

To Launch or not to Launch in Recessions

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Abstract

How does new product success depend on timing of launch in the business cycle? This important managerial question remains unanswered in the marketing literature. This article proposes that density factors at the time of launch form initial conditions that continue to affect the new product's success in the market. The authors analyze the United States automotive industry and 20 United Kingdom FMCG markets to test hypotheses regarding low and high density initial conditions. The Generalized Estimating Equations analyses show three main findings: 1) launching a product during a recession has a positive impact on market share; 2) the sooner after a recession a firm launches a new product the higher the market share; and 3) the closer to the end of a boom a firm launches a new product the lower the market share. The same results emerge from survival analysis using data from the US automotive industry. The authors thus find broad support for their hypotheses extending the initial conditions theory to the success of new products at different parts of the business cycle. For managers, the results show the benefits of countercyclical launching of new products during recessions and to market proactively in low density conditions.

Keywords: new product launch, recession, automotive industry, fast moving consumer goods, low and high density, initial conditions

We are living through a tremendous bust... The auto industry is on pace to sell 28 percent fewer new vehicles this year than it did 10 years ago—and 10 years ago was 2001, when the country was in recession... Consumers, for their part, are coping with a sharp loss of wealth and an uncertain future (and many have discovered that they don't need to buy a new car or stove every few years). (Leonhart 2011)

The 2009 recession has served as a potent reminder of how cyclical contractions can have a substantial detrimental effect on national economies throughout the world. The National Bureau of Economic Research estimates that in the United States, recessions occur on average every six years (<http://www.nber.org/cycles.html>) and have a particularly strong effect on firms, industries, and the economy (Zarnowitz 1985). The extant marketing literature has begun addressing how recessions affect firm decisions on and customer response to advertising, prices, and branding (e.g., Deleersnyder et al. 2009; Srinivasan, Rangaswamy, and Lilien 2005) and research-and-development (R&D) spending (Steenkamp and Fang 2011) but has proposed little about new product success in recession versus boom times (Srinivasan, Lilien, and Sridhar 2011). Do new products have greater chances of success when launched during a recession? Nigel Hollis (2009), chief global analyst at Millward Brown, claims greater opportunities for product launches in recessions because of reduced “noise” in competitor media spending and response. Yet little empirical evidence exists to either support or refute this claim. Answering such questions is crucial for managers who need to decide when to launch an innovation in the market.

In this article, we examine the market success of new product launches in the automobile and FMCG industries. Our hypotheses specify the importance of density at time of launch. In particular, we propose and find that products launched during a recession demonstrate greater

performance through market share than products launched in boom times. Products launched during boom times are more likely to succeed (1) the earlier they are launched after a recession ends and (2) the earlier they are launched before a recession starts.

We make three specific contributions to the extant literature. First, we integrate the important research areas of new product innovation and recession marketing. Both areas have received much research attention, but their intersection has not. To the best of our knowledge, only Srinivasan, Lilien, and Sridhar (2011) and Steenkamp and Fang (2011) investigate whether firms should spend more on R&D during a recession—Srinivasan, Lilien, and Sridhar find that firms with large market shares should, whereas Steenkamp and Fang find that all firms, on average, should. However, these authors do not analyze when the new product based on such R&D should be launched, nor do they differentiate between specific new products launched in boom and recession times.

Second, we provide the first (as far as we are aware) empirical evidence that supports the notion that managers of brands should launch products during recessions thus innovating themselves out of recession (Lamey et al. 2007). Such “countercyclical spending” advice remains contentious among practitioners: While most U.K. finance directors believe that recessions require that firms increase marketing spending (UTalkMarketing.com 2009), other managers believe that it is crucial for firms to “manage their business downward when sales shrink (even if only temporarily)” (Pudles 2006).

Third, we also make a theoretical contribution. The theories of sensitivity to initial conditions and density dependent organizational evolution have predominantly been used in the extant management literature to explain organizational mortality (e.g., Geroski, Mata and Portugal 2010; Swaminathan 1996). We bring these theories into the domain of new product

success or failure to explain the impact of initial conditions at the time of product launch on market performance of the product.

RESEARCH BACKGROUND

New product launch is a key driver of firm performance and often the most expensive component of the new product development process (Di Benedetto 1999). However, it has been relatively underresearched in the marketing literature until recently (for exceptions, see Droge, Calantone, and Harmancioglu 2008; Harvey and Griffith 2007; Talay, Seggie, and Cavusgil 2009). Understanding success factors of product launch is important given the high probability that the launched product fails to generate sufficient demand for its survival in the market (Crawford 1977). The extant research documents the factors that affect the success and failure of new products in a category. For example, Cooper and colleagues (Cooper 1983, 1986; Cooper and Kleinschmidt 1987) demonstrate the importance of the new product development process, including the use of market research during the process, a strong market orientation of the firm engaging in the new product development, and clearly defined target market and customer needs. Cooper and Kleinschmidt (1993, 1996) focus on the role of top management commitment to new product success. In a meta-analysis, Henard and Szymanski (2001) find that product advantage, market potential, meeting of customer needs, and resources dedicated to the new product venture have the strongest impacts on new product performance. What is not yet known, however, is whether the *timing* of launch in the business cycle affects the new product's success and survival.

HYPOTHESIS DEVELOPMENT

In our hypothesis development we extend the general theory of sensitivity to initial conditions (e.g., Swaminathan 1996) from the domain of organizational mortality into the domain of new product success or failure. Specifically we draw upon Hannan's (1986) theory of density

dependent organizational evolution to argue that new product launch displays a sensitivity to initial conditions vis-à-vis the relative density of the marketplace at time of launch. Hannan argues that organizations founded in times of high density are more likely to fail and posits that the reasons for failure are either a scarcity in resources in high-density times or that the high density implies a very crowded niche market. We extend this theory into the product domain to argue that products launched in times of high (low) density are less (more) likely to be successful than those launched in times of low (high) density. We develop our hypotheses for the performance of new products under 3 conditions: recession (low density), start of the boom (higher density), and end of the boom (highest density).

Recessions

We argue that recessions are low density periods both with regard to the economy as a whole and also specifically in relation to new products launched. By definition a recession is a sustained contraction in the economy therefore the economy is less 'dense' than during times of growth. Specifically for new product launches, we observe that firms are reluctant to launch new products in a recession (Roberts 2003) thus we observe specific low density in product launch. Furthermore, firms generally respond to recessions by reducing marketing spending (Andras and Srinivasan 2003; Barwise and Styler 2002; Tellis and Tellis 2009), for example, advertising expenditure is often procyclical (Tellis and Tellis 2009); that is, firms tend to cut back on advertising during a recession. As a result of this reduction in clutter in the market, firms that do engage in product launch during recessions are better able to reach potential customers. Thus we argue that products launched during a recession are being launched into a not very crowded niche in the market. We also argue that in a recession there are greater resources available to a company that chooses to launch its product. First, the labor market for marketers and other

organizational members turns in favor of employers when a recession is looming and remains so throughout the recession (Chaudhuri and Tabrizi 1999). Firms that continue engaging in marketing during these times will be able to attract exceptional employees from competing firms. Second, given the pressure of losing contracts and jobs, a firm's suppliers, channel partners, and employees tend to offer it the best value when the economy turns and stays sour. Third, the recession induces many managers to become more prevention focused and thus careful about launching new projects (Gulati, Nohria, and Wohlgezogen 2010). These three factors imply a higher quality of marketing programs of products launched in recessions. Such higher quality should lead to more repurchases of the product in the future, thus contributing to better performance of products launched in recessions as a consequence of higher quality resources available during this low density period. The combination of availability of higher quality resources and less clutter in the marketplace leads us to propose the following:

H1: Products launched during a recession exhibit better performance than products launched at any other time.

Note that our hypothesis goes against the common wisdom of 'managing downward' during recessions due to lower customer demand (e.g. Leonhart 2011; Pudles 2006). Instead, we posit that the initial conditions of low density on the supply side are more important for new product success than the demand side weakness during a recession.

During the Boom

We separate the boom times into two parts: the period immediately following the recession and the period toward the end of the boom and before the next recession. In the initial stages after a recession ends we observe a gradual shift in the market away from the state of lower density observed during the recession toward a state of higher density. This has two main causes: first, a gradual decrease in the resources available to firms and second, the fact that any new product

launched is now launched into a more and more crowded niche. As the economy moves further and further away from the recession the relative abundance of resources that existed vis-à-vis marketing personnel etc. decreases until we eventually reach a paucity of resources leading to the state of high density. The labor market for marketers and other key personnel that had been so favorable for firms throughout the recession (Chaudhuri and Tabrizi 1999) begins to turn in favor of the employees as more and more firms are in the market for the exceptional talent thus making it more difficult for firms to attract the best. And, post-recession, the pressure of losing contracts and jobs is not as immediate as it was during the recession therefore employees, channel partners and suppliers do not feel the same need to offer as good value as they may have felt during the recession. Therefore, immediately after the recession we will observe greater density than during the recession but not as great as we observe toward the end of the boom and before the next recession.

The more crowded niche is caused by competitors starting to produce more products at the start of a boom as the economy moves out of recession (Francois and Lloyd-Ellis 2003), leading to a gradual increase in clutter in the marketplace in terms of advertising and promotion. This increased clutter moves the economy toward a state of greater density both with regard to the overall market as the economy grows and also in relation to the number of new products launched. As with resources, immediately following the recession we see a slight increase in clutter contributing to greater density than in the recession, however, this density builds as we move away from the recession and toward the next recession as the clutter increases. Taken together these forces lead us to the following two conclusions vis-à-vis the boom times. First, post-recession the most favorable time to launch a new product is as soon as possible after the recession ends before the market reaches its highest level of density. Second, post-recession the

least favorable time to launch a new product is toward the end of the boom (before the next recession begins) as this is the time when the density of the marketplace will be at its highest.

This leads us to propose the following two hypotheses:

H2: The sooner after a recession a product is launched, the greater performance it will exhibit.

H3: The closer to the end of the boom a product is launched, the lower performance it will exhibit.

DATA

We used two data sets for our analysis. Our first data set is population data from the U.S. automotive industry from 1946 (the year that production in the U.S. automobile industry resumed after World War II) to 2008 comprising all automobile manufacturers known to compete in the U.S. automobile market in this period. This data was gathered from *Standard Catalog of American Cars*, *Standard Catalog of Imported Cars*, *New Encyclopedia of Motor Cars*, *World Guide to Automobile Manufacturers*, and *Automotive News*. We gathered recession data for the United States from the National Bureau for Economic Research website (see <http://www.nber.org/cycles.html>) and information on these recessions can be observed in Table 1. For the robustness of our analyses, it was paramount to precisely pinpoint when the model is launched, and withdrawn from, the market. For the vast majority of the models in our data set, this process was fairly simple, however, for models that went through a name change (e.g., Ford renamed its *Windstar* minivan as *Freestar* in 2004) or re-launched after a hiatus (e.g., the first generation of Dodge *Magnum* was available in the U.S. market between 1978 and 1979; then it was revived in 2004 after 25 years of hiatus), we conducted a more thorough reading of the history of that particular model. As a result, name changes were not coded as new models, but rather another feature of new generation of an existing model; while revived models were coded

as new models. Our final data set contains 8203 model-year pairs with information on 1071 models from 146 different brands for our observation period during which 11 recessions occurred.

