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Pricing in the international takeoff of new products

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ABSTRACT

This study focuses on the effect of two dimensions of price (relative price and price volatility) on the international takeoff of new products. The study examines these drivers of takeoff using a novel data set of bimonthly observations of 7 new consumer electronic products in 8 countries. The empirical analysis reveals that both relative price and price volatility significantly impact the hazard of takeoff. However, although the effect of relative price is stable across contexts, the effects of price volatility are moderated by wealth, culture, and contagion. The use of temporally disaggregate data at the bimonthly level allows for the identification of the effect of price volatility and enables a more precise identification of takeoff than that achievable with annual data.

1. Introduction

Takeoff refers to the first dramatic increase in the consumer adoption of new products, marking a transition from the introduction stage to the growth stage of the product life cycle (Golder & Tellis, 1997). Recent research has focused on the identification and patterns of takeoff (Agarwal & Bayus, 2002; Golder & Tellis, 1997), as well as on gaining an understanding of the drivers of takeoff across countries (Chandrasekaran & Tellis, 2007, 2008; Muller, Peres, & Mahajan, 2009; Tellis, Stremersch, & Yin, 2003; Tellis, 2013; Van Everdingen, Fok, & Stremersch, 2009). With respect to this literature, the current study makes two key contributions. First, the study highlights the role of two key dimensions of price that may affect the takeoff of new products in an international context: relative price and price volatility. Second, the study examines the role of country-level macro and contagion factors that may moderate the role of the pricing dimensions on takeoff.

The extant literature has considered the impact of relative price, measured as the current price relative to the initial price of the product, on new product takeoff in national contexts. The idea is that consumers respond to decreases in the prices of new products, particularly during the product's initial years, and this hastens takeoff (e.g., Golder & Tellis, 1997; Wei & Xiao, 2012). Although this research has generated insights into the effect of pricing on takeoff, it is not clear whether these effects hold in an international context and, if so, in which ways. We therefore examine the effect of relative price, accounting for possible influences across countries. The general marketing literature also suggests that consumers' purchase decisions are influenced by short-term pricing volatility, which may lead to a deviation in actual price from an expected price (e.g., Winer, 1986). That is, although a long-run price decrease may be expected, the industry witnesses much short-term price volatility, marked by either price increases or decreases. Fig. 1a, b, and c illustrate the extent of volatility in the product pricing history for several brands in various categories of new consumer electronics. Indeed, the industry has recently experienced the rise of several websites (such as decide.com, nextag.com, and shopobot.com) devoted to facilitate consumer purchase decisions (buy or wait; compare) in the face of uncertainty resulting from such pricing (e.g., Geron, 2011; Needleman, 2011). However, the effect of short-term price volatility on product takeoff has not been examined.

The literature on international takeoff examines the specific impact of cross-national factors on the hazard of takeoff, largely ignoring the role of strategic factors such as price (see Table 1). We not only examine the role of price in conjunction with broader macro factors but also examine the moderating role of important variables such as culture and wealth on the effect of pricing on takeoff. For example, some environments, such as those characterized by greater wealth, may be more receptive to relatively higher prices or more tolerant of higher price volatility than other environments, such as those characterized by lower levels of wealth. Motivated by these issues, the current study attempts to answer the following research questions:

