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Weathering Tight Economic Times: The Sales Evolution of Consumer Durables over the Business Cycle

Barbara Deleersnyder, Marnik G. Dekimpe, Miklos Sarvary, and Philip M. Parker

How do consumers adjust their shopping habits across the business cycle? This study of 24 product categories finds that consumer durables—particularly leisure goods—are harder hit by economic contractions than the general economy.

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Report Summary

Despite the obvious importance of understanding how business cycle fluctuations affect both individual companies and whole industries, not much marketing research focuses on the subject. Often, one only has aggregate information on the state of the national economy, even though cyclical contractions and expansions generally do not have an equal impact on every industry, nor on all firms in any given industry.

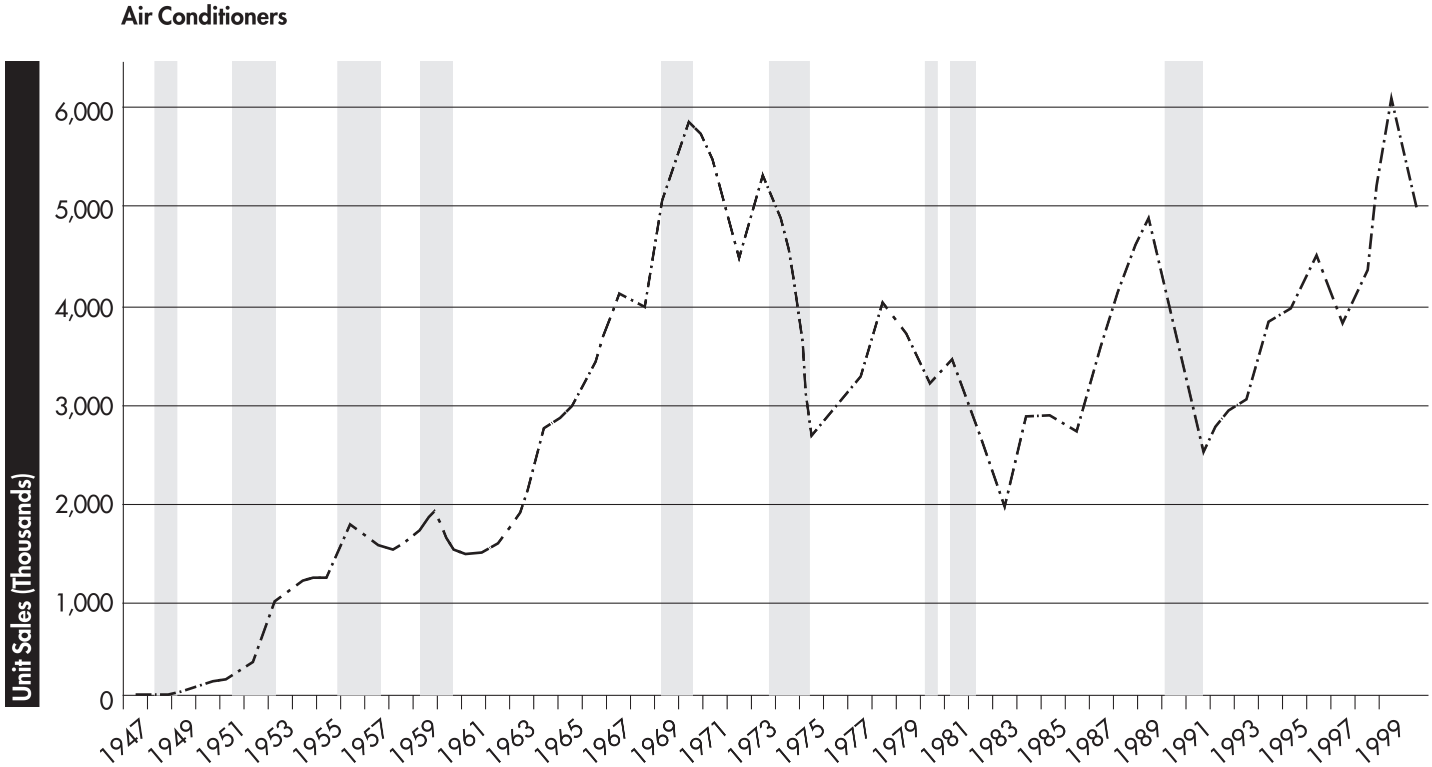
Using recent time-series developments, authors Deleersnyder, Dekimpe, Sarvary, and Parker introduce measures to quantify the extent and nature of the effect of business cycle fluctuations on sales. Specifically, they discuss the notions of cyclical volatility (that is, variability) and cyclical "comovement" with the general economy. They also consider steepness asymmetry (when consumers react more quickly to contractions than to expansions), and deepness asymmetry (when consumers react more extensively to contractions than to expansions). In so doing, they examine how consumers adjust their purchasing behavior across different phases of the business cycle. They apply these concepts to 24 categories of consumer durables, analyzing the cyclical sensitivity in their sales evolution.

Consumer durables are found to be more sensitive to business cycle fluctuations than the general economy is. This finding shows the need for an explicit consideration of cyclical variation in durable sales.

Moreover, even though the authors find no evidence for deepness asymmetry in durable sales, the combined evidence across all durables suggests that asymmetry is present in the speed of up- and downward movement, as durable sales fall much more quickly during contractions than they recover during economic expansions. Finally, key variables related to the industry's pricing activities, the nature of the durable (convenience versus leisure), and the stage in a product's life cycle tend to moderate the extent of cyclical sensitivity in durable sales. ■

Figure 1

Postwar Sales Evolution of U.S. Air Conditioners[a]



[a] The gray bars represent officially registered contractions in the U.S. economy during the observed time period, as identified by the NBER's Business Cycle Dating Committee (www.nber.org/cycles.html).

Introduction

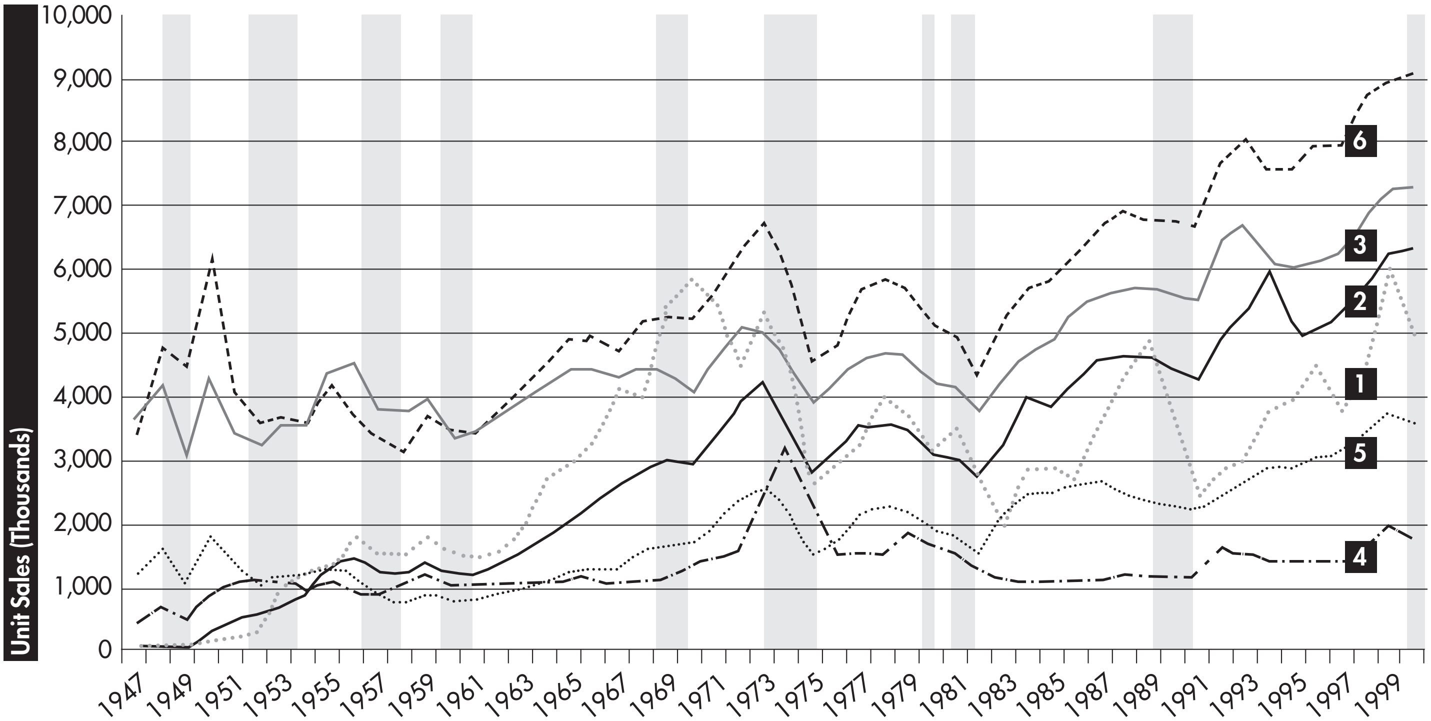
Renewed fears of a widespread economic downturn have reminded companies that macroeconomic developments can be among the most influential determinants of a firm's activities and performance. In a 2002 *Business Week* survey, U.S. companies reported profits that were down by as much as 30% from the previous year, with an especially dramatic drop in sectors such as telecommunications, computer technology, and pharmaceuticals (Arndt and Jesperson 2002, p. 60). Similarly, the *Economist* reported that U.S. retail sales "dropped 3.7% in November 2001, the sharpest month-to-month decline since 1992" (March 7, 2002, p. 4). Given the size of these reductions, it should come as no surprise that management has felt the need to respond actively to such economic downturns. Shama (1993), for example, found that almost all managers he surveyed modify their marketing strategy in response to economic contractions. Still, most companies also indicated they did not use any systematic procedure to determine the impact of an economic contraction on their specific business. Put differently, while companies feel a strong need to make some changes to their marketing tactics and strategies in economic downturns, they are often at a loss for how to assess the impact of these contractions adequately—yet how they perceive the environmental threat posed by a downturn will largely determine whether and how they will adjust their behavior (Dutton and Duncan 1987).

In the academic marketing literature, one occasionally accounts for long-run evolutions in macroeconomic variables generally associated with demand (e.g., Dekimpe and Hanssens

Figure 2

Postwar Sales Evolution of Multiple Consumer Durables[a]

Air Conditioners Clothes Dryers, Electric Washers, Freezers, Ranges, and Refridgerators[b]



[a] The gray bars represent officially registered contractions in the U.S. economy during the observed time period, as identified by the NBER's Business Cycle Dating Committee (www.nber.org/cycles.html).