AiMark supplied our second data set of new products in 20 categories of fast moving consumer goods (henceforth: FMCGs) launched in the United Kingdom between 1995 and 2012. Table 2 shows the wide variety in the type of product (including food such as crisps and personal care such as shampoo) and number of new product launches (from 321 for butter to 9,410 for natural cottage cheese). Table 1 shows information on recessions in the UK, obtained from the Office for National Statistics website (see www.ons.gov.uk). The UK data set contains 1,739,868 product-month pairs with information on 44,615 products launched within our observation period, during which 2 recessions occurred in the United Kingdom.

[Insert Tables 1 and 2 around here]

Variables:

Dependent variable. This study examines the link between market conditions during product launch and performance. We use market share ($MSHARE_{it}$) as the dependent variable. This performance criterion is widely used in the marketing literature (e.g., Rust and Zahorik 1993; Rego, Morgan and Fornell 2013) thus enabling comparison between our study and other extant works and furthermore is considered to be an important performance indicator by both scholars and practitioners (Farris et al. 2006). We calculate the annual market share of a car model in its segment for the US car data; and the monthly market share of an FMCG in its category for the UK FMCG data.

Independent Variables

We incorporated a series of covariates in four main categories: recession-related, model-related, brand-related, and competition-related. As shown in Table 3, the recession-related covariates were consistent across both of our data sets. In contrast, a few control variables (such as reputation) were only available for the US car industry¹, as detailed in the descriptions below.

Recession-related covariates. Launch before a recession (BEFORE_{it}) is a time-varying covariate operationalized as the years to next recession (up to three years²) since the launch of product i . Likewise, launch after recession (AFTER_{it}) is the years since previous recession (with the same three-year cap as the BEFORE variable) from the launch of product i . Launch during recession (DURING_{it}) is a dummy variable coded as 1 if product i was launched during a recession period and 0 if otherwise.³ DURING-MAG_{it} is the GDP decline during the recession in which product i was launched. We also account for the quadratic effects of the recession magnitude (DURING-MAG^2_{it}) because we expect that its effects on market performance of a product are nonmonotonic.

In addition to the economic conditions at product launch, current conditions may affect the post-launch market performance of a product i in period t . We account for the effects of economic recessions with the dummy variable RECESSION_t , which equals 1 for the years (months for the UK data) of recessions and 0 otherwise. Moreover, extant research suggests that periods *immediately* preceding or following a recession have different market conditions and

¹ We also ran the analysis with the same common set of covariates for the US data and the UK data, there were no substantive differences in the results.

² Giving each product a value for the “BEFORE” and “AFTER” variables would yield extensive overlap (e.g., the same product is launched one year before the next recession and five years after the previous recession). We chose the three-year cap as half the average boom period and ran separate estimations with two- and four-year caps. The results for these estimations have the same directionality of the main and interaction effects and similar significance levels.

³ It was not possible for us to accurately pinpoint the exact month of the launch for models in earlier years in the observation period (e.g., 1950s). Therefore, we code data on a yearly basis. We assumed model launches at the midpoint of the year (July 1) and coded the recession-related covariates accordingly. We ran separate estimations for the 1946–1970 period, 1971–2008 period (coded monthly), and the entire observation period. The results for these estimations are similar: The significance and directionality of the main and interaction effects are the same between the analyses conducted on the separate (earlier vs. later periods) and combined data sets.

consumption patterns. Directly before a recession, consumers like to indulge, but they often strive to be more frugal and less wasteful right after a recession (Flatters and Willmott 2009). Therefore, we include the two dummy variables $YEARBEFORE_t$ and $YEARAFTER_t$, which denote the years immediately before and after recessions, respectively, in our analyses.

Model-Related Covariates. We included a range of model-based control covariates for our analyses. Three of these, AGE_{it} , AGE^2_{it} , and $NEWGEN_{it}$, are in both the US automotive data set and also the UK FMCG. To control for the effects of time since launch on performance we included AGE_{it} (time since the launch of a product in years). We further included AGE^2_{it} to control for any U-shaped relationship between age and performance. We also account for the effects of incremental innovations in both of our data sets with the dummy variable $NEWGEN_{it}$, coded as 1 if a new generation of product i was launched in period t and 0 if otherwise.

Data on reputation was only available for the US automotive data set. Quality ratings provided by third parties affect consumer perceptions of quality and reputation/status orderings (Chen and Xie 2005; Rhee and Haunschild 2006). To operationalize the variable $REPUTATION_{it}$ for model i in year t , we use the five-point scale “trouble indexes” in *Consumer Reports*. Specifically, we calculate the mean of the overall problem-rate scores of each model for the *most recent three years* of ownership. This procedure alleviates potential random errors in the ratings and/or consumer awareness of them (e.g., a given consumer may look at an older version of *Consumer Reports*).⁴

⁴ *Consumer Reports* is a trusted third-party provider of such ratings. Consistent with our rationale for higher quality of products launched in recessions (H_1), *Consumer Reports* quality ratings show the worst score for products launched at the end of the boom (73.1/100 vs. the average of 74.9), followed by products launched at the start of the boom (75.8/100) and, finally, products launched during a recession (76.8/100). Each of these differences is significant at the 5% level in Scheffé (1953), Bonferroni (1936), and Šidák (1967) tests.

Brand-Related Covariates. We included a range of brand-related control covariates for the analysis on the US automotive data set only. We control for the effects of technological niche width on performance with our covariate $RANGE_{it}$. This is defined as the range of engine capacity in terms of horsepower across all models produced by each brand at any given point in time (a realized niche). We control for the different demand characteristics of luxury and non-luxury brands through our covariate, $LUXURY_i$, coded as 1 if model i had a luxury brand and 0 if otherwise. We control for country of origin effects with the dummy variable US_i , coded as 1 if model i had a U.S. brand and 0 if otherwise. Finally, we control for the effect of a brand's parent company market share on the market share of the brand with our covariate, $PARENT_SHARE_{it}$, operationalized as the ratio of total unit sales of the parent company of brand i to the unit sales of all firms in the market in year t .

Competition-related covariates. We control for the effects of competition on market performance with two covariates consistent across both data sets, $TOTNEWMODELS_{it}$, and $TOTNEWGENS_{ij}$ and one covariate, $CATSALES_{it}$, unique to the UK FMCG data.

$TOTNEWMODELS_{it}$, is a dummy variable coded as 1 if a new model was introduced to the category of product i in period t . $TOTNEWGENS_{ij}$, is a dummy variable coded as 1 if a new generation of an existing model was introduced to the category of product i in year t .

$CATSALES_{it}$ is the total sales in the category of the product i in month t .

[Insert Table 3 around here]

Descriptive Statistics

Table 4 presents the descriptive statistics for both the US automotive market and 20 UK FMCG categories. Of the 1071 models in our US automotive data set, 336 (31.4%) were launched during a recession period. In our 20 FMCG categories comprising 44,615 products, 4,193 (9.4%)

were launched during a recession. Yearly market share values for the US automotive market data range from a low of less than 0.1% to about 20% (1949 Ford) while in the UK FMCG data monthly market share values range from a low of less than 0.001 to about 18% (Gillette Mach 3 cartridges).

[Insert Table 4 around here]

Table 5 presents the pairwise Pearson correlations for the key variables. Correlations for the US automotive data are presented below the diagonal while those for the UK FMCG data are presented above the diagonal. For the US automotive data, the highest correlation among variables ($\rho = .482$) is between the total numbers of new models ($TOTNEWMODELS_{it}$) and new generations ($TOTNEWGENS_{ij}$) in the segment of model i in year t . Both numbers steadily increase during our observation period. Testing for multicollinearity, we found that the average and maximum variance inflation factor values are 1.49 and 2.79, respectively, both of which are well below the common cutoff value of 10. For the UK FMCG data, the highest correlation among variables ($\rho = .531$) is between the dummy variable which indicates a launch of a product i during a recession ($DURING_{it}$) and the magnitude of that recession ($DURING-MAG_{it}$)⁵. The average and maximum variance inflation factor values are 3.35 and 4.30, respectively, which indicates that multicollinearity is not a problem.

[Insert Table 5 around here]

In Figures 1 and 2 we present two graphs that show market share over time for products where the products are put into three categories depending on the initial conditions at launch time, i.e. during a recession, start of a boom, or end of a boom. These three categories map onto our three hypotheses. In figure 1 we see an interesting pattern whereby at first, market share is lower for a

⁵ Thus, more new products are launched during deep versus shallow recessions in the UK. Consistent with the initial conditions theory, this higher density should lead to lower market share success of new products launched in deep recessions.

new product launched during a recession, however, in the long-run the market shares of these products exceeds both that of products launched at the end of the boom (crossover at around 20 months) and that of products launched at beginning of the boom (crossover at around 40 months). In figure 2, the graphs for the US automotive market are somewhat similar with those products launched during a recession outperforming the rest in the long-run. These graphs provide some ‘model-free’ insights into how new product success varies depending upon launch conditions.

ANALYSIS

We used generalized estimating equations (GEEs), which can accommodate longitudinal data consisting of repeated observations on a set of subjects (Liang & Zeger, 1986) in our panel data analyses. This analytic technique has been used in prior research investigating longitudinal outcomes (e.g., Lee, 2011) and can effectively account for unobserved differences among products as well as intertemporal correlations among outcome variables for individual products. The results of the Wooldridge test indicated the need to account for serial correlation in our data set. Hence, we specified a first-order autoregressive correlation structure and Huber-White-sandwich semi-robust variance estimates, which together provide conservative results (Liang & Zeger, 1986). Controlling for the autoregressive correlation structure produced consistent and more efficient estimated. All analyses were performed using the `xtgee` function in Stata 13.1, with the product set as the grouping variable.

RESULTS

Table 6 presents the results of our analyses. In H_1 , we argued that products launched during a recession exhibit greater performance. The results of our analyses on both the US automotive data and UK FMCG data support this position. We observe a positive relationship between

launching a car model during a recession and market share ($\beta = .147, p < .01$). We also observe a positive relationship between launching a new FMCG product during a recession and market share ($\beta = .019, p < .01$). Thus we find support for H_1 .

