delta_{Comp})^{(t-t_j^0)} \times Component_{j,t_j^0} \quad (2)$$

To account for different technological states in the six car segments and the systematic growth of the component technical-newness measure over time, we use relative measures. Thus, an additional transformation is required for all technical-newness scores, where we divide all each car’s newness scores by the mean technical newness of all car models in the same segment and calendar year.

4.2.3 Product sales

To assess how each car model performed in the market, we use sales yearly figures. Because every new car sold in Germany must be registered with the German central registration office (KBA), model-specific sales figures are publicly available. For the first model year, we use mean monthly sales figures to account for variations in entry timing across new models. To account for systematic differences in sales in different car segments and differences over time, the variable was transformed to a relative measure by dividing it by the average sales of competing models in the same segment and year.

4.2.4. Control variables

As control variables, we considered each car model’s price, a measure of competitive intensity, model-related media expenditures and brand dummies.

Price data on a yearly basis were obtained from *Autokatalog*, a German industry magazine. Again, to account for systematic differences in car segments and over time, we divided the price by the mean model price in the appropriate segment and year. We also assessed competitive intensity for each model on a yearly basis by calculating the mean time span from the time that competitors launched their

new models to the respective segment. A long mean time span means that competitors' models have already been in the market for some time, which implies the segment's low competitive intensity.

We also controlled for model-related media expenditures, which are provided by Nielsen Media Research and include yearly expenditures from 1990 to 2006 for television, radio, and movie-theater campaigns, along with print, poster, and online campaigns. Again, media expenditures are expressed relative to the mean of models within the same segment and calendar year. For models older than 1990, we replaced the missing data with a proxy that captures the relative average yearly media expenditures at the brand level.

Table 3 contains the descriptives for the measures. In addition to these variables, we also employ dummy variables for all car brands to control for unobserved heterogeneity at the brand level.

Table 4: Descriptive statistics for independent variables

	Segment*													
	<i>micro</i>		<i>mini</i>		<i>lower middle</i>		<i>middle</i>		<i>upper middle</i>		<i>luxury</i>		<i>overall</i>	
	<i>mean</i>	<i>std.</i>	<i>mean</i>	<i>std.</i>	<i>mean</i>	<i>std.</i>	<i>Mean</i>	<i>std.</i>	<i>mean</i>	<i>std.</i>	<i>mean</i>	<i>std.</i>	<i>mean</i>	<i>std.</i>
overall technical newness ^a	1.73	0.33	1.95	0.94	2.37	0.92	2.37	1.14	2.89	1.31	4.39	1.30	2.52	1.25
component technical newness ^b	25.70	7.65	22.67	19.67	30.17	24.60	30.27	23.67	31.47	24.75	47.37	26.73	30.07	23.85
product life cycle (PLC)	4.91	2.84	4.06	2.36	3.61	1.99	3.92	2.18	4.40	2.41	4.69	2.71	4.08	2.32
unit price ^c	9,350	1,045	10,592	1,786	13,565	3,206	18,244	4,626	24,584	6,661	47,705	12,660	18,821	11,204
segment competitiveness ^d	4.99	2.05	3.10	0.86	2.61	0.87	3.01	0.64	3.44	0.77	3.64	2.33	3.16	1.18
n models	7		37		44		42		33		12		175	

* segments follow the classification of the German central registration office

^a “Overall the product can be characterized as being based on a very new technology” 7-point Likert-type scale from 1 (=applies not at all) to 7 (= applies completely)

^b “Overall the component can be characterized as being based on a very new technology” 7-point Likert-type scale from 1 (=applies not at all) to 7 (=applies completely) per component aggregated for all components per vehicle

^c inflation adjusted unit price (EUR)

^d mean time between new product launch and last competitor new product launches.

4.3. Models

To assess P1, P2, and H1, we compare the outcomes of four multiple least-squares regressions, which differ according to which of the four measures of technical newness are used. We summarize the four models in Table 4.