[b] With: 1 Air conditioners; 2 Clothes dryers; 3 Electric washers; 4 Freezers; 5 Ranges; 6 Refrigerators.

1995a; Franses 1994). Much less attention has been devoted to the sensitivity of performance and marketing support to cyclical variations in the economy.[1] In a recent review of three leading marketing journals (*Journal of Marketing, Journal of Marketing Research, Marketing Science*), Srinivasan, Lilien, and Rangaswamy (2002) found only three publications on a topic related to economic contractions, with the most recent one published in 1979. This general neglect of business cycle fluctuations in the marketing literature is surprising, as such fluctuations may affect both consumers' and companies' activities.

In this paper, we aim to address that gap by introducing various measures to quantify the extent and nature of business-cycle-related fluctuations in durable sales patterns. We focus on the notions of cyclical volatility, cyclical comovement, and cyclical asymmetry. We measure these phenomena in the sales of a broad set of consumer durables, for which we analyze the cyclical sensitivity in their sales evolution over several decades. Our decision to analyze consumer durables is motivated by the fact that these are expected to be particularly sensitive to cyclical expansions and contractions (Cook 1999; Katona 1975).

As a case in point, we present in Figure 1 data on U.S. sales of air conditioners. The gray bars in Figure 1 represent officially registered contractions in the U.S. economy during the observed time period, as identified by the NBER's Business Cycle Dating Committee (www.nber.org/cycles.html) and widely used in many economic studies (e.g., Christiano and

Fitzgerald 1998; Cogley 1997).[2] Figure 1 shows clear evidence that the business cycle has a strong influence on durable sales over time. Indeed, almost every time the economy suffers a contraction, sales drop significantly, while expansions are generally associated with increasing industry sales. For instance, during the early 1990s, the contraction caused sales to drop from 4.904 million units (in the 1989 peak period) to only 2.481 million units at the end of the contraction in 1991. Moreover, during this same contraction, another interesting characteristic is observable. In less than two years, air conditioner sales fell to almost half their pre-1990 level, while it took more than seven years to recover from that loss (the initial peak of 4.904 million units was not attained until 1999). Similar patterns can be observed during the contractions of 1973 and 1981. Based on these observations, cyclical fluctuations in durable sales seem to be asymmetric: Sales drop very fast but recover much more slowly in subsequent years. The question then arises whether these observed patterns are idiosyncratic to this specific durable, or whether they reflect a more general characteristic in durable sales evolutions. If so, what is it that causes and explains this asymmetry?

In Figure 2, we add the U.S. sales evolution of clothes dryers, electric washing machines, freezers, ranges, and refrigerators, all of which demonstrate comparable cyclical behavior. Still, Figure 2 also reveals that there is some variation across the different sales patterns. Cyclical sensitivity seems to be more pronounced in air conditioner sales, while freezers and electric washers tend to be less affected. In combination, figures 1 and 2 provide us with informal evidence of the existence of a strong cyclical sensitivity in durable sales, asymmetries in up- and downward sales adjustments, and variability in cyclical sensitivity across durable industries.

The main purpose of this study is to provide a rigorous analysis of business-cycle-related fluctuations in durable sales. We first provide two metrics to quantify the sensitivity of sales (or marketing support) series to business cycle fluctuations. Next, we determine how best to characterize the asymmetry we might observe in this cyclical behavior. Finally, we assess a number of factors that may explain the variation in cyclical sensitivity across the different durables under investigation.

Drivers of Cyclical Sensitivity

Cyclical sensitivity in durable sales can be attributed to consumers' adjusting their durable-goods purchase decisions across economic up- and downturns. The tendency to purchase or delay a purchase can be attenuated or reinforced by company reactions.

Consumer-related drivers of cyclical sensitivity

Consumers' actual purchase decisions depend to a considerable extent on their ability to acquire the product, as reflected in their income level (Katona 1975; Mehra 2001). Since income developments move in the same direction as developments in the aggregate economy, contractions can decrease consumption by diminishing consumers' wealth (Stock and Watson 1999). Still, people's attitude and expectations are found to contribute to cyclical fluctuations in excess of the impact of actual changes in their income level (Katona 1975). Hence, even if their income remains largely unaffected, mere changes in consumers' attitude during a contraction can still trigger important reductions in their expenditures. This is especially the case in the context of consumer durables, which are expected to be more vulnerable to business cycle fluctuations for a number of reasons.

First, consumers who want to restrict their purchases during an economic contraction find it more difficult to cut back on most frequently purchased consumer goods (FPCGs), because these purchases have, in many respects, become habitual. Therefore, consumers' ability to constrain their outlays for FPCGs is limited, while discretionary expenditures on durables are often the first to be reconsidered (Katona 1975). Second, while expenditures on many non-durables (such as food or clothes) are seen as necessary, expenditures on durables are often outlays of choice. As there is no pressing need to buy these durables at any given moment, consumers can more easily postpone their acquisition when they are confronted with unfavorable economic prospects (Cook 1999). Third, purchasing a durable can be considered an investment decision on the part of the consumer. Durables are often fairly expensive products that are commonly bought on credit; once obtained, their benefits come from their utility over an extended period of time (Cook 1999; Darby 1972; Horsky 1990). Consumers incur a certain amount of risk and uncertainty when they buy a durable good, both in terms of the technical reliability of the good and in terms of the benefits they will be able to obtain from it, and these future-oriented considerations affect consumers' current purchase decisions (Lemon, White, and Winer 2002; Rust et al. 1999).

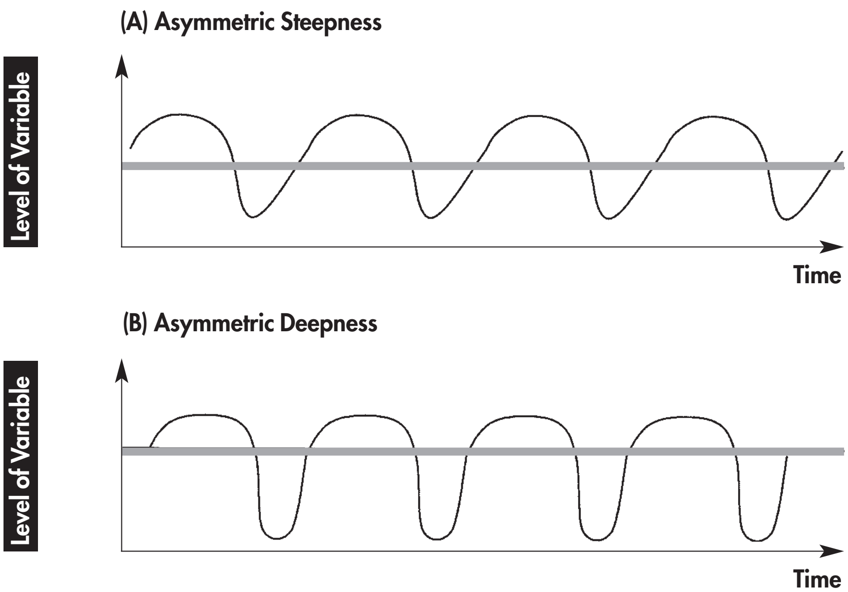
For these reasons, consumers are more inclined to acquire durable goods during favorable economic times. Faced with adverse economic conditions, consumers tend to postpone the acquisition, while current owners of durables may try to lengthen the lives of their product by repairing rather than replacing them (Bayus 1988; Clark, Freeman, and Hanssens 1984).

Purchase postponement may not only contribute to the existence of cyclical sensitivity, it may also cause the cyclical fluctuations to become asymmetric in nature (Gale 1996). During contractions, the consumers' willingness to buy decreases sharply, as people get a strong incentive to delay their spending and wait for better times (Gale 1996). Moreover, as consumer wealth is expected to reach its lowest level right after the downturn, we can expect consumers to continue to postpone their purchases even when the economy starts to recover, to take full advantage of the anticipated increase in future income and wealth (Caballero 1993; Gale 1996). In other words, consumers' downward adjustments during contractions tend to occur quickly, while their upward adjustments may be subject to some delay. When this process occurs across many individual decision makers that are all subject to similar market signals, one can expect asymmetries in aggregate sales (Katona 1975). Thus, the tendency to postpone purchases slows the recovery from a contraction, which causes the cyclical fluctuations in expenditures to evolve asymmetrically across expansions and contractions.

Asymmetric adjustments may also arise from the way consumers gain or lose trust (or confidence) in the economic climate. Consumer confidence has been shown to be an important driver of purchase behavior (e.g., see Kumar, Leone, and Gaskins 1995). During economic contractions, consumer trust is typically lost very easily but is slow to be restored (Holmes and Rempel 1989; Nooteboom, Berger, and Noorderhaven 1997). In addition, consumers' negative expectations tend to be prolonged by a tendency to focus primarily on the negative aspects surrounding them, as people seem to interpret information in a way that confirms their pessimistic attitudes or beliefs (Kramer 2002; Zand 1972). Accordingly, consumer confidence will return only gradually during an expansion. Consumers' attitude changes may therefore contribute to a swift downward sales adjustment during a contraction and to a more gradual increase during economic expansion periods.

Asymmetry in sales may not only manifest itself in a differing speed of adjustment, but also in the extent of the sales adjustment. Behavioral theories posit that consumers react more extensively to unfavorable changes or losses than to comparable gains (Thaler 1985; Tversky and Kahneman 1991). The implications of change or loss aversion for consumer purchase behavior were initially considered in the context of price changes (e.g., Krishnamurthi, Mazumdar, and Raj 1992; Mayhew and Winer 1992; Putler 1992). However, consumers also react asymmetrically to changes in product quality (Hardie, Johnson, and Fader 1993) and to both expected (Shea 1995) and actual (Bowman, Minehart,

Figure 3
Steepness and Deepness Asymmetry



and Rabin 1999) changes in their wages or income level. When families experience or expect a deterioration in their wages or income caused by a negative shift in the economy, they are likely to reduce their spending level considerably, while upward adjustments in income during business cycle expansions tend to trigger more moderate reactions.

Asymmetries in different phases of the business cycle have long been the object of interest to economists (e.g., DeLong and Summer 1986a; Neftçi 1984; Sichel 1993). Sichel (1993) distinguishes in this respect between two different types of cyclical asymmetry, which can exist either separately or in combination: steepness asymmetry and deepness asymmetry. Our previous discussion offered a behavioral rationale for both phenomena, which are illustrated graphically in Figure 3.