Furthermore, we observe that for the US car market, there is an inverted-U shaped relationship between severity of the recession (i.e., decline in GDP) during which a model is launched and its market share in the subsequent years as both the linear ($\beta = .004, p < .05$) and the quadratic ($\beta = -.015, p < .01$) effects of GDP contraction are statistically significant. In contrast to car models though, for the 20 FMCG markets, the market share boost is higher when gross domestic product remains higher ($\beta = -.164, p < .01$). As observed in the positive correlation between new product launch and recession depth, mild recessions represent lower density conditions in the UK FMCG market than deep recessions. However, we do find a floor effect for very deep recessions ($\beta = .026, p < .01$).

In H_2 , we argued that products have better performance the sooner after a recession they are launched. Thus, we expect a negative coefficient for $AFTER_{it}$, which denotes a lower market performance the further after a recession the product is launched. The results for the US automotive industry show a negative relationship between time after a recession a product is launched and market share ($\beta = -.013, p < .05$), and we observe similar results for the UK FMCG data ($\beta = -.001, p < .01$). These findings provide support for H_2 .

In H_3 , we argued that products launched at the end of an economic boom will have lower market performances than average new products. Thus, we expect a positive coefficient for $BEFORE_{it}$. The results of our analyses support H_3 . The results for the US automotive industry show a positive relationship between time before a recession a product is launched and market

share ($\beta = .013, p < .05$), and we observe similar results for the UK FMCG data ($\beta = .004, p < .01$).

[Insert Table 6 around here]

Control Variables

The results for our control variables are in the expected direction. For example, new products launched the year right before the recession have higher market share – consistent with the notion that consumers like to indulge at that time (Flatters and Willmott 2009). The year right after a recession is an especially good time to launch new products in the UK FMCG industry.

In the US automotive industry, reputation increases market share and we observe an inverted-U shaped relationship between a model's age and its market share. This inverted U-shaped relationship is also present in the UK FMCG industry, but in this case the effect of age turns negative already after about 2 months. Thus, product renewal is important for market share success.

Individual Category Estimation

To check the robustness of our findings, for our analyses of market share using the U.K. data, we ran our models for each category separately and found that across-category results are consistent for each individual category as well. These results can be seen in Appendix A.

Supplemental Survival Analysis of US Automotive Market

To check the robustness of our findings in the US automotive industry we conducted a survival analysis. In this analysis our dependent variable was the exit probability of car model i at time t . The observation period in our data set begins with the resumption of production in the U.S. automotive industry post-World War II, thus the data are not left censored. We used the same covariates as in the market share model with the addition of controlling for $SALES_{it}$, the total

sales of model i in year t . To control for the effects of skewness in distribution and the outliers in the data, we use the natural logarithm of this variable. A detailed explanation of how we conducted the analysis can be seen in Web Appendix A.

For our survival analysis the model fit is significant ($\chi^2 = 423.75$, d.f. = 19, $p < .01$), as is the likelihood ratio test for unobserved heterogeneity ($\chi^2 = 10.48$, d.f. = 1, $p < .01$), indicating the need to incorporate the effects of unobserved heterogeneity in the model. The value of the scale parameter of the log-logistic distribution (i.e., γ) is .141, indicating that the hazard rate increases sharply in the initial years of the model launch and decreases over time. The results of our survival analysis provide further evidence to support our hypotheses. As can be seen in Table 7, car models launched during recessions have higher predicted survival rates ($\beta = .175$, $p < .01$) and this increase is proportional to the contraction in gross domestic product ($\beta = .049$, $p < .01$). Furthermore, this effect reverses over time because its quadratic effect is negative and significant ($\beta = -.040$, $p < .01$). This suggests that survival rates are lower for models launched during very deep recessions. Furthermore, a current recession increases model survival ($\beta = .131$, $p < .01$), which suggest that inclement economic conditions strengthen the products that can survive them. These results indicate that new products have higher survival chances when launched s during all but very severe recessions, in support of H₁. The coefficient for AFTER_{it} ($\beta = -.085$, $p < .01$) demonstrates that survival decreases as the launch moves away from a recession, indicating that firms should launch new products sooner rather than later after the recession has ended. This result supports H₂. Finally, the coefficient for BEFORE_{it} ($\beta = .064$, $p < .05$) is positive and significant suggesting that the earlier before a recession a car model is launched, the greater its survival chances. This provides additional support for H₃. Overall the results of our supplementary survival analysis provide further support for our hypotheses. An interesting sign

switch occurs for the YEARBEFORE effect: new car models launched the year right before a recession have higher market share, but worse survival chances. Also, compared to non-luxury cars, new luxury cars have higher survival chances, but lower market shares – consistent with the niche nature of that segment.

[Insert Table 7 around here]

For the survival analysis we conducted several robustness checks. First, following the work of Aboulnasr et al. (2008) and Srinivasan et al. (2009), we analyzed the sensitivity of our results to the censoring date in the sample (2008 in our case). We estimated our model with three different censoring rates: 1980, 1990, and 2000. The results, presented in Table 8, are consistent with the findings presented in Table 7, indicating that our findings are robust to censoring date. Second, following the work of Wang, Chen, and Xie (2010), we also estimated our model using three other commonly used baseline distributions: Weibull, log-normal, log-logistic, and generalized gamma distributions. The results of the models with alternative specifications, presented in Table 9, are consistent with the results presented in Table 7. Third, following the work of Aboulnasr et al. (2008), we examined the robustness of our results to our sample using bootstrapping analysis with 50 repetitions (Table 10); we found the same support for our hypotheses.

[Insert Tables 8, 9 and 10 around here]

Supplemental Analysis of Impact of Covariates on Product Quality

For the US car industry, we have data on the quality scores of new products by Consumer Reports and thus can investigate quality changes over the business cycle⁶. Table 11 shows the result of the generalized estimating equations regression analysis with product quality ratings as the dependent variable. Consistent with the rationale for our hypotheses, quality is higher for

⁶ We thank an anonymous reviewer for this suggestion

new products launched during recessions and for products launched earlier before a recession and shortly after a recession. These findings may encourage future research on how and why the quality of new products varies during the business cycle.

[Insert Table 11 around here]

CONCLUSION

Successful new product launch is crucial to business performance, and this research is the first (as far as we are aware) to study how timing of launch in the business cycle affects new product survival. Thus, this study fills a gap in the research on the impact of recessions on the success of marketing actions, which previously focused on advertising, pricing, and branding (e.g., Deleersnyder et al. 2009; Srinivasan, Rangaswamy, and Lilien 2005; Steenkamp and Fang 2011).

Specifically, we develop a conceptual framework based on sensitivity to initial conditions and density theory to explain how firms can align their new product launch strategies with economic cycles. We test our hypotheses in the context of 20 U.K. fast moving consumer good categories from 1993 to 2005 and of the U.S. automotive industry between 1945 and 2008. The latter 64-year observation period covers all the post-World War II economic recessions in the U.S. economy, with varying durations and levels of contractions. As such, we respond to Srinivasan, Lilien, and Sridhar's (2011) call to account for severity of recessions in analyses. Moreover, we incorporate a rich set of model-, brand-, and competition-related factors into our estimations to more precisely understand the performance implications of product launches during recessions.

Our results demonstrate three important points. First, we find that models launched during an economic recession exhibit better performance, both in terms of market share and survival chances. Second, we find that if a firm plans on launching a new model after a

recession, it should launch immediately afterwards rather than wait. The longer after a recession a product is launched, the higher the density in the market and thus the lower the expected market share and survival chances. Third, market share success and survival chances are slim for products launched when a recession is imminent. These results extend previous studies in several important ways and also entail various theoretical and managerial implications.

Theoretical Implications

Extant marketing literature has recently begun examining how recessions affect firm decisions on and customer response to advertising, R&D, prices, and branding (e.g., Deleersnyder et al. 2009; Srinivasan, Rangaswamy, and Lilien 2005; Steenkamp and Fang 2011). For the most part, our results corroborate the findings of those studies that countercyclical marketing investments may yield better outcomes than procyclical activities. However, we also examine and find boundary conditions to this countercyclical spending advice. The relationship between new product survival chances and the severity of the recession is inverted U shaped, implying that severe recessions are typically not the time to launch new products. Moreover, our study of a microlevel phenomenon (product launch) complements previous studies that analyze aggregate macrolevel measures (e.g., R&D expenditure)—a research stream void that Steenkamp and Fang (2011) note.

Research on economic cycles has shown that business activities in general and new product introductions in particular vary systematically with the cyclical movement of the economy (Devinney 1990). Thus, several studies have argued that the use of countercyclical strategies for various marketing activities might be beneficial for firms. For example, Steenkamp and Fang (2011) and Srinivasan and colleagues (2005, 2011) find that investments in R&D and advertising during contractions have stronger effects on market share and profit than they do

during expansions. Our findings advance this research stream by showing that the performance implications of pro- or countercyclical marketing activities might also differ with their temporal sequences in relation to recessions. Specifically, we find that launching a product before a recession has different performance implications than launching a product after recession.

Finally, we extend the theory of sensitivity to initial conditions. This theory has been employed to explain organizational mortality in contexts such as start-up firms in Portugal (Geroski, Mata and Portugal 2010) and American breweries and Argentinian newspapers (Swaminathan 1996). In this study, we are able to demonstrate the relevance of this theory to the launch of new products and show that initial conditions vis-à-vis the density of the marketplace impact upon the likelihood of new product success.

Managerial implications

In this study, we demonstrate that new products launched during recessions (low density conditions) have higher market share success and survival chances than new products launched in high density conditions (H1). This finding goes against the common wisdom of many companies that cut back on product launches during recessions in the hopes that they can outpace their rivals in boom times. For example, Sony cut R&D spending by 12% during the 2000 downturn and then tried to regain momentum by developing and launching new products during the boom. However, Sony's new electronic book readers, game consoles, and organic light-emitting diode televisions were surpassed by Amazon.com, Microsoft and Nintendo, and Samsung, respectively (Gulati, Nohria, and Wohlgezogen 2010). In contrast, a minority of companies follow the recession strategy of judiciously increasing spending on R&D and marketing during the recession, which may produce only modest gains in the short run but substantial gains in the long run (Gulati, Nohria, and Wohlgezogen 2010). This narrative is

consistent with our findings across 21 product categories and thousands of new product launches: while most companies cut back on product launches during recessions, others launch high quality products in these low density conditions and obtain superior results. These demonstrated benefits of proactive marketing are useful to managers facing the (common) pressures to cut back on new product launches during recessions. Our research suggests that rather than cutting back on new product launches during recession, these managers should continue (and perhaps even increase) new product activity. Evidently, this advice holds at the margin and is based on the low density theory: flooding the market with many new products and/or many competitors increasing new product activity would lead to high density conditions.