Table 4: Overview of regression models

	Overall Technical Newness	Component-based Technical Newness
Non-depreciated	Model 1	Model 2
Depreciated	Model 1a	Model 2a

In P1, we suggest that a depreciated measure of technical newness, which accounts for a decrease of technical newness over time, is better able to explain market performance than a static measure. To challenge this proposition, we compare the findings of the models that employ a non-depreciated technical newness measure (Models 1 and 2) with the two models that use depreciated technical-newness scores (Model 1a, Model 2a).

In P2, we suggest that a component-based measure of technical newness is better able to explain market performance than an overall measure. To challenge this proposition, we compare the findings Models 1 and 1a to those of Model 2 and 2a.

In H1, we state that the effect of technical newness on market performance exhibits an inverted U-shaped relationship over the product life cycle. To test this hypothesis, the regression models must be able to accommodate a time-varying effect of technical newness. Thus, in all four models, the effect of technical newness is allowed to change over time according to a flexible polynomial of order two and is parameterized by β_3 , β_4 and β_5 .

Additionally, we include a quadratic trend to control for general life-cycle effects (β_1 and β_2) and relative model price, media expenditures, and competitive intention, along with brand dummies as additional control variables. All four regression models that we estimate have the following structure:

$$\begin{aligned}
Sales_{i,t} = & \beta_0 + \beta_1 PLC_{i,t} + \beta_2 PLC_{i,t}^2 \\
& + (\beta_3 + \beta_4 PLC_{i,t} + \beta_5 PLC_{i,t}^2) TechnicalNewness_{i,t} \\
& + (\beta_6 + \beta_7 PLC_{i,t}) CompetitiveIntensity_{i,t} \\
& + (\beta_8 + \beta_9 PLC_{i,t}) Price_{i,t} \\
& + (\beta_{10} + \beta_{11} PLC_{i,t}) MediaExpenditures_{i,t} \\
& + \beta_{12} Brand_2 + \dots + \beta_{24} Brand_{14} + \epsilon_{i,t}
\end{aligned} \tag{3}$$

where:

$Sales_{i,t}$	=	relative sales of model i during calendar year t
$PLC_{i,t}$	=	year of product life cycle ($PLC = 1$ in the year the model was introduced, $PLC = 2$ in the second year, etc.) of model i at year t
$TechnicalNewness_{i,t}$	=	relative technical newness of model i in calendar year t
$CompetitiveIntensity_{i,t}$	=	competitive intensity for model i in calendar year t
$Price_{i,t}$	=	relative price of model i in calendar year t
$MediaExpenditures_{i,t}$	=	relative media expenditures of model i in calendar year t
$Brand_k$	=	dummy variable for k^{th} brand
$\epsilon_{i,t}$	=	error term

5. Results

Table 5 displays the estimation results of the four regression models. All regressions are statistically significant at the $p < 0.001$ level and use the same set of observations ($n = 987$). We mean-centered all continuous variables before estimation.

To assess whether a dynamic measure of technical newness is better able than a static measure (P1) to explain market performance, we first need to depreciate both the overall and the component-based technical-newness measures. To find an optimal depreciation rate—that is, one that performs best in explaining the cars' sales performance by their degree of technical newness—we use a grid-search approach. For the overall technical-newness measure, we find that the optimal depreciation rate is 14.9%. For the component-based measure, we obtain an optimal rate of 8.7%. These rates mean that it takes approximately 4.5 (7.5) years before technical newness as an overall (component-based) measure loses more than 50% of its initial effect on sales. Using a depreciated overall measure of technical newness,

Model 1a explains 61.8% of the variance in relative sales. The model with the depreciated component-based technical-newness measure explains 61.9% of the variance. Comparing the outcomes of Model 1 to those of Model 1a and comparing the outcomes of Model 2 to those of Model 2a, we observe that R^2 increases by 0.1 percentage points in both models because of the introduction of a depreciation rate. This finding lends initial support to P1: A dynamic measure of technical newness seems to be slightly better suited to explain market performance.