1. What role do relative price and price volatility play in the international takeoff of new products?

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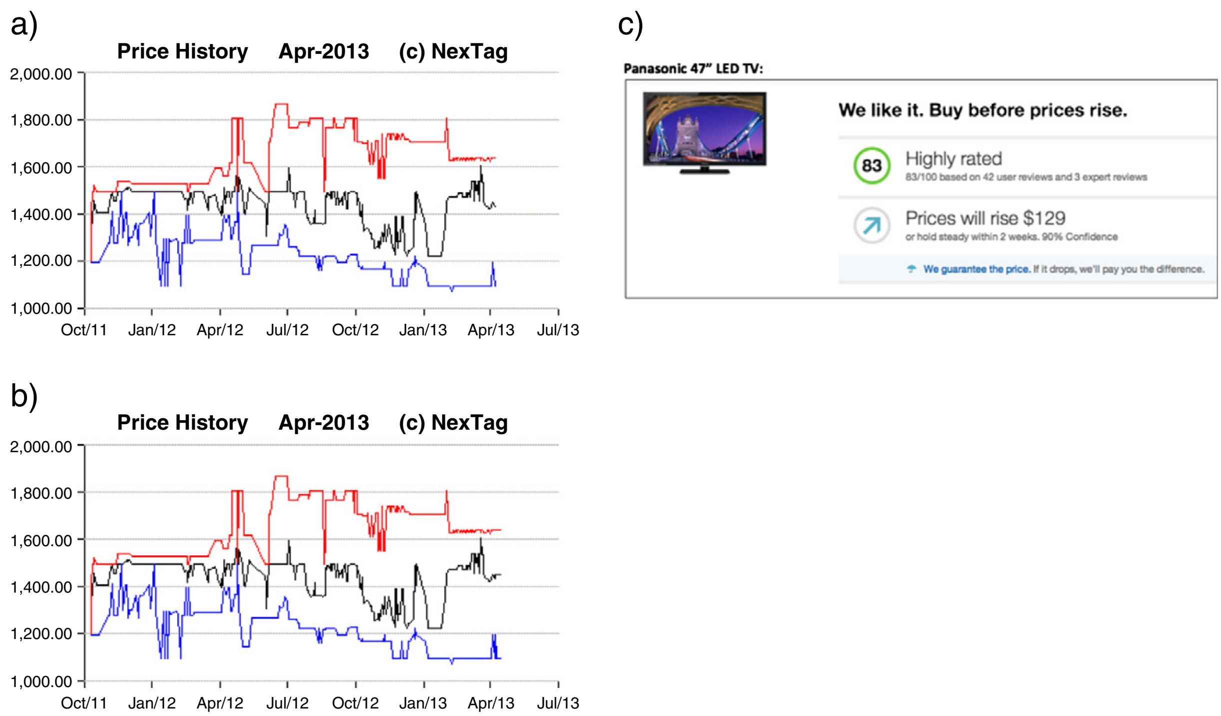


Fig. 1. a. Price History of a Digital SLR Camera Brand (from NexTag, showing Maximum, Median and Minimum prices). b. Price history of a GPS brand (from NexTag, showing Maximum, Median and Minimum prices). c. Expectations of a Short-run Price Increase for a LED tv brand (from Decide).

2. What factors moderate the role of these two variables in the context of international takeoff?

Our contributions are facilitated by the use of disaggregate data (at the bimonthly level). The study uses a unique data set of bimonthly observations of 7 new consumer electronics products in 8 countries. With the exception of a few studies (Goldenberg, Lowengart, & Shapira, 2009; Honisch, Pittnauer, & Stauffer, 2008), much of the academic research on new product growth uses annual data because such data are widely available (e.g., Agarwal & Bayus, 2002; Markovitch & Golder, 2008). However, because of the rapid adoption of categories of new consumer electronics in recent times, managers must model new product takeoff using more immediately accessible monthly, bimonthly, or quarterly data. For instance, Apple recently launched the iPad, stimulating the takeoff of media tablets.[1] Media tablets sold more than 3 million units in the first few months after the introduction of the iPad. Such rapid takeoffs cannot be easily pinpointed using aggregate annual data. The use of temporally disaggregate data has several advantages for this study. First, fluctuations observed in more granular data do not necessarily constitute noise but may provide valuable information (Goldenberg et al., 2009). In this study, we are able to observe and measure price volatility at an inter-temporal level and identify its role with regard to takeoff. For instance, Fig. 2a and b provide the example of the plasma TV in the United Kingdom, comparing annual price data with price data at the bimonthly level. The annual graph indicates that the overall price trend is a decrease after the introductory price. However, the bimonthly graph indicates the extent of inter-temporal price volatility with regard to this trend. Second, temporally disaggregate data allow for more efficient estimates (Clarke, 1976; Judge, Griffiths, Carter Hill, Lütkepohl, & Lee, 1985; Tellis & Franses, 2006). In this study, the use of such data enables a fine-grained identification of takeoff.

The remainder of the paper is organized as follows. We first discuss the theory underlying our model and formulate hypotheses regarding the major contributions of this paper. We then discuss the methods used for the empirical research, including the data, the measures, and the model. Next, we present the findings of this study, along with several robustness checks. We conclude with a discussion of the study's findings and implications.

2. Theoretical framework

Based on prior studies, this section develops a theoretical framework for the drivers of takeoff (Fig. 3).

The literature suggests that four latent factors underlie most explanations for the faster takeoff of certain products: A. within-country macro effects, B. market effects, C. contagion effects, and D. cross-country effects (e.g., Agarwal & Bayus, 2002; Chandrasekaran & Tellis, 2008; Golder & Tellis, 1997; Peres, Muller, & Mahajan, 2010; Tellis et al., 2003; Van Everdingen et al., 2009).