A second managerial implication is that companies should try to launch new products right after the recession (H2); beating the competition to the market. At the beginning of an economic recovery, firms resume producing higher degrees of output than they did during the recession (Francois and Lloyd-Ellis 2003), engage in greater promotion and advertising efforts, and begin introducing new products to achieve a larger share of the pent-up consumer demand. As such, firms should focus on beating the competition to market by launching in the window immediately following the recession, when advantages of launch can still be achieved. The longer the firm waits, the more clutter exists in the market and the more challenging it becomes for the firm to make successful product launches.

The remaining research findings are only to some extent actionable. While it is interesting that launching at the end of a boom suppresses new product success (H3), it is notoriously difficult to predict the next recession (Grewal and Tansuhaj 2001). Likewise, the depth of the recession may be hard to pinpoint though managers can form a general impression of a current recession versus past experiences (BPI/BVA 2009). For example, the 1969–1970 US

recession was mild and mostly expected after a lengthy economic expansion during the 1960s. In contrast, the 1973–1975 US recession was severe, fuelled by high government (war) spending, high inflation rates, and the general wage and price control policies implemented in 1971 to mask inflationary pressures. Our findings on the cyclicity of success in new product launch thus quantify additional benefits for better monitoring and predicting of economic activity. More knowledgeable managers could thus act countercyclically by cutting back on new product launches near the end of a boom and launching these products instead during the recession – thus using the business cycle as an opportunity to overtake weaker competitors.

Reduced competitive activity during a recession provides firms opportunities to more powerfully launch products because of the reduced ability of competitors to respond to product launches and also the reduction in media costs, allowing firms to achieve greater return for their advertising expenditures. Moreover, firms that intensify their R&D activities, prepare a new product pipeline, and update their product mix before the beginning of an economic recovery can enjoy first-mover advantage by meeting the increased demand with state-of-the-art products, features, and styles as consumer spending begins to increase.

Limitations and Further Research

This research has several limitations that offer opportunities for further research. In this study, we focused on product innovations, not process innovations. Managers are forced to cut discretionary spending and improve efficiency of their firms. They also become more risk averse when making business decisions. Product development projects are, by their very nature, more costly and risky, and thus managers may be more inclined to scale back on product development. In contrast, process innovations not only are less costly and risky but also help firms decrease operational costs through increased efficiency. Therefore, in times of economic downturns, firms

may focus on process innovations while suspending, albeit until the end of recession, product innovations. Needless to say, firms will exhibit different behaviors in their reallocation of resources from the former to the latter. Likewise, new products launched during recessions may differ from others in several ways discussed in the innovation literature: major versus minor innovation compared to the old product, relative advantage and relative cost over competing alternatives, initial and continued R&D and marketing spending, etc. We lacked the data in this study to investigate such patterns in firm innovation and product support behavior. However, we did find that car models launched during recessions have higher quality. This result may encourage future research to look into the mechanisms that may explain business cycle differences in firm decisions to allocate resources to different types of innovation projects and to choose launch times and marketing support of new products.

While this research analyzed both a durable product (automotive) and 20 fast moving good categories, we do not know whether our findings apply to credence products, which would improve the external validity and generalizations of the results. Expanding the geographical coverage to include multiple countries could also yield valuable insights. Deleersnyder and colleagues (2009) report that elasticities of advertising spending to business cycles vary systematically by national culture. In a similar vein, cultural factors may also moderate the sensitivity of innovative activity to economic expansions and downturns. Innovative activities inherently involve risk, and people in high-uncertainty-avoidance cultures place more emphasis on reduction, and avoidance if possible, of risk than people in low-uncertainty-avoidance cultures. Further research might examine how such traits are reflected in the production and consumption of innovations throughout the economic cycles. Manager- and consumer-based perceptual measures would be useful in this regard. This would allow for the discernment of the

dynamics of innovative activity and macroeconomic fluctuations in a global environment and might provide mediation between new product strategies and market-based performance. In addition to cultural dimensions, socio-economic factors should be taken into account when developing marketing strategies with regard to economic cycles.

Additional specifications of the model could also provide further revelations. Additional research might incorporate other constructs and factors such as organizational resources, core competencies, strategic intent, and organizational culture. Incorporating cognitive factors such as risk aversion and long-term orientation of the management might provide invaluable insights into both the drivers and the outcomes of the sensitivity of product innovations to economic recessions.

Its limitations notwithstanding, this study provides a notable and relevant explanation of the performance implications of product launch with regard to economic recessions. Specifically, we show that (1) a countercyclical product launch strategy may be valuable because products launched during recessions have greater performance and long-term survival chances, (2) there is an inverted U-shaped relationship between the severity of the recession and the survival chances of a product launched during a recession, and (3) launching a product immediately after a recession, rather than stalling a launch to wait for the economy recovery to ramp up, significantly increases market share and decreases the failure likelihood. We hope that the findings of this study will stimulate further research in this important area of study as managers continue to search for ways to develop and execute recession-proof product strategies and manage portfolios in the global marketplace.

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FIGURE 1
MARKET SHARE BY LAUNCH TIME FOR UK FMCG MARKET

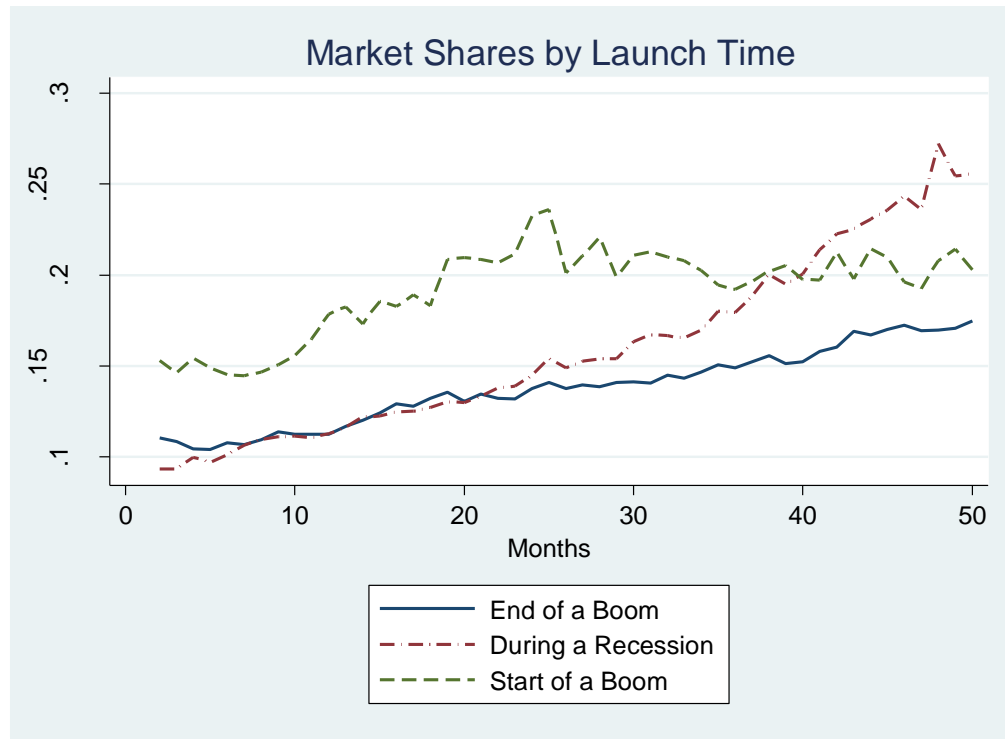


FIGURE 2
MARKET SHARE BY LAUNCH TIME FOR US AUTOMOTIVE MARKET

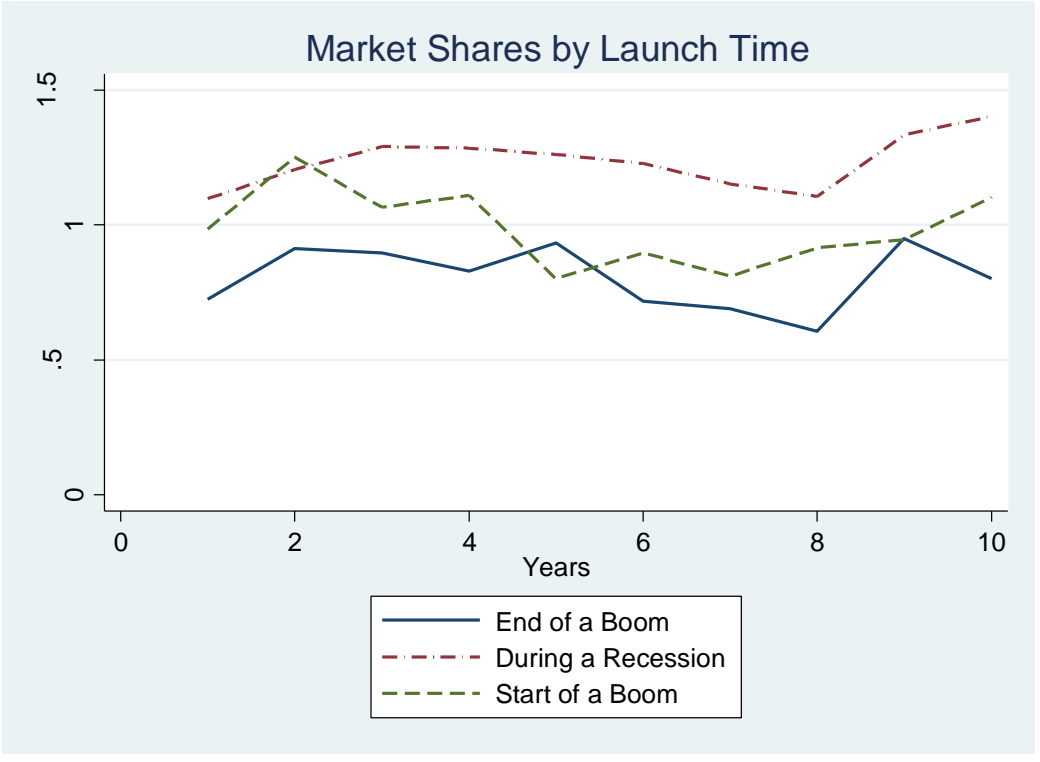


TABLE 1
BUSINESS CYCLE REFERENCE DATES INCLUDED IN THE ANALYSES

Beginning	End	Real GDP Decline	Contraction	Expansion	Cycle	
			Beginning to End ⁷	Previous end to this beginning ⁷	End from Previous End ⁷	Beginning from Previous Beginning ⁷
<i>United States</i>						
November 1948	- October 1949	-1.7%	11	37	48	45
July 1953	- May 1954	-2.6%	10	45	55	56
August 1957	- April 1958	-3.7%	8	39	47	49
April 1960	- February 1961	-1.6%	10	24	34	32
December 1969	- November 1970	-0.6%	11	106	117	116
November 1973	- March 1975	-3.2%	16	36	52	47
January 1980	- July 1980	-2.2%	6	58	64	74
July 1981	- November 1982	-2.7%	16	12	28	18
July 1990	- March 1991	-1.4%	8	92	100	108
March 2001	- November 2001	-0.3%	8	120	128	128
December 2007	- June 2009	-4.3%	18	73	91	81
<i>United Kingdom</i>						
May 2008	- January 2010	-7.2%	20	194	214	216
August 2010	- February 2012	-0.5%	18	7	25	27