To understand whether a component-based measure of technical newness is better able than an overall measure (P2) to explain market performance, we compare the outcomes of Model 1 to those of Model 2 and the outcomes of Model 1a to those of Model 2a. Because both comparisons lead to very similar results, we extensively discuss only the Model 1–Model 2 comparison. Model 1 uses the overall measure of technical newness and explains 61.7% of the variance in relative sales. We find that only the main effect is significant ($\beta_{3, \text{Model1}} = .391, p < .001$), producing a positive but practically static effect over the life cycle. Model 2 uses the component score of technical newness and explains 61.8% of the variance in relative sales. We find that all three newness coefficients are significant ($\beta_{3, \text{Model2}} = .213, p < .001$; $\beta_{4, \text{Model2}} = .066, p < .001$; $\beta_{5, \text{Model2}} = -.013, p < .045$). Other model-selection criteria emphasize the small difference between the two measures: The difference in BIC scores are small but favor Model 2 ($\text{BIC}_{\text{Model1}} = 1743.8$ vs. $\text{BIC}_{\text{Model2}} = 1739.6$). Comparing Model 1a to Model 2a gives very similar results, so we conclude that the component-based measure is preferred over the overall measure of technical newness.

To assess H1, the effect of technical newness is allowed to change over time in all four models. Figure 1 illustrates the partial effects of all four technical-newness measures over the life cycle. We can observe that the non-depreciated component measure (Model 2) produces an inverted U-shaped pattern over the life cycle. In the first two years, the partial effect on relative sales is insignificant. The effect then increases and reaches its maximum impact in the seventh year, before it declines again and becomes insignificant as of the ninth year. The use of a depreciation rate does not seem to have a substantial effect

on the strength and direction of the life-cycle effects of the component measure. The partial effect also reaches its peak in the seventh year and becomes insignificant between the ninth and tenth years.

Table 5: Estimation results of regression models

		Model 1 <i>Overall TN</i>		Model 1a <i>Overall TN</i> (depreciated)		Model 2 <i>Comp. TN</i>		Model 2a <i>Comp. TN</i> (depreciated)
PLC	β_1	0.000 (-0.01)		0.031 * (2.19)		0.001 (0.10)		0.003 (0.31)
PLC ²	β_2	-0.015 *** (-5.24)		-0.023 *** (-5.58)		-0.014 *** (-4.47)		-0.014 *** (-4.46)
Tech. Newness	β_3	0.391 *** (-4.15)		0.455 *** (5.06)		0.213 *** (3.73)		0.208 *** (3.74)
Tech. Newness x PLC	β_4	0.007 (0.24)		-0.005 (-0.15)		0.066 *** (4.06)		0.057 *** (3.83)
Tech. Newness x PLC ²	β_5	0.001 (0.15)		-0.022 * (-2.51)		-0.013 * (-2.01)		-0.010 (-1.74)
Comp.Intens.	β_6	-0.034 * (-2.44)		-0.074 *** (-4.54)		-0.044 ** (-3.11)		-0.044 ** (-3.11)
Comp.Intens. x PLC	β_7	0.003 (0.55)		0.006 (0.87)		0.002 (0.37)		0.002 (0.34)
Price	β_8	0.026 (0.13)		0.063 (0.31)		0.185 (1.02)		0.147 (0.80)
Price x PLC	β_9	0.114 (1.27)		0.165 (1.81)		0.021 (0.26)		0.010 (0.13)
Media Expend.	β_{10}	0.27 *** (6.83)		0.271 *** (6.82)		0.268 *** (6.74)		0.266 *** (6.70)
Media Expend. x PLC	β_{11}	-0.04 ** (-2.75)		-0.039 ** (-2.58)		-0.035 * (-2.33)		-0.037 * (-2.48)
Brand_BMW	β_{12}	0.279 ** (3.14)		0.28 ** (3.17)		0.152 (1.74)		0.141 (1.62)
Brand_Mercedes	β_{13}	0.691 *** (5.78)		0.715 *** (6.01)		0.650 *** (5.98)		0.631 *** (5.83)
Brand_Opel	β_{14}	0.251 ** (2.90)		0.241 ** (2.78)		0.205 * (2.41)		0.202 * (2.37)
Brand_Renault	β_{15}	-0.686 *** (-9.34)		-0.684 *** (-9.34)		-0.800 *** (-11.55)		-0.820 *** (-11.89)
Brand_Toyota	β_{16}	-0.876 *** (-11.81)		-0.881 *** (-11.95)		-1.012 *** (-15.60)		-1.010 *** (-15.52)
Brand_Volkswagen	β_{17}	0.737 *** (7.03)		0.738 *** (7.06)		0.724 *** (6.93)		0.716 *** (6.87)
Brand_FIAT	β_{18}	-0.45 *** (-5.70)		-0.445 *** (-5.72)		-0.587 *** (-7.97)		-0.584 *** (-7.98)
Brand_Ford	β_{19}	0.064 (0.74)		0.069 (0.80)		-0.081 (-1.01)		-0.091 (-1.13)
Brand_Mitsubishi	β_{20}	-0.564 *** (-6.30)		-0.584 *** (-6.69)		-0.745 *** (-10.17)		-0.732 *** (-9.94)
Brand_Peugeot	β_{21}	-0.68 *** (-8.200)		-0.691 *** (-8.39)		-0.793 *** (-10.45)		-0.800 *** (-10.57)