Most previous empirical research has focused on what Sichel labels steepness asymmetry. Steepness asymmetry is present in a cycle if contractions are steeper than expansions. Steepness thus contrasts how quickly an industry (or the economy as a whole) falls into a contraction with how quickly it recovers. If purchase postponement and trust breakdown indeed slow down the speed of recovery, durable sales should exhibit asymmetric steepness. Deepness asymmetry is defined as the characteristic that troughs are further below mean or trend than peaks are tall. Deepness asymmetry is consistent with consumers' reacting more extensively to contractions than to the corresponding expansions. Industries that experience negative steepness asymmetry or deepness asymmetry (or both) will suffer more during contractions than they benefit during expansions: Sales will fall faster (steepness asymmetry) and/or further (deepness asymmetry) during contractions than they increase during expansion periods.

Firm-related drivers of cyclical sensitivity

The above patterns may be reinforced or attenuated by the marketing activities of the players in the market. Mascarenhas and Aaker (1989), for example, find evidence that firms' strategies for dealing with the different stages of the business cycle differ significantly from one another. Companies' main strategic reaction to economic downturns is to cut costs of all kinds, especially those that do not immediately increase sales revenue (Dobbs, Karakolev, and Malige 2002). This has been criticized, as it may further reduce consumers' propensity to buy during unfavorable economic conditions and may even endanger the company's survival potential (*The Economist*, March 7, 2002, pp. 12-4). Some managers not only reduce budgets, they also tend to reallocate marketing funds to those activities that are prone to generate short-term cash flows. For example, marketing managers have been found to use significantly more coupons and price promotions during contractions to keep their sales up (de Chernatony, Knox, and Chedgey 1991; Goerne 1991).

While this tends to be the dominant reaction pattern, other firms are known to adopt the opposite strategy: They increase their spending during a downturn, especially on advertising. There is empirical evidence that companies that view the downturn as an opportunity and develop aggressive advertising responses to it can improve their performance, even during the contraction (Dhalla 1980; Rigby 2001; Srinivasan, Lilien, and Rangaswamy 2002). Similarly, a recent PIMS-based study revealed that such firms were not significantly less profitable during contraction periods, while they outperformed their competitors during recovery (Hillier 1999).

A similar ambiguity exists with respect to pricing practice. Some have argued that during contractions, prices should move down (Green and Porter 1984; Tirole 2001, p. 252), while others have argued the opposite (e.g., Rotemberg and Saloner 1986).[3] Ball and Mankiw (1994) argue that price rigidity tends to be asymmetric; that is, prices are more flexible when going up than when going down, which may amplify consumer-related asymmetric sales adjustment.

Industry heterogeneity in cyclical sensitivity

Business cycle fluctuations have been studied extensively at the macroeconomic (national) level. Using U.S. postwar data, Stock and Watson (1999) examined the empirical relationship between aggregate business cycles (reflected in GDP) and various aspects of the U.S. economy, such as aggregate production, interest rates, and employment. Englund, Persson, and Svensson (1992) studied cyclical fluctuations on a comparable set of Swedish macroeconomic variables. Other studies focused on business cycle patterns across countries (e.g., Backus and Kehoe 1992; Christodoulakis, Dimelis, and Kollintzas 1995; Mills 2001).

However, there is increasing evidence that contractions observed at the national level need not be representative of what happens at a more disaggregate, industry level (Berman and Pfleeger 1997; Jacobs 1998; Shama 1993). It has been argued that in a national downturn, only 60% of all industrial sectors actually experience the downturn (*The Economist*, March 7, 2002, p. 5). Some industries, such as the advertising industry, are known to be hit particularly hard by contractions. The healthcare industry, by contrast, seems to benefit from unfavorable economic perspectives (Berman and Pfleeger 1997). While this variability was apparent in Figure 2, little is known about what drives differences in cyclical variability across industries, or, in our case, across different categories of durables. In our moderator analyses we will provide an exploratory analysis of some of these drivers.

Methodology

We conducted our research in two stages. First we extracted the business cycle component, and then we quantified how sensitive performance was to business cycle fluctuations.

Stage 1: Extracting the business cycle component

Since firms' reactions to sales fluctuations are heavily dependent on how these are perceived and understood (Dutton and Duncan 1987), it is crucial for management to know to what extent the sales variations they experience can be attributed to business cycle fluctuations. Therefore, our first task was to disentangle business cycle fluctuations from over-time fluctuations in general.

In this paper, we adopted the band-pass filter formalized in Baxter and King (1999) and applied in Cogley (1997), Mills (2001), and Stock and Watson (1999), among others, to isolate the business cycle component in each individual series. Many NBER researchers (e.g., Burns and Mitchell 1946; Christiano and Fitzgerald 1998) have observed that U.S. business cycles typically last between 1.5 and 8 years. The underlying idea of the band-pass filter is to pass through all components of a time series with periodic fluctuations between 6 and 32 quarters. Because we worked with annual data, we had the band-pass filter admit periodic components between 8 and 32 quarters rather than between 6 and 32, as the Nyquist frequency—that is, the highest frequency for which we have direct information—is 2 years when using annual data (see Granger and Hatanaka 1964 and Vilasuso 1997 for technical details).

The Baxter and King filter originates in the theory of spectral analysis;[4] we, however, undertake our filtering entirely in the time domain. Baxter and King's (1999) original study provides a detailed discussion of both the design of the filter in the frequency domain and its translation back into the time domain in the form of a symmetric (in terms of leads and lags) moving-average filter. An ideal or optimal band-pass filter would isolate only those components in the series that lie within the specified periodicity range. Such a filter, however, would require an infinite-order moving average, so that in practice an approximation is needed. The proposed approximation is based on a symmetric three-year centered moving-average transformation, where the weights are chosen to approximate as closely as possible the optimal filter. For annual data, this approximate filter can be shown to equal

$$c_t = .7741y_t - .2010(y_{t-1} + y_{t+1}) - .1351 (y_{t-2} + y_{t+2}) - .0510(y_{t-3} + y_{t+3}), \quad (1)$$

where y_t is the original series in year t, and c_t is the cyclical component to be used in further analyses (see Baxter and King, 1999 for details).[5, 6]

This filter has several appealing features. First, it extracts the specified range of periodicity while leaving key properties (such as asymmetries) of the original series unaffected. Second, it does not introduce a phase shift, in that it does not alter the timing of the cycles, so that contraction and expansion dates in the filtered series correspond to the same dates as in the original series. Third, it removes unit roots up to the second order and eliminates quadratic deterministic trends (Baxter and King 1999). The latter property is especially relevant in our study. Indeed, according to the product life cycle hypothesis, product performance goes through distinct stages, and modeling a category's sales evolution from onset through maturity and into eventual decline often requires the inclusion of a higher- (likely second-) order deterministic or stochastic trend (Franses 1994). In addition, earlier research confirms that sales series often contain a unit root, while the likelihood of finding nonstationarity increases when the sample period considered becomes longer (Dekimpe and Hanssens 1995b). In this study, we consider sales patterns over multiple decades, which makes a filtering procedure that can properly handle unit root series more appealing. A final advantage of the band-pass filter is that it is easy to implement, thereby satisfying an important decision calculus criterion (Little 1970).

Even though the band-pass filter has been used extensively in the (macro)economic literature (e.g., Baxter and King 1999; Cogley 1997; Stock and Watson 1999; Vilasuso 1997), every filter involves some subjectivity. We therefore used the Hodrick and Prescott (HP) filter, which is frequently used to isolate the cyclical component, to validate our substantive conclusions.

Having extracted the business cycle component, we next derived four summary statistics from the cyclical component (c_t) isolated during that process. These four statistics parsimoniously describe the extent and nature of the cyclical sensitivity in a given series. Specifically, they describe the extent of cyclical volatility and cyclical comovement (Stage 2a, below), and examine the two aforementioned kinds of cyclical asymmetry—deepness and steepness (Stage 2b, below).

Stage 2a: Quantifying the extent of cyclical sensitivity

To quantify the extent of cyclical variations, we looked at the durables' cyclical variability (volatility) and examined their degree of cyclical comovement with the general economy. Cyclical variability is quantified as the standard deviation of the isolated cyclical component $\sigma(c)$ (see Hodrick and Prescott 1997 or DeLong and Summer 1986b for a similar operationalization). Since these standard deviations are comparable across series only when the series have the same unit, we analyzed the series in logarithms, so that the units (when multiplied by 100) represented percentage deviations from the series' growth path (Stock and Watson 1999, p. 29).

Cyclical volatility focuses on the size of the ups and downs at business cycle periodicities, but is not concerned with whether or how this pattern is synchronized with the overall economic cycle. That property is captured through the notion of cyclical comovement, which measures the extent to which business cycle fluctuations in the economy as a whole translate into cyclical fluctuations in a specific durable's sales performance. We operationalize the concept by regressing the cyclical component of the durable series ($c_{i,t}$) on the cyclical component in real GNP ($c_{i,t}^{GNP}$). This approach is conceptually similar to that of Stock and Watson (1999), who use corr($c_{i,t}, c_{i,t}^{GNP}$) as their comovement statistic.[7]

$$c_{i,t} = \alpha_i + \beta_i \, c_{i,t}^{GNP} + \mu_{i,t} \,, \tag{2}$$

Although the business cycle technically is defined through a comovement across many sectors in the economy, fluctuations in aggregate output are at the core of the business cycle, and the cyclical component of GNP is therefore a useful proxy for the overall business cycle. Note also that because in Equation 2 both $c_{i,t}$ and $c_{i,t}^{GNP}$ represent percentage deviations, β_i can be interpreted as an elasticity, making the comovement measure comparable across different industries.

Although both statistics describe the extent of business cycle sensitivity in durable industries, they approach cyclical sensitivity from distinct, yet complementary, perspectives. Cyclical volatility ($\sigma(c)$) is a univariate concept and measures the size of the deviations from the series' growth path that occur at business cycle periodicities. This statistic is always positive (≥ 0), and larger values indicate a larger degree of variability in the cyclical component of the series. The extent of cyclical variability within a series, however, is not fully informative on how these fluctuations relate to overall economic activity. Large (univariate) cyclical swings may be either procyclical (when changes occur in the same direction as the trend in the aggregate economy) or countercyclical (when movements are in the opposite direction). Also, univariate variability does not reflect the extent to which a durable's cyclical fluctuations are synchronized with fluctuations in more general economic indicators. The comovement elasticity (β_i), by contrast, quantifies both the sign of this relationship and the extent to which overall economic expansions and contractions translate into attenuated ($|\beta_i| < 1$) or amplified ($|\beta_i| > 1$) cyclical swings in the sales of a specific durable.