⁷ The numbers in this column refer to months

TABLE 2
NUMBER OF PRODUCT LAUNCHES IN EACH FMCG CATEGORY

Category	Number of Product Launches
Crisps	2,469
Natural Cottage & Cream Cheese	9,410
Breakfast Cereals	3,842
Yoghurt	4,595
Margarine	391
Butter	321
Liquid Soups In Tins & Cartons	2,935
Processed Cheese & Cheese Spread	761
Cream -Dairy And Non Dairy	807
Canned Pasta	538
Toilet Tissue	1,624
Dentifrice	870
Shampoos	2,716
Tissues& Facial Tissues	947
Razor Blades	731
Hair Colorants	536
Hairsprays (Women's Only)	559
Cat Food	5,448
Dog Food	3,644
Salad Dressing	1,471
TOTAL	44.615

TABLE 3
COVARIATES IN THE MODEL

Variable	Definition	US Data	UK Data
Recession-Related Covariates			
BEFORE _{it}	: Number of years till the next recession (up to three years) after a product is launched	✓	✓
DURING _{it}	: Coded as 1 if a model is launched during a recession	✓	✓
DURING-MAG _{it}	: Percentage decline in GDP during the recession in which a product is launched	✓	✓
AFTER _{it}	: Number of years since the next recession (up to three years) before a product is launched	✓	✓
RECESSION _t	: Coded as 1 for the year(s) during a recession	✓	✓
YEARBEFORE _t	: Coded as 1 for the year before a recession	✓	✓
YEARAFTER _t	: Coded as 1 for the year after a recession	✓	✓
Model-Related Covariates			
AGE _{it}	: Difference between time <i>t</i> and the year model launched	✓	✓
NEWGEN _{it}	: 1 if a new generation of model <i>i</i> was launched in year <i>t</i> and 0 if otherwise	✓	✓
REPUTATION _{it}	: 5-point scale trouble indexes from <i>Consumer Reports</i>	✓	
Brand-Related Covariates			
RANGE _{it}	: Range of engine capacity in terms of horsepower	✓	
LUXURY _i	: Coded as 1 if a model <i>i</i> is a luxury brand and 0 if otherwise.	✓	
US _i	: Coded as 1 if a model <i>i</i> is a U.S. brand and 0 if otherwise	✓	
PARENT_SHARE _{it}	: Ratio of total unit sales of the parent company of brand <i>i</i> to the unit sales of all firms in the market in year <i>t</i>	✓	
Competition-Related Covariates			
TOTNEWMODELS _{it}	: Coded 1 if a new model was introduced to the segment of model <i>i</i> in year <i>t</i> and 0 if otherwise	✓	✓
TOTNEWGENS _{it}	: Coded 1 if a new generation of an existing model was introduced to the segment of model <i>i</i> in year <i>t</i>	✓	✓
CATSALES _{it}	: Total sales in the category of the product <i>i</i> in month <i>t</i>		✓
Decade dummies	: Starting with 1946, each decade is represented with a dummy variable	✓	
Yearly dummies	: Starting with 1995, each year is represented with a dummy variable		✓

TABLE 4
DESCRIPTIVE STATISTICS

U.S. Automotive Market (1946 – 2007)										U.K. FMCG Market (1995 – 2012)							
Variable	Models Launched During Nonrecession Periods (N = 735)				Models Launched During Recession Periods (N = 336)				Products Launched During Nonrecession Periods (N = 40,422)				Products Launched During Recession Periods (N = 4,193)				
	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max	
1 MSHARE _{it}	0.010	0.015	0.000	0.150	0.012	0.019	0.000	0.209	0.001	0.004	0.000	0.179	0.001	0.003	0.000	0.123	
2 BEFORE _{it}	0.402	1.291	0.000	8.147	0.473	1.744	-0.956	10.147	6.667	3.726	0.000	13.250	0.000	0.000	0.000	0.000	
3 DURING _{it}	0.000	0.000	0.000	0.000	1.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	1.000	
4 DURING-MAG _{it}	0.000	0.000	0.000	0.000	0.794	1.231	0.000	4.100	0.000	0.000	0.000	0.000	-1.018	0.919	0.612	7.254	
5 AFTER _{it}	0.427	1.366	0.000	9.750	0.164	0.922	0.000	9.750	9.510	3.989	0.083	16.667	0.000	0.000	0.000	0.000	
6 RECESSION _t	0.266	0.442	0.000	1.000	0.360	0.480	0.000	1.000	0.147	0.354	0.000	1.000	0.432	0.495	0.000	1.000	
7 YEARBEFORE _t	0.165	0.371	0.000	1.000	0.109	0.312	0.000	1.000	0.147	0.354	0.000	1.000	0.224	0.417	0.000	1.000	
8 YEARAFTER _t	0.149	0.356	0.000	1.000	0.181	0.385	0.000	1.000	0.077	0.266	0.000	1.000	0.344	0.475	0.000	1.000	
9 SALES _{it}	10.080	1.956	1.099	13.575	10.027	2.036	0.000	13.735	-	-	-	-	-	-	-	-	
10 AGE _{it}	8.253	8.663	1.000	51.000	7.608	8.094	1.000	56.000	3.381	3.167	0.083	19.250	1.574	1.137	0.083	4.917	
11 NEWGEN _{it}	0.092	0.289	0.000	1.000	0.086	0.281	0.000	1.000	0.238	0.426	0.000	1.000	0.251	0.434	0.000	1.000	
12 REPUTATION _{it}	65.867	14.309	23.529	100.000	65.676	13.994	31.250	100.000	-	-	-	-	-	-	-	-	
13 RANGE _{it}	89.537	87.993	0.000	762.000	86.313	82.642	0.000	762.000	-	-	-	-	-	-	-	-	
14 LUXURY _i	0.288	0.453	0.000	1.000	0.331	0.470	0.000	1.000	-	-	-	-	-	-	-	-	
15 US _i	0.522	0.500	0.000	1.000	0.476	0.500	0.000	1.000	-	-	-	-	-	-	-	-	
16 PARENT_SHARE _{it}	0.179	0.166	0.000	3.371	0.180	0.167	0.000	0.545	-	-	-	-	-	-	-	-	
17 TOTNEWMODELS _{it}	2.356	2.719	0.000	24.000	2.487	2.556	0.000	15.000	3.390	4.267	0.000	77.000	2.435	3.655	0.000	36.000	
18 TOTNEWGENS _{ij}	4.285	3.509	0.000	24.000	4.330	3.527	0.000	20.000	14.635	20.667	0.000	333.000	11.005	17.481	0.000	81.000	
19 CATSALES _{it}	-	-	-	-	-	-	-	-	10.174	0.987	6.780	12.032	10.637	0.981	6.975	12.032	

TABLE 5
CORRELATION MATRIX (above diagonal for UK data, below diagonal for US data)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 MSHARE _{it}	1	.059	-.019	.011	-.025	.001	-.004	.006		.122	.040	-.092						-.125	-.207
2 BEFORE _{it}	-.015	1	-.406	.297	-.368	-.320	-.272	-.254		.287	-.040	-.012						.057	-.324
3 DURING _{it}	.057	.042	1	-.531	-.410	.185	.052	.222		-.140	.007	-.054						-.043	.112
4 DURING-MAG _{it}	.058	.044	.467	1	.373	-.173	-.022	-.135		.098	-.004	.034						.024	-.081
5 AFTER _{it}	-.025	.430	-.082	-.082	1	.082	.099	-.060		-.042	.021	.116						.038	.125
6 RECESSION _t	.041	.055	.066	.073	-.081	1	-.187	-.142		.175	.016	-.049						-.049	.203
7 YEARBEFORE _t	.005	-.089	-.060	-.061	.060	-.264	1	-.135		.130	.014	.015						-.035	.174
8 YEARAFTER _t	.010	.025	.037	.035	-.045	-.246	-.098	1		.150	.010	-.069						-.050	.134
9 SALES _{it}	.392	-.062	.001	.002	-.066	.041	.005	.009	1										
10 AGE _{it}	-.050	-.237	-.028	-.029	-.217	-.072	-.024	-.030	.088	1	.011	-.074						-.097	.119
11 NEWGEN _{it}	.047	-.094	-.015	-.015	-.086	-.012	-.021	.021	.083	.077	1	-.006						-.129	-.127
12 REPUTATION _{it}	-.019	.020	-.012	-.013	-.002	-.131	.036	-.019	-.126	-.008	.003	1							
13 RANGE _{it}	.012	-.035	-.002	-.004	-.025	-.134	-.043	-.019	.098	.128	.032	.043	1						
14 LUXURY _i	-.225	.007	.039	.037	.022	-.092	.010	-.031	-.353	.027	-.034	.111	-.102	1					
15 US _i	.197	-.044	-.030	-.029	-.018	.135	.030	.057	.302	.090	.004	-.326	.049	-.404	1				
16 PARENT_SHARE _{it}	.260	-.054	.006	.007	-.037	.095	.007	.046	.334	.142	.013	-.254	.096	-.175	.417	1			
17 TOTNEWMODELS _{it}	.178	.231	.020	.021	.133	.078	-.028	.118	.085	-.198	-.030	-.013	-.134	-.179	.140	.066	1	.421	.205
18 TOTNEWGENS _{ij}	.185	.152	-.003	-.002	.088	.066	-.054	.106	.121	-.137	.158	-.006	-.051	-.274	.179	.093	.482	1	.363
19 CATSALES _{it}																			1

Notes: 1) All correlations except the ones in **bold, italicized** fonts are significant at .05 level
2) Correlations below and above the diagonal are for the U.S. and U.K. data, respectively

TABLE 6
IMPACT OF PRODUCT LAUNCH TIME ON MARKET SHARE

Variable	US Data		UK Data	
	Coefficient	SE	Coefficient	SE
Recession-Related Covariates				
<i>BEFORE_{it}</i>	0.013**	0.006	0.004***	0.001
<i>DURING_{it}</i>	0.147***	0.042	0.019***	0.003
<i>DURING-MAG_{it}</i>	0.004**	0.002	-0.164***	0.003
<i>DURING-MAG²_{it}</i>	-0.015***	0.003	0.026***	0.004
<i>AFTER_{it}</i>	-0.013**	0.005	-0.001***	0.000
<i>RECESSION_t</i>	0.080***	0.027	0.015***	0.002
<i>YEARBEFORE_t</i>	0.044**	0.015	0.009***	0.003
<i>YEARAFTER_t</i>	0.005	0.022	0.014***	0.003
Model-Related Covariates				
<i>AGE_{it}</i>	0.046**	0.006	0.001***	0.001
<i>AGE²_{it}</i>	-0.004***	0.001	-0.004***	0.001
<i>NEWGEN_{it}</i>	0.082***	0.026	0.016***	0.004
<i>REPUTATION_{it}</i>	0.002**	0.001		
Brand-Related Covariates				
<i>RANGE_{it}</i>	0.002*	0.001		
<i>LUXURY_i</i>	-0.439***	0.064		
<i>US_i</i>	-0.201***	0.026		
<i>PARENT_SHARE_{it}</i>	0.136	0.102		
Competition-Related Covariates				
<i>TOTNEWMODELS_{it}</i>	-0.008**	0.004	-0.005***	0.001
<i>TOTNEWGENS_{ij}</i>	-0.009***	0.004	-0.003***	0.001
<i>CATSALES_{it}</i>			-0.072***	0.001
<hr/>				
<i>Number of observations</i>		7,772		863,873
<i>Number of products</i>		1,024		25,310
<i>Wald χ^2</i>		274.32***		3987.32***

Note: ***, **, * indicate a significance level of .01, .05, and .10, respectively.