Brand_Volvo	β_{22}	-0.705 *** (-8.89)	-0.712 *** (-9.10)	-0.870 *** (-13.03)	-0.867 *** (-12.99)
Brand_Seat	β_{23}	-0.503 *** (-6.26)	-0.526 *** (-6.70)	-0.658 *** (-9.49)	-0.656 *** (-9.59)
Brand_Skoda	β_{24}	-0.343 *** (-3.51)	-0.343 *** (-3.54)	-0.514 *** (-5.45)	-0.517 *** (-5.47)
Const.	β_0	1.184 *** (17.64)	1.217 *** (18.40)	1.284 *** (20.61)	1.293 *** (20.75)
R ²		0.617	0.618	0.618	0.619
Adj. R ²		0.607	0.608	0.609	0.610
Obs.		987	987	987	987
AIC		1621.4	1618.7	1617.2	1615.3
BIC		1743.8	1741	1739.6	1737.6
F		79.1 ***	80.29 ***	81.85 ***	81.88 ***
ΔR^2 due to TN measure (relative increase in R ²)		0.015 *** 2.4%	0.016 *** 2.6%	0.016 *** 2.7%	0.017 *** 2.8%
Optimal depreciation rate		n.a.	14.93%	n.a.	8.67%

* p<0.05, ** p<0.01, *** p<0.001

Note: All models are estimated with robust standard errors. *Sales*, *Technical Newness measures*, *Media Expenditures* and *Price* relative to models within same segment and calendar year.

All continuous IVs are mean-centered. t-values in parentheses. Omitted brand is "Audi".

We observe that the non-depreciated overall measure (Model 1) exhibits a linear relation with sales over time. However, we find that the use of a depreciation rate alters the shape of the effect. In Model 1a, we observe that the interaction with PLC² becomes significant and an inverted U-shaped pattern emerges over the life cycle. The marginal effect of the depreciated overall measure increases over the life cycle and reaches its maximum impact in the fourth year. The effect then declines and becomes insignificant around the seventh year of the product life cycle.

The shape of the partial effect is similar to the shape of the effect using both specifications of the component measures (Model 2 and 2a). In addition, it supports the theoretical arguments for the relationship between a product's technical newness and sales. We therefore conclude that a depreciated overall measure is better able to describe the relationship between a product's technical newness and sales.