Stage 2b: Identification of cyclical asymmetries

Following the pioneering work of Sichel (1993), we derive cyclical (a)symmetries based on the third-order moment, i.e., the skewness statistic, of the filtered series. If a time series exhibits deepness asymmetry, it should exhibit negative skewness relative to the mean or trend, indicating that it should have fewer observations below its mean or trend, with a larger (absolute) average value compared with the observations above. Such behavior is illustrated in Figure 3, panel B. To construct a formal test for deepness asymmetry, the following coefficient of skewness is computed:

$$D(c_t) = \frac{\left[T^{-1} \sum_{t=1}^{T} (c_t - \bar{c})^3 \right]}{\sigma(c)^3} \tag{3}$$

where $\bar{c}$ is the mean of the cyclical component c_t, $\sigma(c)$ its standard deviation, and T the sample size (Sichel 1993).

If a time series exhibits steepness asymmetry, its first difference, representing the slope or rate of change, should exhibit negative skewness. As such, decreases in the series corresponding to

Table 1
Description of the Data Set

Category	Years studied	Launch year[a]	Average price (in $)	Price range (in $)
Range	1947–2000	1908	657	338–1,022
Refrigerator	1947–2000	1914	819	479–1,190
Vacuum cleaner	1947–1984	1911	240	148–355
Electric washer	1947–2000	1921	614	265–885
Air conditioner	1947–2000	1934	728	236–2,044
Black-and-white TV	1947–2000	1946	429	33–2,039
Freezer	1947–2000	1935	767	231–1,487
Electric blanket	1947–1980	1940	82	37–191
Clothes dryer	1947–2000	1937	545	221–960
Dishwasher	1947–2000	1940	651	265–1,198
Disposer	1947–2000	1938	230	72–563
Steam iron	1947–1985	1938	52	30–76
Blender	1948–1985	1937	83	22–157
Built-in range	1954–2000	1953	588	349–1,070
Corn popper	1954–1985	?	24	17–34
Can opener	1958–1985	1956	36	16 – 91
Color TV	1960–2000	1954	821	146–2,206
Electric toothbrush	1963–1985	1955	34	20–62
Electric knife	1964–1985	?	38	19–82
Water pulsator	1966–1985	1966	39	24–107
Hair setter	1968–1985	?	38	24–69
Microwave oven	1970–2000	1967	545	165–1,282
Trash compactor	1971–2000	?	337	216–639
Calculator	1972–1987	1972	100	21–508

[a] Details on the specific operationalization of this variable are given in Appendix B.

contractions should be larger, but less frequent, than the more moderate increases during expansions. Figure 3, panel A, illustrates this behavior graphically. The formal test statistic for steepness asymmetry is based on the coefficient of skewness for Δc_t, the first difference of the cyclical component:

$$ST(\Delta c_t) = \frac{\left[T^{-1}\sum_{t=1}^{T}(\Delta c_t - \overline{\Delta c})^3\right]}{\sigma(\Delta c)^3} \tag{4}$$

where $\overline{\Delta c}$ and $\sigma(\Delta c)$ are, respectively, the mean and standard deviation of Δc_t (Sichel 1993).[8]

Data

Our data are postwar annual U.S. time series of unit sales for 24 consumer durables. Sales patterns for some of these durables have been presented above in figures 1 and 2. As illustrated in Table 1, the durables cover a wide range of household appliances, such as blenders, dishwashers, and steam irons, while also including leisure goods such as televisions (both color and black and white).

Table 2
Results on the Extent of Cyclical Sensitivity

	Average size (median)	Range	No. of Durables > 1
Cyclical volatility			
Durables	.091 (.096)	.017–.162	23[b]
GNP	.021 (.020)	.019–.028[a]	NA[c]
Comovement	2.013 (2.204)	–.176–3.619	20[d]

[a] Since the volatility for the respective durables was derived over different time periods, we assessed the volatility in GNP over the corresponding sample periods. The range in GNP thus reflects the difference in the stability of the economy across different time periods.
[b] Represents the number of durables for which the ratio of an individual durable's cyclical volatility to the cyclical volatility in GNP over the corresponding sample periods is larger than 1.
[c] NA = not applicable.
[d] Represents the number of durables with a comovement elasticity in excess of 1.

The data span several decades, ranging from 16 (1972–1987) years for calculators to 54 (1947–2000) years for durables such as ranges, refrigerators, and electric washers, with an average (median) duration of 39 years. Based on U.S. national statistics from the NBER (www.nber.org/cycles.html), the postwar data period considered was characterized by 10 complete business cycles, with an average duration of about 5 years; the longest recorded cycle being 10 ½ years. As such, all durables analyzed cover multiple business cycles. From Table 1, it can also be seen that there were a number of new introductions across the sample period; the current data therefore offer a mix of both new and established durables, which can be expected to be in different stages of their life cycle (earliest introduction = 1908; latest introduction = 1972).

The data reflect total sales at the product category level and therefore comprise both trial and replacement purchases. Accordingly, for durables introduced earlier, replacements are likely to make up a larger portion of their current sales and to constitute a major part of the total durable performance (Bayus 1988; Steffens 2001).

In addition to unit sales data, sales in retail value ($ sales) were also available, which allowed us to derive over-time unit prices. These prices were adjusted for inflation using the U.S. Consumer Price Index (CPI).[9] As can be seen in Table 1, the 24 durables exhibit considerable variability in terms of average prices, the most expensive being color televisions and the least expensive being corn poppers.

Real GNP is a good proxy for overall economic activity and thus a useful benchmark for comparisons across multiple series (DeLong and Summer 1986b). Therefore, we used the summary statistics introduced above to assess the cyclical sensitivity of U.S. postwar real GNP. Data on annual U.S. real GNP (1947–2000), measuring the nation's general economic activity, was obtained from the U.S. Census Bureau (*Statistical Abstract of the United States: 2001*).

Empirical Results

As described below, our hypothesis regarding durables' sensitivity to business cycle fluctuations was born out, as was our hypothesis regarding steepness—but not deepness—asymmetry.

Quantifying the extent of cyclical sensitivity

The key findings related to the extent of cyclical sensitivity are summarized in Table 2, while detailed results on the 24 individual durables are presented in Appendix A.

A first substantive conclusion is that consumer durables are affected by business cycle fluctuations more than overall economic activity is, as reflected in real GNP. Based on the ratio of an individual durable's cyclical volatility to the cyclical volatility in GNP, $\sigma(c_i)/(c_i^{GNP})$, we find that in only one case (calculators) did durables have a ratio smaller than 1, meaning that only for calculators was cyclical volatility smaller than the volatility observed in GNP over the corresponding time horizon. Focusing on the volatility across all 24 durables, we find an average value of .091 (9.1%), ranging from .017

(1.7%) for calculators to .162 (16.2%) for black-and-white televisions. The cyclical volatility in postwar real GNP, by contrast, is on average only .021. *As measured by cyclical volatility, durables are therefore more than four times as sensitive to business cycle fluctuations than is the general economy*. This finding calls for a more explicit consideration of the cyclical variability in the sales evolution of consumer durables in both market response and diffusion models. As for the former, two recent surveys (Hanssens, Parsons, and Schultz 2001; Leeflang et al. 2000) do not report on any study that explicitly considers business cycle fluctuations when analyzing sales patterns. A similar observation applies in the context of diffusion models: Neither Mahajan, Muller, and Bass (1990) nor Rogers (1983) identify any study that takes into account a durable's excessive business cycle sensitivity.[10]

Business cycle fluctuations in durable sales move closely with the aggregate cycle. Based on Equation 2, we find that all durables except one (calculators) have a positive β-coefficient, meaning that economic contractions (expansions) cause durable sales to drop (rise). In addition, the overall degree of comovement is high, as 20 durables have a comovement elasticity larger than 1, implying that general business cycle swings get amplified in the context of durable sales. The average degree of comovement between durable goods and the business cycle component in GNP, as measured by β_i, is 2.013, ranging between −.176 (calculators) and 3.619 (trash compactors). *This again confirms that, compared with GNP, durables are much harder hit by contractions*.

Although cyclical volatility and comovement focus on business cycle sensitivity from different points of view, we find that for durable industries, results from both statistics are fairly congruent. The correlation between both summary statistics is positive and significant (.57, $p < .01$). If we use a median split to classify the 24 durables into four cells based on their cyclical volatility and comovement, we find that 20 out of 24 durables are located in the diagonal cells, as their above-(below-)median volatility corresponds to an above-(below-)median comovement elasticity.

Identification of cyclical asymmetries

Based on the skewness analyses, we find that only 5 of the 24 (log-transformed) series (a mere 21%) have the expected negative sign for the deepness statistic, and in none of those cases did the statistic turn out to be significant. The deepness statistic also exhibits a positive average value of .43. *Therefore, our results indicate that there is little, if any, evidence of deepness asymmetry in durable sales*. Steepness asymmetry, on the other hand, is found to be more prevalent: 18 out of 24 series (75%) have the expected negative sign for the steepness statistic, and also the average value for asymmetric steepness is negative (−.39). However, only for one durable (steam irons) was the steepness statistic found to be significant at a 10% significance level.

Even though log transformation is called for when deriving the extent of cyclical sensitivity, it may distort one's inferences about the (a)symmetric nature of a given time series (e.g., see Atkinson 1985; Burbidge, Magee, and Robb 1988; Ruppert and Aldershof 1989).[11] In our case, however, we obtained comparable results when testing for asymmetries on the original (nontransformed) data: Few series (seven) had a negative sign for the deepness statistic, and the average value for the deepness statistic was .45. In contrast, 20 out of 24 series had the expected negative value for the steepness statistic, resulting in a mean value of −.40. None of the individual cases was significant at conventional significance levels.

As it has been argued that the power of the individual skewness tests tends to be rather low (Mills 2001; Razzak 2001; Verbrugge 1997), especially when working with annual data, we conducted a meta-analysis to derive the combined evidence of cyclical asymmetry across all 24 durables. To do so, we used the one-sided p-values associated with the deepness and steepness statistic, applying the method of adding weighted Z's (Rosenthal 1991).[12] This should offer a stronger test for the presence of cyclical asymmetries than the individual impact estimates.