TABLE 7
COMPARISON OF MARKET SHARE AND SURVIVAL IN THE US MARKET

	ANALYSIS OF MARKET SHARE		ANALYSIS OF SURVIVAL	
Variable	Coefficient	SE	Coefficient	SE
Recession-Related Covariates				
<i>BEFORE_{it}</i>	0.013**	0.006	0.064**	0.030
<i>DURING_{it}</i>	0.147***	0.042	0.175***	0.067
<i>DURING-MAG_{it}</i>	0.004**	0.002	0.049***	0.019
<i>DURING-MAG²_{it}</i>	-0.015***	0.003	-0.040***	0.010
<i>AFTER_{it}</i>	-0.013**	0.005	-0.085***	0.012
<i>RECESSION_t</i>	0.080***	0.027	0.131**	0.060
<i>YEARBEFORE_t</i>	0.044**	0.015	-0.087***	0.032
<i>YEARAFTER_t</i>	0.005	0.022	-0.037	0.033
Model-Related Covariates				
<i>SALES_{it}</i>			0.095***	0.018
<i>AGE_{it}</i>	0.046**	0.006	0.130***	0.008
<i>AGE²_{it}</i>	-0.004***	0.001	-0.003***	0.001
<i>NEWGEN_{it}</i>	0.082***	0.026	0.296***	0.080
<i>REPUTATION_{it}</i>	0.002**	0.001	0.003***	0.001
Brand-Related Covariates				
<i>RANGE_{it}</i>	0.002*	0.001	0.001***	0.000
<i>LUXURY_i</i>	-0.439***	0.064	0.128***	0.044
<i>US_i</i>	-0.201***	0.026	-0.156***	0.044
<i>PARENT_SHARE_{it}</i>	0.136	0.102	0.124	0.148
Competition-Related Covariates				
<i>TOTNEWMODELS_{it}</i>	-0.008**	0.004	-0.020***	0.008
<i>TOTNEWGENS_{ij}</i>	-0.009***	0.004	-0.012**	0.006

TABLE 8
ANALYSES OF SURVIVAL USING THREE DIFFERENT CENSORING DATES

Variable	Censoring Year 2000		Censoring Year 1990		Censoring Year 1980	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Recession-Related Covariates						
<i>BEFORE_{it}</i>	0.071**	0.028	0.09***	0.029	0.101***	0.031
<i>DURING_{it}</i>	0.188***	0.069	0.15**	0.069	0.165**	0.072
<i>DURING-MAG_{it}</i>	0.066***	0.021	0.042**	0.02	0.058**	0.025
<i>DURING-MAG²_{it}</i>	-0.035**	0.015	-0.028*	0.015	-0.027*	0.016
<i>AFTER_{it}</i>	-0.084***	0.011	-0.087***	0.01	-0.085***	0.016
<i>RECESSION_t</i>	0.136**	0.062	0.123**	0.062	0.111*	0.064
<i>YEARBEFORE_t</i>	-0.084**	0.035	-0.083**	0.041	-0.08*	0.045
<i>YEARAFTER_t</i>	-0.033	0.035	-0.041	0.038	-0.019	0.041
Model-Related Covariates						
<i>SALES_{it}</i>	0.095***	0.018	0.089***	0.02	0.088***	0.021
<i>AGE_{it}</i>	0.131***	0.009	0.139***	0.011	0.14***	0.015
<i>AGE²_{it}</i>	-0.002**	0.001	-0.004**	0.002	-0.007***	0.002
<i>NEWGEN_{it}</i>	0.302***	0.088	0.328***	0.097	0.371***	0.107
<i>REPUTATION_{it}</i>	0.002**	0.001	0.005**	0.002	0.007**	0.003
Brand-Related Covariates						
<i>RANGE_{it}</i>	0.001**	0.0005	0.003***	0.001	0.004**	0.002
<i>LUXURY_i</i>	0.133***	0.05	0.142**	0.057	0.149**	0.063
<i>US_i</i>	-0.155***	0.047	-0.116**	0.052	-0.133**	0.064
<i>PARENT_SHARE_{it}</i>	0.130	0.172	0.131	0.189	0.156	0.197
Competition-Related Covariates						
<i>TOTNEWMODELS_{it}</i>	-0.022**	0.010	-0.021*	0.011	-0.027	0.017
<i>TOTNEWGENS_{ij}</i>	-0.018**	0.008	-0.015	0.011	-0.021	0.013

Note: ***, **, * indicate a significance level of .01, .05, and .10, respectively.

TABLE 9⁸
ANALYSES OF SURVIVAL USING FOUR DIFFERENT DISTRIBUTIONS

Variable	Exponential Distribution		Gompertz Distribution		Log-Normal Distribution		Weibull Distribution	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Recession-Related Covariates								
<i>BEFORE_{it}</i>	0.811***	0.225	-0.812***	0.225	0.003	0.031	0.167	0.087
<i>DURING_{it}</i>	0.154***	0.010	-0.152***	0.011	0.051***	0.003	0.085***	0.005
<i>DURING-MAG_{it}</i>	0.176*	0.089	-0.195*	0.089	0.082***	0.024	0.149***	0.035
<i>DURING-MAG²_{it}</i>	-0.002*	0.001	0.002*	0.001	-0.001***	0.000	-0.001***	0.000
<i>AFTER_{it}</i>	0.045	0.087	-0.046	0.088	-0.084***	0.013	-0.073*	0.032
<i>RECESSION_t</i>	0.202	0.158	-0.245	0.157	0.040	0.040	0.189**	0.064
<i>YEARBEFORE_t</i>	-0.363**	0.136	0.371**	0.136	-0.110**	0.038	-0.163**	0.055
<i>YEARAFTER_t</i>	-0.106	0.157	0.107	0.157	-0.057	0.042	-0.052	0.063
Model-Related Covariates								
<i>SALES_{it}</i>	0.407***	0.028	-0.406***	0.028	0.124***	0.013	0.163***	0.012
<i>AGE_{it}</i>	-0.011	0.011	-0.021	0.011	0.121***	0.004	0.089***	0.005
<i>AGE²_{it}</i>	0.001	0.000	-0.001	0.000	-0.003***	0.000	-0.001***	0.000
<i>NEWGEN_{it}</i>	1.389***	0.311	-1.389***	0.311	0.358***	0.064	0.598***	0.125
<i>REPUTATION_{it}</i>	0.012**	0.004	-0.012**	0.004	0.004***	0.001	0.006***	0.002
Brand-Related Covariates								
<i>RANGE_{it}</i>	0.001	0.001	-0.001	0.001	0.000	0.000	0.001*	0.000
<i>LUXURY_i</i>	0.670***	0.167	-0.705***	0.167	0.195***	0.048	0.425***	0.069
<i>US_i</i>	-0.426	0.237	0.390	0.238	-0.145**	0.056	-0.090	0.105
<i>PARENT_SHARE_{it}</i>	0.668	0.743	-0.613	0.746	0.161	0.170	0.227	0.311
Competition-Related Covariates								
<i>TOTNEWMODELS_{it}</i>	-0.074*	0.036	0.073*	0.036	-0.026**	0.009	-0.023	0.015
<i>TOTNEWGENS_{ij}</i>	0.052	0.028	-0.051	0.028	-0.016*	0.007	0.020	0.011

⁸ Results of the Exponential, Log-Normal, and Weibull distributions are in the AFT format, while those of the Gompertz Distribution are in PH format. As such, the results of the analyses are consistent.

TABLE 10
ANALYSIS OF SURVIVAL USING BOOTSTRAP RESAMPLING WITH 50
REPETITIONS

US Automotive Data		
Variable	Coefficient	Bootstrap Standard Errors
Recession-Related Covariates		
<i>BEFORE_{it}</i>	0.064**	0.042
<i>DURING_{it}</i>	0.175***	0.071
<i>DURING-MAG_{it}</i>	0.049***	0.017
<i>DURING-MAG²_{it}</i>	-0.040***	0.009
<i>AFTER_{it}</i>	-0.085***	0.010
<i>RECESSION_t</i>	0.131**	0.055
<i>YEARBEFORE_t</i>	-0.087***	0.034
<i>YEARAFTER_t</i>	-0.037	0.037
Model-Related Covariates		
<i>SALES_{it}</i>	0.095***	0.027
<i>AGE_{it}</i>	0.130***	0.008
<i>AGE²_{it}</i>	-0.003***	0.001
<i>NEWGEN_{it}</i>	0.296***	0.091
<i>REPUTATION_{it}</i>	0.003***	0.001
Brand-Related Covariates		
<i>RANGE_{it}</i>	0.001***	0.000
<i>LUXURY_i</i>	0.128***	0.046
<i>US_i</i>	-0.156***	0.048
<i>PARENT_SHARE_{it}</i>	0.124	0.173
Competition-Related Covariates		
<i>TOTNEWMODELS_{it}</i>	-0.020***	0.008
<i>TOTNEWGENS_{ij}</i>	-0.012**	0.007

Note: ***, **, * indicate a significance level of .01, .05, and .10, respectively.