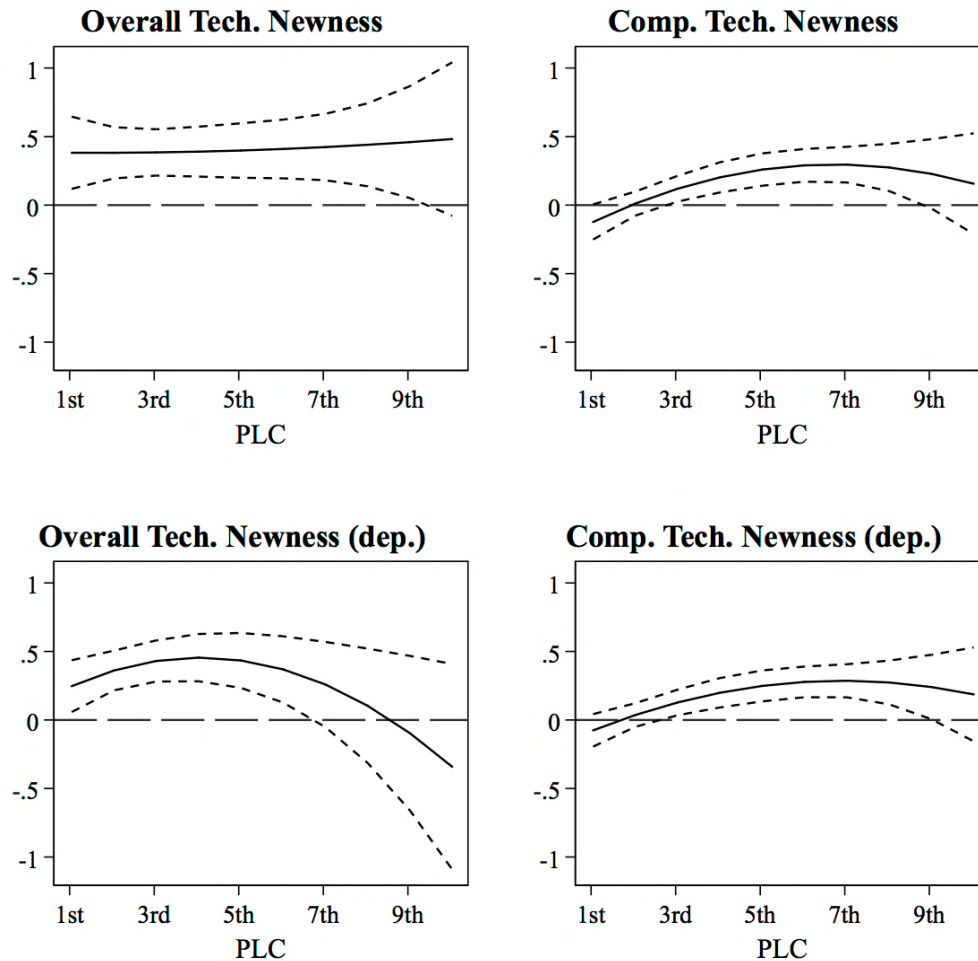
Overall, the results support that the performance effect of technical newness over the product's life cycle exhibits an inverted U-shaped relationship.

The main coefficient of relative price and its interaction with the product life cycle is not significant. This means that reduced prices at later stages of the life cycle will not have an effect on sales. However, pricing policies are quite homogeneous on a brand level, and the effect of price may be absorbed by the brand dummies, so that price coefficients become insignificant. The linear effect of competitive intensity is significantly negative. Contrary to our expectations, the longer the competing models are on the market, the more negative the entrants' sales performance. Both the main effect of relative media expenditures and the interaction with PLC are significant in all models. Thus, media expenditures have a strong and stable influence on sales across all models. In the first six years of the life cycle, companies can boost their sales by investing in advertising, but starting around the seventh year of the product life cycle, the effect becomes insignificant.

As expected, most brand dummies are significant. Apparently the brand dummies not only control for heterogeneity at the brand level but also capture country-of-origin effects (Chao 1998, Bilkey and Nes

1982). The positive sign of the coefficients indicates a performance advantage for German brands (Audi, BMW, Mercedes, Opel, and Volkswagen) compared to their international counterparts.