The meta-analysis confirmed the absence of any deepness asymmetry in the sales evolution of the consumer durables under study (p = .96). For steepness asymmetry, on the other hand, *the collective, meta-analytic result indicated significant evidence of steepness*, with the null hypothesis of symmetry rejected at a 5% significance level (p = .03). These results suggest that *expenditures on consumer durables do not necessarily fall more extensively during contractions than they rise during expansions, but they do fall faster than they rise*. This observation is consistent with the general prediction that households tend to postpone acquisition of durables in response to negative changes in their wealth (Caballero 1993; Clark, Freeman, and Hanssens 1984; Cook 1999), and it corroborates Gale's (1996) theoretical finding that purchase postponement causes sluggish adjustment.[13]

Moderator analyses and validation

Our earlier results found durable sales to be affected to a much larger extent by business cycle fluctuations than the general economy was. It is interesting to note, though, that there exists quite some variation in this cyclical sensitivity across the 24 durables studied, as discussed in the results section. Analyzing this cross-sectional variation in cyclical volatility and comovement should yield additional insights into how and why buying patterns for durables change in response to aggregate economic fluctuations. We did not perform a second-stage analysis on the asymmetry statistics because individually almost none of the durables experienced significant deepness or steepness asymmetry. In addition, a formal chi-square homogeneity test (Rosenthal 1991) revealed that there was not enough variation present in the effect sizes of deepness and steepness to be further explored; that is, there was no significant heterogeneity among the 24 deepness ($\chi^2(23) = 6.09$; p = .99) and steepness ($\chi^2(23) = 4.22$; p = .99) statistics.

To that extent, we will explore in subsequent analyses the relationship between the observed extent of cyclical sensitivity (reflected in cyclical volatility and comovement) and (1) industry price reactions, (2) the extent of price stability, (3) the product's expensiveness, (4) the nature of the durable (convenience or leisure), (5) the state of the economy during launch, and (6) the importance of replacement buying. First, we provide our expectations regarding the sign of these relationships, followed by a description of the adopted testing procedures and a discussion of the empirical findings. Appendix B details the specific operationalizations we adopted for each of the constructs.

Prior expectations

Industry Price Reaction. Industry can either reinforce or attenuate business-cycle-related cyclical sensitivity in sales depending on whether it increases or decreases prices during a contraction. Normative arguments on the nature of price changes during a contraction have been made in both directions. The established view in the industrial-organization literature is based on the work by Green and Porter (1984), who show that lower prices should occur when demand is unexpectedly low. Firms then switch from collusive, high prices to lower, competitive prices because they attribute the lower profits (caused by lower demand) to cheating on the part of their rivals (Green and Porter 1984; Tirole 2001, p. 252). Rotemberg and Saloner (1986) challenged this view and argued that, especially during high-demand periods, it is more beneficial to undercut on the high collusive price, implying that collusion will be less likely to be sustained. This leads to lower competitive prices during expansions and higher collusive prices during contractions. Moreover, Marn, Roegner, and Zawada (2003) argue that increasing prices (p) during a contraction allows companies to offset revenue losses ($p.q$) caused by reduced sales (q) levels. Empirical analyses on the issue predominantly support the view that prices are higher during contractions (Rotemberg and Saloner's view; see Backus and Kehoe 1992; Rotemberg and Saloner 1986; Rotemberg and Woodford 1999).

The direction of price changes may, in turn, influence the extent of business cycle fluctuations in durable sales patterns. Increasing prices during contractions can be expected to further reduce consumers' propensity to buy durables at that time, suggesting that industries themselves tend to enhance their cyclical sensitivity (Frantzen 1986).

Industry Price Stability. Bishop, Graham, and Jones (1984) underscore the importance of a flexible pricing system that makes it possible to respond quickly and adequately to changing market conditions such as economic contractions, thereby reducing swings in performance. Industries in which prices are more flexible (as reflected in higher over-time price variability) can adjust prices more easily in response to economic fluctuations. In contrast, industries which are characterized by sticky prices (lower price variability), are more likely to leave prices at suboptimal levels during contractions (Ball and Mankiw 1994; Tinsley and Krieger 1997). Such rigid pricing practices are expected to further reduce output during contractions and to amplify cyclical swings in durable sales (Frantzen 1986).

Expensiveness. For more expensive durables that represent an important share of the household budget, consumers' relative willingness and ability to pay decreases more substantially during contractions due to the shrinking of their income (Horsky 1990), when the purchase of an expensive durable would put a severe burden on the family in already unfavorable economic conditions. Households are therefore expected to refrain sooner from buying expensive durables during contractions than they are from buying less expensive ones (Cook 1999).

Type of Product. Time-saving convenience goods may be less sensitive to economic fluctuations than leisure durables, as consumers come to depend on time-saving goods to free them up from labor-intensive household activities (Horsky 1990; Parker 1992; Tellis, Stremersch, and Yin 2003).

State of the Economy during Launch. Devinney (1990) and Clark, Freeman, and Hanssens (1984) argue that it is unwise to introduce new durables during an economic contraction unless the product is truly superior, so that consumers are willing to buy it despite their relatively unfavorable economic circumstances. We will test whether any initial superiority is able to protect the durable in subsequent periods, causing a reduced cyclical sensitivity.

Importance of Replacement Buying. Replacement purchases occur not only because of product failure, but also for such varied reasons as the availability of the product with new or improved features and changing styles, tastes, and fashion (Bayus 1988; Steffens 2001). This suggests that consumers tend to be quite flexible about when they make a replacement purchase. When faced with worsening economic conditions, owners of durables can be expected to prolong the lives of their existing products rather than replace them. Therefore, replacement purchases can be argued to be more sensitive to cyclical variation than trial purchases. The opposite argument may be made, however, on the rationale that consumers may become habituated to the durables they currently own, in which case they are less likely to be deterred from repurchase by adverse economic conditions should the product fail (Kamakura and Balasubramanian 1987). Moreover, the considerable risk associated with trial purchases may inhibit consumers from making an initial acquisition during economic contractions, which could cause business cycle fluctuations to be more pronounced in trial purchases (Parker and Neelamegham 1997).

Testing procedure and empirical findings

To determine the direction of price changes during economic contractions, we regressed the cyclical component in each durable's price ($c_{Pi,t}$) on the cyclical component of total U.S. expenditures on durables (c_t^{TOTDUR}), an aggregate series covering the expenditures on all consumer durables in the United States, as published by the Bureau of Economic Analysis (www.bea.doc.gov). To avoid potential endogeneity problems, we used total U.S. expenditures on durables (a much larger figure than even the combined sales of our 24 durables—which represent on average only 8% of U.S. consumer durables outlays over the last 54 years, with a range of .8% to 19% depending on the year) rather than a given durable's sales pattern. The following equation was estimated for each of the 24 durables:

$$c_{Pi,t} = \gamma_i + \delta_i \, c_t^{TOTDUR} + \mu_{i,t} \, , \qquad (5)$$

for $t = 1, \ldots, T_i$, with T_i the sample size (number of observations) for durable i. After all 24 regressions were estimated, we performed a meta-analysis on δ_i to quantify the overall direction of price changes across industries. A negative δ_i-value in Equation 5 is consistent with a price increase during contraction periods. In line with most previous research, most durable industries indeed seemed to increase prices during an economic contraction, while decreasing prices during an expansion. For 19 out of 24 durables, δ_i was negative, and the subsequent meta-analysis on the combined significance of a negative price reaction indicated strong support for a consistent negative δ across all durables ($p = .01$). This result is in line with the findings of Backus and Kehoe (1992) and Rotemberg and Woodford (1999), who also found prices to increase during economic contractions.

Such countercyclical pricing is likely to induce enhanced cyclical sensitivity in durable sales. To test this conjecture, we included the estimated δ_i as an explanatory variable in a regression framework, which made it possible to see if industries characterized by countercyclical pricing (more negative δ_i) also have a higher degree of cyclical sensitivity.

The impact of these industry price reactions on the extent of cyclical sensitivity, along with the impact of price stability, expensiveness, and nature of the durable, was derived by regressing $\sigma(c_i)$ (cyclical volatility) and β_i (comovement elasticity) against, respectively, δ_i (as estimated in Equation 5), PRice VOLatility, EXPENSiveness and product TYPE. This resulted in the following test equation:

$$\begin{bmatrix} \sigma(c_i) \\ \beta_i \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} \\ b_{2,1} & b_{2,2} & b_{2,3} & b_{2,4} & 0 \end{bmatrix} \begin{bmatrix} \delta_i \\ PR\ VOL_i \\ EXPENS_i \\ TYPE_i \\ \sigma(c_i^{GNP}) \end{bmatrix} + \begin{bmatrix} \mu_{1,i} \\ \mu_{2,i} \end{bmatrix} \qquad (6)$$

for $i = 1 \ldots 24$. Because the values for the dependent variables were characterized by differing degrees of estimation accuracy, Ordinary Least Squares (OLS) might yield biased estimates if heteroskedasticity is present. However, based on the White test, we found no heteroskedasticity in any of the individual regressions, and we therefore applied OLS instead of Weighted Least Squares (WLS; see Narasimhan, Neslin, and Sen 1996 or Nijs et al. 2001 for a similar approach). δ_i is also an estimated parameter used as a predictor variable; the associated parameter estimate in Equation 6 can therefore be expected to be biased towards zero, which makes our results conservative (Leeflang and Wittink 2001). Since the dependent variable $\sigma(c_i)$ was obtained for individual durables across different time periods, we included the cyclical volatility of GNP over the corresponding period to control for a potentially confounding impact of overall economic stability in the time span under consideration. Due to the nature of the comovement statistic (i.e., that it is derived by a regression on $c_{i,t}^{GNP}$ in Equation 2), there was no need to include this control variable for the second dependent variable in Equation 6.Finally, to capitalize on potential efficiency gains from a joint estimation, we determined the impact of the respective covariates on $\sigma(c_i)$ and β_i simultaneously using Seemingly Unrelated Regression (SUR). Parameter estimates are summarized in Table 3.

As expected, industries that increased prices more during economic contractions (more

Table 3
Parameter Estimates for the Moderator Analysis of Equation 6

	Volatility	Comovement
Industry price reaction	−.063[b]	−2.231[b]
Industry price stability	−.392[b]	−16.356[a]
Expensiveness	.009	.196
Type of product: convenience good	−.038[b]	−.363

[a] = $p < .01$ (one-sided); [b] = $p < .05$ (one-sided).

negative δ_i) were found to suffer from a higher cyclical volatility in sales, as $b_{1,1}$ turned out to be negative and significant ($b_{1,1} = -.06, p = .02$).[14] The same result held with respect to cyclical comovement, where $b_{2,1}$ is −2.23 ($p = .02$). These results suggest that increasing prices during contractions tends to enhance the cyclical sensitivity in sales fluctuations, as argued by Frantzen (1986).