TABLE 11
IMPACT OF LAUNCH TIME ON PRODUCT QUALITY

Dependent variable = Product Quality	US Data	
Variable	Coefficient	SE
Recession-Related Covariates		
<i>BEFORE_{it}</i>	0.189***	0.053
<i>DURING_{it}</i>	0.571**	0.281
<i>DURING-MAG_{it}</i>	-0.178**	0.777
<i>DURING-MAG²_{it}</i>	0.009	0.005
<i>AFTER_{it}</i>	-0.320*	0.182
<i>RECESSION_t</i>	0.252	0.432
<i>YEARBEFORE_t</i>	0.068	0.455
<i>YEARAFTER_t</i>	-0.804***	0.246
Model-Related Covariates		
<i>SALES_{it}</i>		
<i>AGE_{it}</i>	0.009	0.091
<i>AGE²_{it}</i>	0.004	0.003
<i>NEWGEN_{it}</i>	0.862***	0.340
<i>REPUTATION_{it}</i>	-	-
Brand-Related Covariates		
<i>RANGE_{it}</i>	0.137***	0.004
<i>LUXURY_i</i>	0.405***	0.010
<i>US_i</i>	0.468***	0.138
<i>PARENT_SHARE_{it}</i>		
Competition-Related Covariates		
<i>TOTNEWMODELS_{it}</i>	-0.082	0.109
<i>TOTNEWGENS_{ij}</i>	0.172**	0.070
<i>CATSALES_{it}</i>	-	-
<hr/>		
<i>Number of observations</i>	7,772	
<i>Number of products</i>	1024	
<i>Wald χ^2</i>	174.06***	

APPENDIX A

TABLE A1: CATEGORY BY CATEGORY ANALYSES OF MARKET SHARE

Category	Hairsprays (Women's Only)	Razor Blades	Hair Colorants	Shampoos	Tissues / Facial Tissues	Breakfast Cereals	Canned Pasta	Liquid Soups	Dentifrice	Toilet Tissue
Recession-Related Covariates										
<i>BEFORE_{it}</i>	0.019***	0.017***	0.016***	0.013***	0.015***	0.013***	0.015***	0.013***	0.016***	0.020***
<i>DURING_{it}</i>	0.028**	0.031**	0.033***	0.037***	0.033***	0.033***	0.035***	0.034***	0.035***	0.037***
<i>DURING-MAG_{it}</i>	-0.042***	-0.042***	-0.043***	-0.042***	-0.043***	-0.043***	-0.043***	-0.042***	-0.043***	-0.043***
<i>DURING-MAG²_{it}</i>	-0.024***	-0.024***	-0.024***	-0.024***	-0.025***	-0.024***	-0.024***	-0.024***	-0.024***	-0.025***
<i>AFTER_{it}</i>	0.018***	0.009***	0.004**	-0.006***	0.001	-0.004***	-0.002	-0.004***	0.001	0.008***
<i>RECESSION_t</i>	-0.011***	-0.011***	-0.014***	-0.018**	-0.012**	-0.004**	-0.01*	-0.01*	-0.013**	-0.007*
<i>YEARBEFORE_t</i>	0.01**	0.009***	0.012***	0.017*	0.011**	0.003**	0.009*	0.009*	0.012**	0.005
<i>YEARAFTER_t</i>	-0.012***	-0.01***	-0.013***	-0.018**	-0.012**	-0.004**	-0.01*	-0.01*	-0.012**	-0.007*
Model-Related Covariates										
<i>AGE_{it}</i>	0.027***	0.027***	0.026***	0.027***	0.026***	0.025***	0.027***	0.026***	0.027***	0.029***
<i>AGE²_{it}</i>	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001**	0.001*	0.001*	-0.001*	0.001**
<i>NEWGEN_{it}</i>	0.043***	0.051***	0.046***	0.043***	0.041***	0.044***	0.044***	0.045***	0.049***	0.043***
<i>REPUTATION_{it}</i>	-	-	-	-	-	-	-	-	-	-
Brand-Related Covariates										
<i>RANGE_{it}</i>	-	-	-	-	-	-	-	-	-	-
<i>LUXURY_i</i>	-	-	-	-	-	-	-	-	-	-
<i>US_i</i>	-	-	-	-	-	-	-	-	-	-
<i>PARENT_SHARE_{it}</i>	-	-	-	-	-	-	-	-	-	-
Competition-Related Covariates										
<i>TOTNEWMODELS_{it}</i>	-0.005**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.004**	-0.004**	-0.003**	-0.003**
<i>TOTNEWGENS_{ij}</i>	-0.004**	-0.003**	-0.002**	-0.002**	-0.003**	-0.002**	-0.002**	-0.002**	-0.002**	-0.003**
<i>CATEGORY SALES</i>	-0.053***	-0.052***	-0.055***	-0.055***	-0.055***	-0.053***	-0.054***	-0.048***	-0.055***	-0.062***

APPENDIX A
TABLE A1: CATEGORY BY CATEGORY ANALYSES OF MARKET SHARE (continued)

Category	Dog Food	Cat Food	Yoghurt	Butter	Margarine	Salad Dressing	Crisps	Natural Cottage & Cream Cheese	Processed Cheese & Cheese Spread	Cream - Dairy And Non Dairy
Recession-Related Covariates										
<i>BEFORE_{it}</i>	0.011***	0.011***	0.014***	0.015***	0.016***	0.012***	0.013***	0.009***	0.017***	0.015***
<i>DURING_{it}</i>	0.034***	0.032***	0.035***	0.031***	0.031***	0.033***	0.030***	0.025**	0.031***	0.026**
<i>DURING-MAG_{it}</i>	-0.042***	-0.042***	-0.042***	-0.043***	-0.043***	-0.043***	-0.043***	-0.044***	-0.042***	-0.044***
<i>DURING-MAG²_{it}</i>	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.025***	-0.025***	-0.024***	-0.024***
<i>AFTER_{it}</i>	-0.008***	-0.006***	-0.002**	0.004**	0.006**	-0.004***	0.001	-0.003***	0.007***	0.010***
<i>RECESSION_t</i>	-0.009**	-0.010***	-0.006**	-0.013***	-0.013***	-0.013***	-0.008**	-0.010***	-0.002**	-0.012***
<i>YEARBEFORE_t</i>	0.009**	0.01**	0.005**	0.012***	0.012***	0.013***	0.007**	0.009**	0.001**	0.011***
<i>YEARAFTER_t</i>	-0.009**	-0.010***	-0.006**	-0.013***	-0.013***	-0.013***	-0.008**	-0.009**	-0.002**	-0.012***
Model-Related Covariates										
<i>AGE_{it}</i>	0.025***	0.024***	0.026***	0.026***	0.025***	0.027***	0.025***	0.021***	0.027***	0.028***
<i>AGE²_{it}</i>	-0.001*	-0.001**	-0.001*	0.001**	-0.001*	-0.001**	-0.001**	-0.001*	-0.001*	-0.001*
<i>NEWGEN_{it}</i>	0.042***	0.040***	0.047***	0.048***	0.048***	0.048***	0.044***	0.048***	0.044***	0.044***
<i>REPUTATION_{it}</i>	-	-	-	-	-	-	-	-	-	-
Brand-Related Covariates										
<i>RANGE_{it}</i>	-	-	-	-	-	-	-	-	-	-
<i>LUXURY_i</i>	-	-	-	-	-	-	-	-	-	-
<i>US_i</i>	-	-	-	-	-	-	-	-	-	-
<i>PARENT_SHARE_{it}</i>	-	-	-	-	-	-	-	-	-	-
Competition-Related Covariates										
<i>TOTNEWMODELS_{it}</i>	-0.004**	-0.004**	-0.003**	-0.003**	-0.003**	-0.003**	-0.004**	-0.004**	-0.005**	-0.003**
<i>TOTNEWGENS_{ij}</i>	-0.002**	-0.002**	-0.003**	-0.002**	-0.002**	-0.003**	-0.002**	-0.001**	-0.002**	-0.002**
<i>CATEGORY SALES</i>	-0.053***	-0.053***	-0.050***	-0.054***	-0.054***	-0.058***	-0.051***	-0.050***	-0.053***	-0.045***

WEB APPENDIX A
DETAILED EXPLANATION OF SUPPLEMENTARY SURVIVAL ANALYSIS

Hazard Model

For the US automotive data set we further analyzed the likelihood of survival of new products launched. Standard regression approaches are not suitable for the analysis of survival times, because such data are right censored — that is, not all models in the data set have failed by the end of the observation period. Therefore, we test our hypotheses using a parametric hazard model not only because it can address the right-censoring problem but also because it enables us to analyze the effects of time-varying and time-constant covariates on a model’s probability of failure (Helsen and Schmittlein 1993). Using STATA 13.1, we estimate a hazard model with log-logistic distribution using time-varying and time-constant covariates and inverse Gaussian shared frailty. The survivor and density functions of the generalized log-logistic model are

$$S(t) = \left\{1 + (\lambda t)^{\frac{1}{\gamma}}\right\}^{-1}$$

and

$$f(t) = \frac{\lambda^{\frac{1}{\gamma}} t^{\frac{1}{\gamma}-1}}{\gamma \left\{1 + (\lambda t)^{\frac{1}{\gamma}}\right\}^2}$$

We implement this model by parameterizing $\lambda_j = \exp(-\mathbf{x}_j\boldsymbol{\beta})$ and treating γ , the scale parameter, as ancillary to be estimated from the data.

To analyze the robustness of our findings to model specification, we also estimate our model using three other commonly used baseline distributions (Wang, Chen, and Xie 2010):

Weibull, log-normal, and generalized gamma distributions. Finally, we perform a bootstrapping analysis with 50 repetitions (Aboulnasr et al. 2008).

Nonparametric Analyses of Hazard

Before the final model estimation, we obtain key insights with nonparametric hazard functions that do not account for covariates. We present the failure probabilities of car models launched one year before, during, and one year after economic recessions. Figure 1 shows the U-shaped pattern in the hazard rates for all models in our data set, regardless of their launch timing. After a high hazard in the early years, the hazard rate steadily declines until approximately 35 years after launch. The hazard rate increases monotonically as model age exceeds 35.

[Insert Web Appendix A Figure 1 around here]

Directly relevant to our hypotheses, Figure 2 compares the hazard functions of models launched before, during, and after the recession with other models. First, we find that models launched one year before always have higher hazard rates throughout their lifespan when compared with the models launched during or after recessions. Furthermore, as their relatively shorter hazard rate curve indicates, they tend to live shorter as well. Second, models launched during a recession have lower hazard rates than models launched both before and after recessions, which indicates support for our main premise. Third, our analyses reveal that models launched the year following the end of an economic recession maintain lower hazard rates than those launched before a recession.

[Insert Web Appendix A Figure 2 around here]

In summary, the hazard patterns are consistent with our hypotheses. However, these patterns are virtually unconditional (i.e., they do not account for the effects of any covariates), and therefore we proceed to conduct a parametric analyses.