Figure 1: Partial Effect of Technical-Newness Measures Over the PLC^a



^a The dashed lines indicate the 95% confidence interval.

6. Discussion

This paper's main theme is the investigation of the impact of technical newness on sales performance throughout the product life cycle. Following the rationale of adoption and diffusion theory, we suggest that the strength of the performance impact of technical newness will change over time. We choose a longitudinal perspective and track the sales of 175 cars over their life cycle. The longitudinal perspective allows refinement of the conceptualization of the technical-newness construct.

The longitudinal perspective enables a comparison of the performance effect of a dynamic technical-newness score to a static measure at different points in time. With ongoing technological development and increased diffusion in the market, customers become accustomed to new technologies. The familiarization process may also simply be driven by the presence of the innovation on the market for some time. We therefore propose that technical newness must be depreciated to reflect the decrease of perceived newness over time in addition to potential life-cycle effects.

The standard approach to assessing a product's technical newness has considered the product as a whole. We note that many of today's products are based on multiple technological components, which may differ significantly in their level of newness. In addition, in many product categories, technological features are updated throughout the product life cycle. To better represent a product's newness and to capture potential technological changes over the product life cycle, we propose that technical newness should be assessed on the basis of central product components instead of the overall product level.

For our analyses, we constructed four measures of technical newness and ran the same regression with each of the four measures. In line with our first research proposition, our results support the notion that technical newness should be conceptualized as a dynamic measure. The decrease of the technical-newness measure over time reflects the declining economic benefit of a technological innovation. We therefore searched for a depreciation rate that best explains product performance. The search led to similar depreciation rates for both measures (14.9% for the overall measure, 8.7% for the component measure) that are comparable to other empirically established depreciation rates (see Table 2). When a deterministic rate of 15% is used, as in the economics literature to depreciate technological knowledge, the results remain similar. The robustness against the choice of the depreciation rate is in line with previous findings that depreciate other intangible assets (e.g., Grimpe et al. 2014). Because we were able to endogenously estimate meaningful depreciation rates, which led to an increase in explanatory power, our conceptual rationale is supported: A product's technical newness decreases as technology development continues, the technology

diffuses in the market, and customers become increasingly familiar with the state of the product's technology.

Our results also support the second research proposition that a component-based measure of technical newness is better able to explain market performance than an overall measure. The component approach thus appears to be the preferred alternative to measure technical newness. However, the improvement in model fit and other model-selection criteria is relatively small. This effect may be caused by the construction of the component measure. Our intention was to reflect the perspective of the average customer when making a purchase decision. Therefore, on the advice of industry experts, the measure encompasses only central component innovations that the average customer should be able to observe since such innovations are mentioned in the automotive press, highlighted in the reports of automobile TV shows (e.g., *Top Gear*), or noted in the OEMs' promotion materials. Consequently, the component measure does not capture the added technical newness of, for example, less prominent components or improvements of existing components that have not been promoted or appreciated by the media. In addition, some component innovations may have more impact than others on the overall perception of a car's technical newness. For the sake of parsimony and objectivity, we did not assign components different weights before aggregating them into the final score. However, both aspects may be captured implicitly with an overall assessment of technical newness, and offer opportunities for improving the component-based measure for technical newness further.

To test our hypothesis that the relationship between technical newness and performance varies over time in a nonlinear fashion, we interpret the performance effect of all four technical-newness measures. First, the results show that technical newness is a significant and economically relevant predictor of sales performance. All four measures show a substantial direct influence on sales.

Moreover, our findings largely imply that the effect varies over time in a nonlinear fashion (see Figure 1). We observe that for the component measure, all three newness coefficients are significant,

producing an inverted U-shaped pattern over the cars' life cycle. Introducing a depreciation rate improves the model fit, but does not affect the coefficients substantially, so that the nonlinear effect persists.