We also found our expectation that industry price inertia amplifies cyclical sensitivity in sales borne out. Industries with more flexible price adjustments were characterized by a reduced cyclical volatility, as reflected in the negative and significant value for the $b_{1,2}$-estimate ($b_{1,2} = -.39, p = .04$). Similarly, industries in which swift price adjustments occur were found to have a lower comovement elasticity ($b_{2,2} = -16.36, p < .01$).[15]

The parameters $b_{1,3}$ and $b_{2,3}$, which measure the impact of expensiveness on cyclical volatility and cyclical comovement, respectively, turned out to be positive but failed to reach significance (i.e., $b_{1,3} = .01, p > .10$; $b_{2,3} = .20, p > .10$). Hence, we find no support for the contention that consumers are more likely to refrain from buying more expensive durables during unfavorable economic times.

We found convenience goods to be less volatile than leisure goods, as the $b_{1,4}$-estimate associated with the type dummy turned out negative and significant ($b_{1,4} = -.04, p = .04$). We also obtained a negative parameter estimate when we used the comovement elasticity as dependent variable, but this estimate failed to reach significance ($b_{2,4} = -.36, p > .10$). We therefore conclude that there is partial support for the proposition that time-saving convenience goods are less sensitive to business cycle fluctuations than their leisure counterparts.

To assess the impact of the economy during product launch, we added a dummy variable to Equation 6 that captured the state of the economy at the time the product was launched. As described in Appendix B, we lost four observations due to missing information on the state of the economy during launch. Even so, we found when we added the economy dummy variable that the substantive results with respect to industry price reactions, price volatility, expensiveness, and type of durable remained similar when estimated on the remaining 20 durables. As for the dummy variable, we found that the parameter estimates were not significant ($b_1 = -.01, p > .10$; $b_2 = .28, p > .10$). More research is needed, however, to assess whether this lack of empirical support is due to the absence of the presumed superior quality during product launch or whether any initial superiority failed to carry over into subsequent contraction periods.

For more mature durables, a larger component of total sales is due to the replacement of existing units (Bayus 1988; Steffens 2001). We therefore ran our cyclical sensitivity analysis separately on first the early and then the later half of the sample period (cf. Clark, Freeman, and Hanssens 1984). For the most recently introduced durables, however, it could be argued that insufficient data are available to conduct a split-half analysis and that those durables have not yet reached maturity. They could therefore be judged less useful in assessing the impact of replacement purchases, which become dominant in later stages in the product life cycle (PLC). For that reason, we excluded the five durables for which less than 25 years of sales data were available.[16] We subsequently regressed all resulting 38 (19 durables x 2) volatility/comovement statistics on a dummy variable (PLC_j), taking the value of 1 in the later stage of the durables' life cycle and 0 otherwise:

$$\begin{bmatrix} \sigma(c_j) \\ \beta_j \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} d_{1,1} & d_{1,2} \\ d_{2,1} & 0 \end{bmatrix} \begin{bmatrix} PLC_j \\ \sigma(c_j^{GNP}) \end{bmatrix} + \begin{bmatrix} \upsilon_{1,j} \\ \upsilon_{2,j} \end{bmatrix} \quad (7)$$

for $j = 1 \ldots 38$. Again, when we assessed the impact of the moderator on cyclical volatility ($\sigma(c_j)$), we controlled for the general economic stability through $\sigma(c_j^{GNP})$ and estimated Equation 7 using SUR. We find empirical support for the hypothesis that a later stage in the PLC is associated with lower cyclical volatility ($d_{1,1} = -.02$, $p = .04$).[17] When regressing the PLC dummy on the cyclical comovement statistic, the $d_{2,1}$ estimate was again negative, but failed to reach statistical significance ($d_{2,1} = -.53$, $p > .10$). We thus find partial evidence that replacement purchases are less sensitive than trial purchases to business cycle fluctuations. This result is consistent with our hypothesis that currently owned durables may have become indispensable and that therefore consumers are more willing to replace them when they fail, even during an economic contraction. The more excessive sensitivity of trial purchases underscores further the importance of considering such fluctuations in new product diffusion models, as these models are intended to capture the dynamics at play in trial purchases.

Validation

We validated our results in several ways. First, we assessed the representativeness of our sample and compared our substantive findings on the extent of cyclical sensitivity to the findings obtained when analyzing total U.S. expenditures on consumer durables. Next, we evaluated whether our asymmetry findings could be replicated when adopting a nonparametric testing procedure instead of the parametric skewness approach we applied. Finally, we assessed to what extent our findings are idiosyncratic to the specific filtering procedure that was adopted to extract the cyclical component from the different sales series. Specifically, we used the Hodrick-Prescott (HP) filter as an alternative to the Baxter and King approach adopted in previous sections. Details on these validation checks, which all confirmed the robustness of our substantive findings, are presented in Appendix C.

Conclusion

Despite the fact that business cycles can have a profound impact on companies and industries, not much prior research has systematically considered the extent and nature of cyclical sensitivity in marketing performance. To address this lack, we undertook the present investigation. We found that, on average, consumer durables are much more sensitive to business cycle fluctuations than the general economy is, as expressed in an average cyclical volatility of more than four times that in GNP. In addition, durables have a mean cyclical comovement elasticity in excess of 2, so that every percentage decrease in the cyclical component of GNP translates to a drop in the cyclical component of durable sales by, on average, more than 2%.

In investigating the reasons for durable goods' substantial vulnerability to business cycle fluctuations, we found that consumers tend to postpone purchases of durables, as evidenced by the presence of asymmetric steepness in durable sales. We also found that companies' pricing practices amplify the cyclical sensitivity in durable sales, as companies tend to increase prices during an economic contraction, while decreasing them during an expansion. Business cycle fluctuations in sales patterns were more pronounced in industries for which such price reactions were larger. In addition, we found evidence for a higher cyclical sensitivity in industries characterized by sticky (inert) pricing practices. Hence, durable industries that are less used to adjusting their prices tend to be hit harder by economic downturns. Given that fact, companies have two immediate strategies at hand to reduce their cyclical sensitivity: First, they can adjust prices quickly, and second, they can adjust them in a cyclical (rather than the usual/observed countercyclical) way.

The nature of the durable turned out to be important as well. We found leisure goods to be more sensitive to business cycle fluctuations than convenience goods. Managers should also be aware that intrinsic cyclical fluctuations are likely to become less pronounced in later stages of the product's life, that is, when replacement purchases become a more substantial fraction of total sales. This observation underscores the importance of having a diversified offering of products at different stages of their life cycle (Harrigan and Porter 1983).

Limitations and Further Research

Our analysis is subject to a number of limitations that open immediate avenues for further research. First, we limited the analysis to 24 durable goods; further research should consider other industries, both durable and nondurable. In particular, it would be interesting to study business cycle sensitivity in industrial markets, where every change in the demand for consumer goods may cause larger changes in the derived demand for factors of production of those goods (Bishop, Graham, and Jones 1984). This phenomenon is comparable to the bullwhip effect in the supply-chain literature (e.g., see Hanssens 1998; Lee, Padmanabhan, and Whang 1997). Second, our methodological procedure starts by extracting from the sales series those fluctuations that are related to business cycles. Previous research has pointed out that the choice of filtering technique may influence the findings (Cogley 1997). Although we did validate our findings using an alternative filter, we cannot fully dismiss this caveat, and more extensive validation exercises may be feasible along this dimension. Cogley (1997), for instance, proposes to detrend macroeconomic series by regressing them on aggregate consumption expenditures for nondurables.

Third, the temporal aggregation level of our data has certain limitations. As different up- and downward phases in the business cycle can also be (partly) present within one year, certain fluctuations in sales may be masked when analyzing yearly data. In addition, as suggested by DeLong and Summer (1986a), temporal aggregation may affect the power of our tests. In the analysis, we tried to accommodate for this in two ways: We performed a meta-analysis that offers a stronger test for the presence (absence) of cyclical asymmetry than the individual impact estimates, and we validated our asymmetry results using a more powerful nonparametric test. Still, it would be beneficial to reconsider the topic using temporally more disaggregate data. Moreover, the Baxter and King filtering procedure would still be applicable when using data at a level of temporal aggregation smaller than one year (although it would require somewhat different weights than the ones given in Equation 1), as it is able to identify and suppress fluctuations in the series that occur with a periodicity smaller than two years (see Baxter and King 1999, and Vilasuso 1997 for more details). This should allow for a better approximation of the range of business cycle periodicities of 1.5 to 8 years identified by the NBER than when working with annual data.

Fourth, one could argue that our results may be confounded by gradual and/or cyclical quality improvements over time. We believe, however, that the confounding impact from quality improvements is rather limited for durable goods. Long-run or gradual quality improvements, as reflected in a durable's changing mean replacement age, may indeed be present (Steffens 2001). However, our filtering approach removes all long-run developments from the series such that they do not intervene with our cyclical findings, as discussed above in our section on methodology. Alternatively, one might argue that consumers may switch to lower-quality (cheaper) products during economic contractions. Yet, we find empirical evidence that average prices paid increase during contractions, suggesting that our current conclusion may be a conservative one.