Parametric Analyses

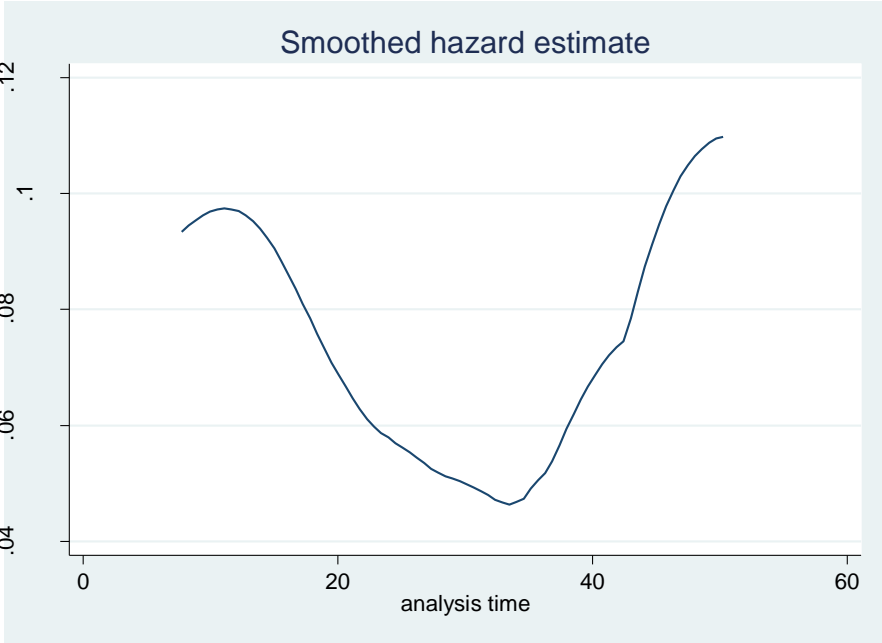
The parametric duration models assume a particular shape for the hazard rate and use a distribution (e.g., Exponential, Weibull, Lognormal, Log-Logistic, Gompertz, and Generalized Gamma) to approximate that shape. That is, each of these different distributions enables the estimation of a particular shape for the hazard rate i.e. the time dependency. For example, the exponential assumes a flat hazard; the Weibull assumes a monotonic hazard; the log-normal and log-logistic assume a non-monotonic hazard. The precision and accuracy of the parameter estimates depend on the correct characterization of the underlying time-dependency. Therefore, it was important for our analyses to determine whether the base hazard rate (i.e., the instantaneous probability that a model will fail at time t) was constant, increasing, or decreasing with time, so that we could investigate a model's risk of failure over time. We considered alternative base hazard functions, including the exponential, gamma, log-normal, log-logistic, and Weibull, for which the AFT method allows, and following Srinivasan, Lilien, and Rangaswamy (2004), we used a multistep approach to determine the distribution that best represents the survival times of pioneers in networked markets. We were unable to estimate the gamma model with our data because of convergence problems, which is often the case for the generalized gamma distribution; even if it is estimable, it is difficult to judge the shape of the hazard function from the estimated parameters (Allison 1995, p. 74). We estimated the exponential model, which assumes a constant hazard rate (a special case of the Weibull model, with scale parameter set to 1), and we found that this model can be rejected ($p < .001$). Therefore, we estimated our model using three distribution functions (log-normal, log-logistic, and Weibull) that accommodate monotonically and non-monotonically changing hazard rates. Although the general pattern of results is similar across the models, based on the Akaike

information criterion (AIC), the model estimated with the log-logistic hazard function fits the data slightly better than those estimated with the log-normal and the log-logistic functions.

Figure 3 presents the hazard rates based on our parametric analysis of survival in the car industry (final model with covariates), showing that models launched during recessions have the lowest hazard rates, whereas models launched before recessions have the highest hazard rates.

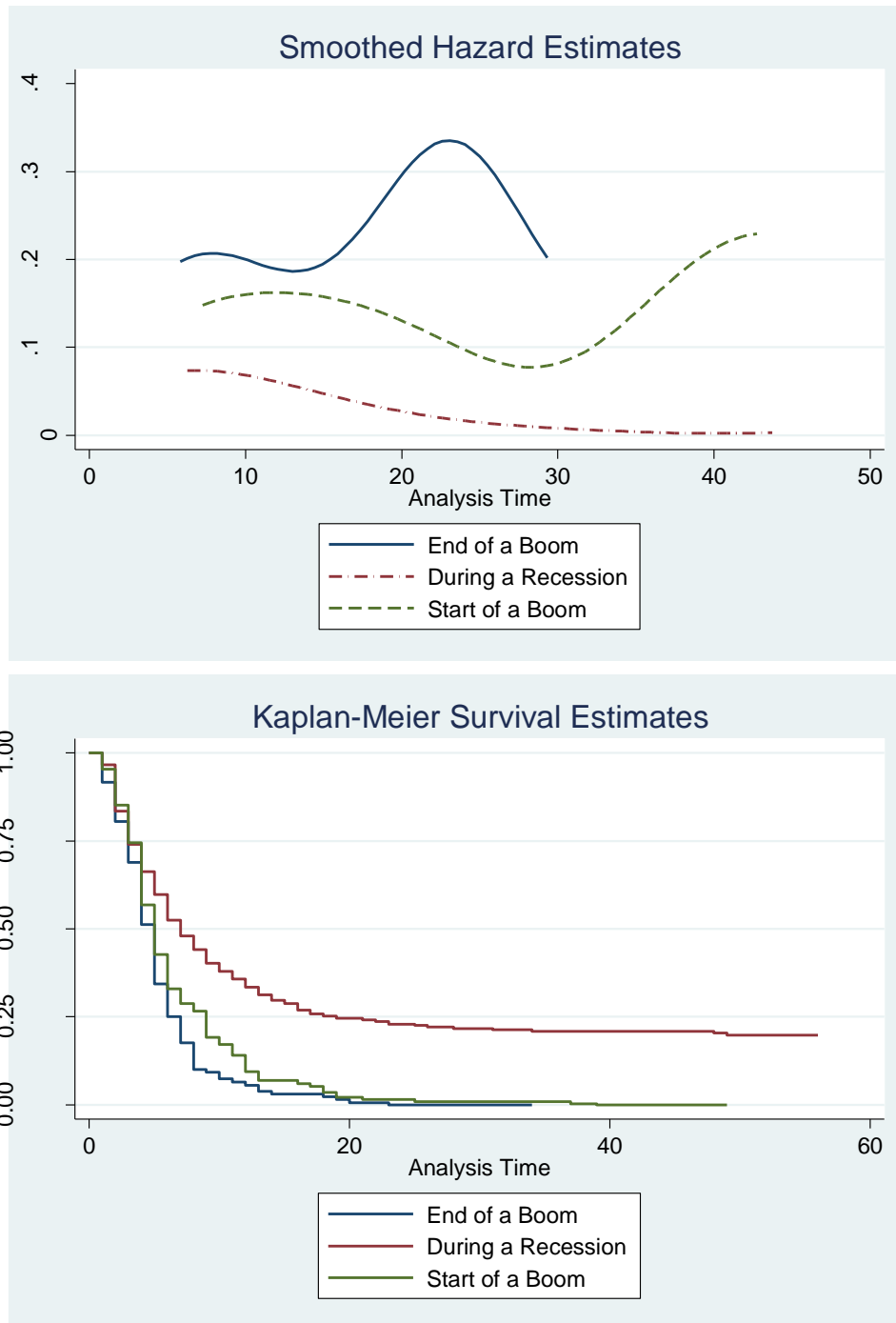
[Insert Web Appendix A Figure 3 around here]

WEB APPENDIX A FIGURE 1
SMOOTHED HAZARD ESTIMATES FOR ALL MODELS IN THE OBSERVATION PERIOD

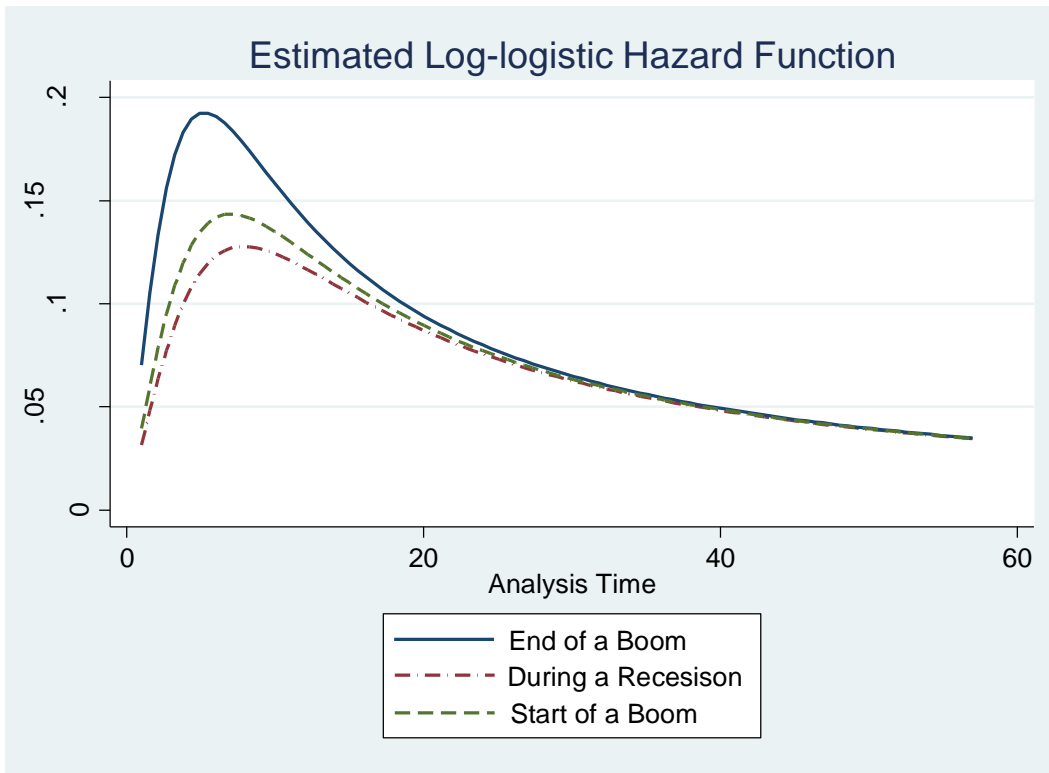


WEB APPENDIX A FIGURE 2

SMOOTHED HAZARD ESTIMATES AND KAPLAN-MEIER SURVIVAL ESTIMATES FOR MODELS LAUNCHED IN RECESSION, START OF A BOOM AND END OF A BOOM



WEB APPENDIX A FIGURE 3
ESTIMATED LOG-LOGISTIC HAZARD FUNCTION



WEB APPENDIX REFERENCES

- Aboulnasr, K., Om Narasimhan, Edward Blair, and Rajesh Chandy (2008), "Competitive Response to Radical Product Innovations," *Journal of Marketing*, 72 (3), 94-110.
- Allison, Paul D. (1995), *Survival Analysis Using the SAS System*. Cary, NC: SAS Institute Inc
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