For the overall technical-newness measure, we find that the non-depreciated score produces a nearly static, positive effect on performance over the life cycle. Depreciating the measure improves the model fit. At the same time, the time-varying behavior of the measure is affected. The performance effect is altered to an inverted U-shaped pattern, which is similar to the inter-temporal pattern of both component-based measures. Both findings—the improved model fit and the change to an inverted U-shaped pattern over the product life cycle—apply both for the endogenously estimated depreciation rate and for a deterministic depreciation rate of 15%. Because the depreciated measure of overall technical newness is better able to explain performance while remaining robust with respect to the choice of depreciation rate, it supports the notion that this measure more realistically captures the relation with market performance.

The results indicate that a reasonable conclusion is that the relationship between technical newness and performance varies over time in a nonlinear fashion. The inverted U-shaped pattern over the life cycle is also in line with our conceptual rationale. A time-varying performance effect of technical newness indicates that information about potential advantages of novel technologies needs time to diffuse in the market, implying that the initial effect of technical newness on sales is limited. Over time, as more customers learn about the technology and its benefits, the risk associated with a novel technology decreases and the effect on sales associated with that technology increases. At later stages of the product's life cycle, competition is likely to intensify through introduction of similarly equipped, lower-priced products or products with superior technology. Thus, the effect of technical newness on sales decreases toward the end of the product's life cycle.

The time-varying performance effect of technical newness across the product life cycle also suggests that novel technological features help sustain a competitive advantage at later stages in the product life cycle. We find that the effect becomes insignificant only toward the end of the product life cycle (around the seventh year with the overall newness score and around the ninth year with the component score). A

high degree of technical newness in later stages of the product life cycle can lead to considerable competitive advantage. For example, an increase in relative media expenditures by one standard deviation from the mean in the sixth year leads *ceteris paribus* to an increase of 11.6 percentage points in relative sales. However, increasing the depreciated component-based newness measure in the same fashion is associated with an increase of 18.4 percentage points in relative sales (17.1 percentage points for the depreciated overall newness measure). This result means that in later stages of the life cycle, products with novel technologies help companies maintain a much stronger competitive advantage than that from traditional promotional activities.

The nonlinear result may also help explain some of the mixed findings for the performance effect of technical newness. For products with novel technologies, the performance impact can be expected to be at maximum strength toward the middle of the product life cycle. Thus, studies that include such products in their samples and assess performance toward the middle of the product life cycle will show stronger performance effects than either studies that measure performance at the beginning or end of the product life cycle or studies that use a less innovative sample.

In summary, our results lead us to conclude that life-cycle considerations are crucial both when assessing a product's technical newness and when analyzing its implications. Otherwise, the size of the estimated performance effect is likely to be over- or underestimated.

7. Conclusion

The results of this study indicate that new products with innovative technical features are better able to meet customers' latent needs and generate higher sales than their less innovative competitors. For managers and policy makers, this finding underlines the importance of deliberately fostering higher degrees of technology-related product newness. For managers, this fostering may include defining explicit objectives for a product's technical newness that guide the entire new product development process. Policy makers may integrate technical newness as a criterion in the formulation of funding programs or in the evaluation of grant applications.

However, the finding that the effect of technical newness follows an inverted U-shaped pattern suggests that at the beginning of the life cycle initial sales are likely to be slow. To avoid confusion with underperforming products that fail to transfer from the niche to the mass market, managers have to consider that the performance of highly innovative products varies over the product life cycle. Because the results indicate that the positive effect increases toward the middle of the life cycle, product managers are advised to speak up if financial controllers suggest taking a new product off the market, because such a decision may be premature. Instead, to increase early sales, managers should argue for investments to address customers' initial resistance and ease the understanding and appreciation of new features and functions (Talke and Heidenreich 2014). Policy makers may help companies make it through the dry spell in early life-cycle stages by granting special funding for products with novel technologies.