Fifth, we only focused on one country, the United States, so it is not yet clear whether our results are generalizable to other countries. Sixth, we focused on industry-level sales. Shama (1993), however, has pointed out that even within one industry, companies may both be affected differently and respond differently to business cycle fluctuations. More research is needed on the cyclical sensitivity of performance at the company level, where appropriate strategic modification during contraction and expansion periods may give some companies a competitive advantage (e.g., Srinivasan, Lilien, and Rangaswamy 2002). Finally, we also advocate going into more detail on the potential moderating role of other key marketing variables, such as advertising and promotional activities. ■

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Appendix A. Cyclical Sensitivity Statistics for 24 Consumer Durables

Category	Volatility	Comovement	Deepness[a]	Steepness[a]
Range	.098	3.041	–.144	–.270
Refrigerator	.080	2.177	1.018	–1.043
Vacuum cleaner	.062	1.611	.222	–.046
Electric washer	.061	1.743	.332	–.200
Air conditioner	.147	2.680	–.071	–.176
Black and white TV	.162	2.092	1.366	–.037
Freezer	.100	.272	2.010	–.089
Electric bed cover	.057	1.138	.883	–.116
Clothes dryer	.096	3.282	.491	–.996
Dishwasher	.093	3.248	–.228	–.070
Disposer	.096	2.837	–.505	–.165
Steam iron	.078	1.966	–.056	–.690
Blender	.110	2.702	1.599	–.435
Built-in range	.108	2.753	.097	–.302
Corn popper	.116	2.258	.920	–.288
Can opener	.050	.434	.181	.017
Color TV	.106	3.342	.121	.083
Oral hygiene device	.084	1.280	.971	–.730
Electric knife	.086	1.240	.406	–1.785
Water pulsator	.099	2.234	.292	.019
Hair setter	.083	.320	–.101	–.916
Microwave oven	.099	2.231	.539	–.152
Trash compactor	.103	3.619	.653	–1.340
Calculator	.017	–.176	–.088	.202
Average	**.091**	**2.013**	**.454**	**–.397**

[a] The asymmetry statistics are presented for the non-ln-transformed series.

Appendix B. Measurement of Moderators

Industry Price Reaction

The price reactions assessed in this study are those induced by business cycle fluctuations. As such, we used the same filtering procedure discussed in our methodology section to extract only those price movements that can be related to business cycles. A similar approach to assess the behavior of prices at business cycle frequencies was adopted by Backus and Kehoe (1992) and Rotemberg and Woodford (1999), among others.

Industry Price Volatility

Industry price volatility represents the flexibility in durable price adjustments over time. Because price flexibility refers to a company's ability to change prices quickly, we followed Van de Gucht, Dekimpe, and Kwok (1996) and captured short-run price variability by the standard deviation of the first difference in real, over-time prices. To control for the differences in absolute price levels, we derived price volatility from log-transformed data. The mean price volatility among the 24 durables is .08, ranging from .04 (dishwashers) to .20 (calculators).

Expensiveness

The expensiveness of a durable is expressed as a percentage of average annual household income. Following the procedure advocated in Parker (1992), we derive the average annual income of U.S. families by dividing real U.S. GNP by the total number of families in the nation (as published by the U.S. Census Bureau; www.census.gov). Next, deflated durable unit prices were divided by this average annual family income. This yearly value is subsequently averaged over the life cycle of the product. The mean value ranged from .05% (corn poppers) to 1.94% (refrigerators), with an average across all 24 durables of .83%.

Type of Product

We used a dummy variable to capture the distinction between time-saving convenience goods on the one hand and "amusement-enhancing" or leisure goods on the other hand. The dummy variable takes the value of 1 if the durable is classified as a convenience good and 0 if it is a leisure good. Two of the 24 durables considered are classified as leisure goods: black-and-white televisions and color televisions (see also Horsky 1990).

State of the Economy during Launch

We coded the phase of launch as a dummy variable that had a value of 1 if the durable's introduction took place during a contraction and 0 if the introduction took place during an expansion. To determine which value to assign, we compared the durable's launch year, as published in Parker (1992), with the contraction dates proposed by the NBER dating committee (www.nber.org/cycles.html). We obtained some missing launch years from Agarwal and Bayus (2002) and Golder and Tellis (1997), but we were unable to trace the launch year for four durables (corn poppers, electric knives, hair setters, and trash compactors). We considered any launch year for which at least six months were located in a U.S. contraction period (according to the NBER) to be a contraction launch year; otherwise the introduction year was classified as an expansion launch year. Six durables (blenders, built-in ranges, clothes dryers, electric washers, refrigerators, and vacuum cleaners) were introduced during an economic contraction, while the 14 others were introduced during an expansion. This observation is consistent with Devinney (1990), who showed that the number of new product introductions varies systematically over the business cycle, with relatively fewer introductions during unfavorable economic times.

Importance of Replacement Buying

During later stages in the product life cycle, replacement purchases make up a larger portion of existing sales (Bayus 1988; Steffens 2001). We distinguished between phases with relatively more first purchases and phases with more replacement purchases during the durable's product life cycle, the first being the early phase and the second being the late phase (cf. Clark, Freeman, and Hanssens 1984). Specifically, we create a dummy variable with a value of 0 in the early stage and 1 during the later stage, where the early stage in the durables' life cycle is defined as the first half of the sample period and the later stage is defined as the second half.

Appendix C. Validation Checks

Representativeness of the Consumer Durables in our Sample

The 24 durables included in our analysis are mainly household appliances items. Consumers spend a considerable part of their budget on other durables, however, such as motor vehicles and furniture. To assess whether our empirical generalizations are representative for the broader set of durable goods typically bought by households, we analyzed the cyclical sensitivity in *total* U.S. expenditures on durables (see our moderator analyses for a more detailed discussion of this variable).

The results are very comparable. The cyclical volatility statistic for the aggregate durable series is .053. Comparing this value with the volatility in GNP we report in our results section confirms our earlier observation that business cycle fluctuations are more strongly pronounced in the context of consumer durables. This finding is in line with the conclusion of Cook (1999) and Hodrick and Prescott (1997), who also examined the evolution of aggregate U.S. expenditures on durables. Cook (1999) plotted the cyclical component of U.S. expenditures on both durables and nondurables and concluded based on a visual inspection of the graph that the former are more vulnerable to business cycles. Hodrick and Prescott (1997) found that postwar consumer durable expenditures have been more than three times as volatile as real GNP. In addition, the mean cyclical comovement derived from the

Table A4
Summary of Empirical Results

A: Extent of Cyclical Sensitivity

	BP-filtered data	HP-filtered data
Cyclical volatility		
average (median)	.091 (.096)	.174 (.180)
range	.017–.162	.077–.322
Comovement		
average (median)	2.013 (2.204)	1.957 (1.790)
range	−.176–3.619	−1.668–5.271

B: Deepness Asymmetry

		BP-filtered data		HP-filtered data	
		parametric test: skewness statistic	**nonparametric test:** triples test	**parametric test:** skewness statistic	**nonparametric test:** triples test
sample size		24	24	24	24
no. negative		7	5	5	6
no. negative	sign (5%)	0	0	0	0
	sign (10%)	0	0	0	1
Meta-analysis		$p = .96$	$p = .99$	$p = .96$	$p = .99$

C: Steepness Asymmetry

		BP-filtered data		HP-filtered data	
		parametric test: skewness statistic	**nonparametric test:** triples test	**parametric test:** skewness statistic	**nonparametric test:** triples test
sample size		24	24	24	24
no. negative		20	17	15	17
no. negative	sign (5%)	0	1	0	0
	sign (10%)	0	3	0	0
Meta-analysis		$p = .03$	$p = .02$	$p = .20$	$p = .09$

total U.S. expenditures on durables is 2.007, which corresponds closely to the average comovement statistic derived from the 24 durables in our dataset (2.013).

The skewness results for total U.S. expenditures on durables also confirm our earlier findings. As with those findings, there is no evidence for deepness asymmetry, as the mean deepness statistic is rather low (mean $D(c_t) = -.16$). The steepness statistic for the aggregate series has an average value of −.43, close to the average value across our 24 durables (−.40).

Alternative Asymmetry Test: Nonparametric Triples Test

While frequently used and intuitively appealing, the parametric approach proposed by Sichel (1993) to test for cyclical asymmetries has been criticized for possibly lacking the power to reject the null hypothesis of symmetry (Razzak 2001; Verbrugge 1997). Low power is certainly a problem for temporally aggregated data, as aggregation may dampen the cyclical properties of the series, and the lack of evidence of asymmetry could therefore be an unfortunate statistical artifact (Mills 2001). DeLong and

Summer (1986a), for instance, tested for asymmetries in U.S. unemployment rates using both quarterly and annual data. Based on the magnitude of the skewness statistic, the annual data suggested as much asymmetry as their quarterly counterparts, but skewness in the annual data turned out to be insignificant.

Even though our meta-analytical procedure corrects to some extent for the potentially low power of each individual test, we also applied the nonparametric triples test proposed by Verbrugge (1997) and Razzak (2001), which has been argued to be more powerful. Appendix D offers a more detailed exposition on the nature of the triples test.

The asymmetry results based on this nonparametric test are very similar to the results described in the empirical results section. With respect to deepness asymmetry, five durables had the expected negative sign, close to the seven durables based on the parametric test for deepness. Also the meta-analysis confirmed our earlier conclusion: Deepness asymmetry was again strongly rejected, with a (meta) p-value of .99. In addition, the steepness results from the triples test supported our earlier findings. As before, most durables (17) had a negative skewness statistic. However, with the triples test three of these steepness effects were statistically significant (trash compactors, $p < .05$; steam irons and electric knives, $p < .10$), which is in line with the presumably higher power of the test. As before, we were able to reject the null hypothesis of symmetry with regard to steepness based on the meta-analysis ($p = .02$).

Robustness with Respect to the Filtering Technique

As indicated in the methodology section, a crucial issue is how to extract the cyclical component in the time series. The empirical literature on business cycles contains a wide variety of competing filtering methods, all of which extract a slightly different cyclical component (Cogley 1997) and hence may also affect subsequent inferences on the extent and potential asymmetry of the series' cyclicality. We therefore validated our substantive findings using the well-known Hodrick-Prescott filter, which has a long history of use in the economics literature as a method for extracting business cycles (e.g., Backus and Kehoe 1992; Cook 1999; Holly and Stannett 1995).[1,2]

Detailed results are provided in Table A4. In accordance with our earlier findings, we again observe that consumer durables are more sensitive to cyclical fluctuations than GNP. The cyclical volatility for all durables increased somewhat, with an average increase of .083 (average volatility, BP-filtered series = .091; average volatility, HP-filtered series = 0174; see part A of Table A4). At the same time, the HP-filtered volatility in GNP is also slightly higher (BP-filtered GNP volatility = .021; HP-filtered GNP volatility = .029). As such, based on the HP-filtered data, consumer durables are found to be, on average, six times more volatile than GNP, as opposed to a ratio of 4.28 for BP-filtered series. The conclusions with respect to cyclical comovement were not affected by the adopted filtering technique either. If we extract the cyclical component using the HP-filter, 22 durables had a positive comovement elasticity, as opposed to 23 durables using the BP-filtered data. In addition, the majority of the durables (18) had a β_i-coefficient larger than one (20 durables had a β_i-coefficient larger than one when using the BP-filter), and the average comovement elasticity remained high (mean BP-filtered comovement statistic = 2.013; mean HP-filtered comovement statistic = 1.957).