Our findings substantiate the relevance of continuous innovation activity and of technology development in particular. Because these results are based on a detailed and fact-related assessment of technical newness integrated into a comprehensive econometric model, and because performance is measured with objective sales data, our findings can serve as a reliable reference. Thus, our results may help managers justify investments in technology-based innovation that compete with alternative investment options, which may be perceived as having a more immediate effect on performance, such as investments in the sales force or in advertising campaigns.

Even if a company has launched a product that is technologically superior to its competitors, our results should remind managers that they cannot rest on their laurels. Our results underline that technical newness wears off over time as customers become accustomed to the current state of technology and perceive the product as less new. Therefore, a manufacturer's position on the technological landscape is threatened not only by competitors' product launches but also by the dynamic deterioration of newness. Thus, our results emphasize the need for constant innovation to retain a technological advantage.

So far, directions for managers and policy makers have largely been derived from studies relating to the overall product level. However, directing the focus to the component level may help to define

objectives. Using a component-based measure makes the elements of newness obvious, which is likely to facilitate companies' prediction of how a change in components will influence a product's perceived technical newness and thus its technological position with respect to competitors. In addition, a component-based measure fosters a coherent understanding at the management level with respect to the product's technological competitive advantage. This understanding is particularly valuable for industries that use design platforms or modular systems, where changes in the configuration of components can lead to a variety of individual products. Apart from automobiles, popular examples include consumer electronics, computer hardware and software, and engineering companies (Crawford and Di Benedetto 2014, Furlan et al. 2014, Staudenmayer et al. 2005).

This notion has significant strategic implications for the new product development process. For example, when competitors introduce a technologically more advanced product, managers can ask experts to rate the newness of the component(s) from which the competing product's technological advantage originates. Using this information, managers can decide either to update existing components or to develop novel ones to regain their technological advantage. For such applications, an overall measure of technical newness is of only limited usefulness.

On the advice of industry experts, our component-based measure contains the most relevant component innovations of the product category. Despite its reliance on a subset of all innovations built into the product, the measure performs as well as the overall technical-newness measure in explaining sales performance. This finding suggests that managers should focus on introducing particularly novel components, which are relevant to the average customers' purchase decision, instead of innovating in areas of limited relevance to increase a product's overall technical innovativeness. Policy makers can act as enforcers by investing in funding programs that support research in relevant technology areas to complement and expand industry knowledge. They may also direct research to future technological solutions they deem important for the economy and wish to see developed further.

Our results suggest that assessing technical newness on the basis of components seems to be more appropriate than the established assessment at the overall product level. However, the differences in model fit are relatively small. For management practice, this finding may have interesting implications. In the study of products with numerous core component innovations relative to the number of products in the sample, assessing technical newness at the overall product level seems more efficient. If the number of central components relative to the number of products in the sample is limited, a more efficient approach may be to assess technical newness as an aggregation of the components' newness. Thus, in recognizing that technical newness is a phenomenon that occurs at the component level, we present an alternative that can lead to a more efficient assessment of a product's technical newness.

To arrive at the final score for the component-based measure of technical newness, we used an equal weighting method (Dawes 1979) and summed the different newness scores of the individual components. The component-based measure could be further refined by accounting for customers' benefit perception, as suggested by research on multi-attribute product evaluation based on attribute weights (Jia et al. 1998, Mittal et al. 1999). In a representative survey, customers could rate the importance of all component innovations. This information could then be used to weight the component newness scores before summation. Our study covers a very long time span, from 1978 to 2006, and customers' benefit perception will have changed over time. Thus, this approach would have distorted our results due to a hindsight bias.

From our study, we can conclude that technical newness diminishes continuously over the product life cycle. Thus, to avoid drawing the wrong conclusions, managers should account for the construct's dynamic nature. However, academics may be interested in exploring whether depreciation rates vary when optimized for individual components or categories of component innovations—for example, components that improve safety and components that improve comfort. A finding of different depreciation rates would imply that some innovations offer a more sustainable benefit to customers. This result would further

emphasize that technical newness varies at the component level of products, an assumption in line with, for example, the rationale of Henderson and Clark (1990).

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