The skewness results based on the HP-filtered series revealed the same general patterns as before: Only a minority of durables had a negative deepness statistic (part B of Table A4), while the majority had a negative steepness statistic (part C of Table A4), a pattern observed for both the parametric and the nonparametric procedures described earlier. Based on the meta-analyses in part B, we once more reject the deepness asymmetry hypothesis overwhelmingly (parametric $p = .96$; nonparametric $p = .99$). The meta-analytical results also confirm our earlier conclusion that steepness asymmetry is present. We found weak support for such asymmetry in the HP-filtered data based on the skewness statistic ($p = .20$), while the more powerful nonparametric triples test rejected the null hypothesis of symmetry at the 10% significance level ($p = .09$).

Finally, we also assessed the affect of the filtering procedure on the stability of the results from the moderator analysis. When working with the HP-filtered cyclical component, we obtained the same substantive findings. We again found collective evidence of higher prices during economic contractions. In addition, we found cyclical sensitivity to be higher for leisure durables, when companies increase prices more during contractions, and when prices display more inertia, while cyclical sensitivity was less severe in the latter half of the PLC, which is dominated more by replacement purchases.

Appendix Notes

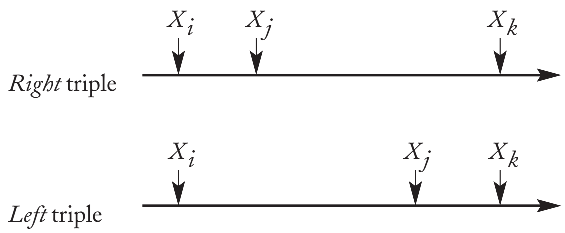
1. In the marketing literature, two well-known and frequently used detrending procedures are a prior regression on a linear trend (e.g., Lal and Padmanabhan 1995) and the first-difference filter (e.g., Dekimpe and Hanssens 1995a). Both filters are less suited to extracting the cyclical component from a series. Removing a linear trend is inappropriate when the series contains a unit root (Baxter and King 1999; Tinsley and Krieger 1997), as do many marketing time series (Dekimpe and Hanssens 1995b). The first-difference filter reweighs periodic fluctuations at different frequencies. Specifically, this filter tends to put a higher weight on the short-term, irregular, component, while down-weighting both the business cycle component of interest and the long-run component (Baxter 1994).

2. For technical details, we refer readers to the studies of Hodrick and Prescott (1980, 1997).

Appendix D. Nonparametric Triples Test

The parametric skewness-based test proposed by Sichel (1993) has been criticized for having only low power to reject the null hypothesis of symmetry while being sensitive to outliers (Razzak 2001; Verbrugge 1997). Therefore, a nonparametric triples test, first developed by Randles et al. (1980) and introduced in the economics literature by Verbrugge (1997), has been suggested as an alternative, more powerful test to derive cyclical asymmetry (Razzak 2001; Verbrugge 1997).

A triple of observations (X_i, X_j, X_k) forms a right triple (i.e., is skewed to the right) if the middle observation (X_j) is closer to the smallest observation (X_i) than to the largest observation (X_k). Conversely, a left triple (skewed to the left) is one where the middle observation (X_j) is closer to the larger observation (X_k) than to the smaller observation (X_i). Both triple types are graphically illustrated below:



This distinction is formalized through the following function:

$$f*(X_i, X_j, X_k) = \frac{\lfloor sign(X_i + X_j - 2X_k) + sign(X_i + X_k - 2X_j) + sign(X_j + X_k - 2X_i)\rfloor}{3} \quad \text{(D1)}$$

which can be shown to take on the value of 1/3 in case of a right triple, −1/3 in case of a left triple, and 0 in case of a symmetric triple.

To formally test for symmetry in business cycles, one should consider all possible triples from the sample (a sample of size T has $\binom{T}{3}$ combinations), and determine whether most of the triples are right or left skewed. Applying Equation D1 to all triples, the following (relative) statistic is obtained:

$$\hat{\eta} = \binom{T}{3}^{-1} \sum_{i<j<k} f*(X_i, X_j, X_k) \quad \text{(D2)}$$

which can be shown to equal

$$\hat{\eta} = \frac{[(number\ of\ right\ triples) - (number\ of\ left\ triples)]}{3\binom{T}{3}} \quad \text{(D3)}$$

Obviously, if there are more (less) right triples than left triples, the value for η will be positive (negative), while η will be zero in case of a perfect symmetric distribution. To test $\eta = 0$ against the alternative $\eta < 0$, one uses the following test statistic

$$\frac{\eta}{\sqrt{\hat{\sigma}^2_\eta / T}} \quad \text{(D4)}$$

which can be shown to have a limiting N(0,1) distribution. We refer readers to the study of Randles et al. (1980) for both a more elaborate discussion and description of the methodology, and for the derivation of $\hat{\sigma}^2_\eta$.

Notes

1. Cyclical variations in the economy have been studied extensively by macroeconomists, but these studies concentrate on aggregate economic variables such as GDP, while we concentrate on individual durable categories. Marketing papers considering the effect of cyclical variations in the economy include Clark, Freeman, and Hanssens (1984), Coulson (1979), Cundiff (1975), Devinney (1990), and Yang (1964).

2. A contraction, according to the NBER's Business Cycle Dating Committee, is defined as a period of significant decline in economic activity, reflected in a substantial reduction in such variables as total output, income, unemployment, and trade. Specifically, the NBER identifies a month when the economy reaches a peak of activity and a later month when the economy reaches a trough. The time in between is defined as the contraction (www.nber.org/cycles.html).

3. We refer readers to our moderator analyses for a more detailed discussion of this issue.

4. See Bronnenberg, Mela, and Boulding (2002) or Parsons and Henry (1972) for marketing applications of the spectral approach to time-series analysis.

5. In the frequency domain, one expresses a time series as the sum (integral) of mutually orthogonal periodic components $\xi(\omega)$, i.e., $y_t = \int_{-\pi}^{\pi} \xi(\omega)d\omega$. In a filtered series, one assigns weights $\alpha(\omega)$ to the different periodic components to obtain $y_t^* = \int_{-\pi}^{\pi} \alpha(\omega)\xi(\omega)d\omega$. When deriving a business cycle filter, one wants a filter that eliminates (i.e., attaches very low weight to) very slow-moving (or trend) components and very high-frequency (irregular) components while retaining the intermediate components, which correspond with the periodicity of a typical business cycle. Marketing researchers (see Dekimpe and Hanssens 2004 for an extensive review) are, however, more used to working in the time, rather than the frequency, domain (exceptions include Parsons and Henry 1972 and Bronnenberg, Mela, and Boulding 2002). Based on the notion that moving averages can alter the relative impor-

tance of various periodic components in a time series (e.g., Harvey 1981, Ch. 3), Baxter and King (1999) determined what lead/lag length and what weights should be applied in a moving-average filter to suppress as much as possible the undesirable frequencies, while maintaining the desirable ones. Equation 1 gives these weights for annual data; and Baxter and King (1999, Table 4) also give the weights for quarterly data.

6. Note that because of leads and lags in Equation 1, six observations are lost in the derivation of the cyclical component. No such loss is incurred in the Hodrick-Prescott (HP) filter that we used to validate our findings.

7. We regressed the cyclical component of the durable on the cyclical component of GNP over the corresponding time period and added a durable-specific subscript to $c^{GNP}_{i,t}$ to indicate differences in sample length.

8. To determine the significance of both test statistics, asymptotic standard errors are derived as follows. For deepness asymmetry, we regress $z_t = (c_t - \overline{c})^3/\sigma(c)^3$ on a constant, the significance of which corresponds to the significance of $D(c_t)$. Indeed, the coefficient estimate associated with the constant equals the deepness statistic, and the corresponding standard error measures its statistical reliability. Since the observations on c_t are serially correlated, the correction suggested by Newey and West (1987) is implemented in the derivation of the standard errors. Asymptotic, Newey-West-corrected standard errors for the steepness statistic can be calculated using a similar procedure, but with $z_t = (\Delta c_t - \overline{\Delta c})^3/\sigma(\Delta c)^3$.

9. Source: U.S. Census Bureau, *Statistical Abstract of the United States: 2001*.

10. International studies on the diffusion of consumer durables have occasionally taken into account the different countries' macroeconomic conditions, as reflected in their GNP per capita, urbanization rate, etc. (e.g., Dekimpe, Parker, and Sarvary 2000; Helsen, Jedidi, and DeSarbo 1993). However, only cross-sectional variation along those dimensions was considered, in that only information on a single year (in the case of Dekimpe, Parker, and Sarvary 2000) or the average across a number of years (in the case of Helsen, Jedidi, and DeSarbo 1993) was used. The over-time variation in these macroeconomic conditions, however, was still ignored.

11. To avoid this potential distortion, we report on the (a)symmetric nature of the original series in both the meta-analytic and validation exercises.

12. To implement this meta-analytic procedure, one computes the Z-value associated with each of the individual (one-tailed) p-values. The sum of these Z's, divided by the square root of the number of elements in the sum (in our case, 24), yields a new statistic which is again distributed as Z. As some of the durables had more data points, we weighted the contributing Z's with their respective sample sizes, as suggested in Rosenthal (1991, p. 90).

13. As for GNP, we find no evidence of asymmetry, with average values for the deepness (mean D $(c_t) = -.06$), and steepness (mean ST $(c_t) = -.18$) statistics approximating a perfectly symmetric distribution (where skewness = 0). DeLong and Summer (1986a) and Sichel (1993) also failed to detect any evidence of steepness asymmetry in U.S. GNP, while Sichel found very weak evidence of deepness asymmetry in (quarterly) postwar GNP.

14. p-values are one-sided for the directional expectations formulated in our moderator analyses.

15. Note that our two price measures capture two distinct dimensions of a firm's pricing practice: the direction (or sign) of the price changes over business cycle frequencies (i.e., δ_i) and the short-run price variability in the industry. This is in line with recent research that pricing strategy is a multifaceted construct (e.g., Shankar and Bolton 2004) whose effects may also vary depending on the time horizon (periodicity) considered (cf. Bronnenberg, Mela, and Boulding 2002). In our regression, we quantify the impact of one dimension while controlling for the other.

16. Specifically, calculators, electric knives, hair setters, oral hygiene devices, and water pulsators are excluded from the analysis.

17. For the impact of replacement buying, we did not postulate a directional proposition, so the reported p-values for this moderator are two sided.

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