In terms of country-level factors, the key discussion centers on the role of economics, which is measured predominantly in terms of national wealth, and culture, which is measured predominantly in terms of uncertainty avoidance (Chandrasekaran & Tellis, 2008; Golder & Tellis, 1997; Tellis et al., 2003; Van Everdingen et al., 2009). In terms of the market dimension, the takeoff literature suggests that two factors are important: relative price and innovative activity (Agarwal & Bayus, 2002; Bayus, Kang, & Agarwal, 2007; Chandrasekaran & Tellis, 2008; Golder & Tellis, 1997; Tellis et al., 2003). In terms of contagion effects, a direct examination of the role of intra-country and interpersonal interactions on takeoff, either via word-of-mouth (W-O-M) or signals, has not been performed. In terms of cross-country effects, much of the takeoff literature has focused on the effect of prior foreign takeoffs on takeoff in focal countries (Chandrasekaran & Tellis, 2008; Tellis, Stremersch, & Yin 2003; Van Everdingen et al., 2009).

We contribute to the literature by examining a contingency framework for the effect of pricing on takeoff while controlling for other major drivers. At the core of our framework is the direct impact of pricing in terms of relative price and price volatility on product takeoff. Although the impact of relative price on takeoff has been examined, albeit not in an international context, the temporally

[1] http://www.cellular-news.com/story/47442.php?s=h.

Table 1
Review of literature on product takeoff.[a]

	Variables	Golder and Tellis (1997)	Agarwal and Bayus (2002)	Tellis et al. (2003)	Bayus et al. (2007)	Stremersch, Tellis, Franses, & Binken (2007)	Markovitch and Golder (2008)	Chandrasekaran and Tellis (2008)	Van Everdingen et al. (2009)	Islam and Meade (2011)	This study
	Products/categories	31	27	10	30	9	4 (with 71 public firms)	16	8	1	7
	Countries	1	1	16	1	1(6)/1(2)/1(1)	1	31	55	70	8
	Level of aggregation	Annual	Annual	Annual	Annual	Annual	Annual	Annual	Annual	Annual	Bimonthly
A. Time	Time/vintage effects	x	**x**	x	x			**x**	**x**		*x*
B. Market/strategic	Price declines	**x**			x					**x**	*x*
	Price volatility										*x*
	Firm entry/Competition		**x**		**x**					x	*x*
	Innovative activity				x						*x*
C. Macro	Economics[b]	x		x				**x**	**x**	**x**	*x*
	Inequality			x				**x**	**x**	x	*x*
	No. of households/population density	x		[c]		[c]		[c]	**x**		[c]
	Culture[d]			**x**				**x**	**x**	x	*x*
D. Others	Contagion/cumulative sales or penetration	**x**	x	**x**	x						*x*
	Prior introductions/takeoffs/spillovers			**x**				**x**	**x**	x	*x*
	Seasonality										*x*
	Competitive/complementary/network effects					[e]				x	N/A
	Product class/dummy	x	**x**	**x**				**x**			N/A
	Stock returns						[e]				N/A
E. Interaction effects	Change in price * R&D costs				x						
	Relative price * National wealth										*x*
	Price volatility * National wealth										*x*
	Relative price * Uncertainty avoidance										*x*
	Price volatility * Uncertainty avoidance										*x*
	Relative price * Intra-country contagion										*x*
	Price volatility * Intra-country contagion										*x*
	Relative price * Foreign takeoffs										*x*
	Price volatility * Foreign takeoffs										*x*

Notes.
x Variable included in prior studies.
x Variable found to have a significant impact in prior studies.
N/A Our data-set did not facilitate the measurement of these metrics.
[a] Only empirical studies examining drivers of takeoff considered.
[b] Economics includes measures of wealth and other correlated measures and/or factors.
[c] Study considers penetration/sales thresholds for takeoff.
[d] Culture includes various combinations of uncertainty avoidance, individualism, masculinity, power distance, industriousness, ethnicity, religiosity and/or other factors.
[e] Descriptive statistics indicate a relationship.

disaggregate nature of our data permits us to examine the importance of a second important dimension of pricing, i.e., price volatility.

The following sections propose hypotheses regarding the main effect of two price dimensions and the moderating influence of country and contagion factors in the influence on takeoff. In addition, we discuss relevant control variables.

2.1. Price

Pricing is a critical variable determining the behavior of both the firm and the consumer (Tellis, 1986). For the firm, pricing determines an innovation's profit potential (e.g., Simon, 1992). For the consumer, pricing represents the cost to be paid for the benefits he/she receives and functions as signal of quality (e.g., Zeithaml, 1988). We consider two dimensions of pricing. First, we study the impact of the relative price, which we define as the current price relative to the introductory price. Second, we consider price volatility, which we define as the influence of short-run deviations from the expected trend in price. Below, we formulate hypotheses on both effects.

2.1.1. Relative price

Prior research on new product pricing suggests that relative price plays an important role in stimulating the sales growth of new products. The premise is that consumers do not respond directly to an absolute price, but rather, relative to the reference price (Rajendran & Tellis, 1994; Thaler, 1985). According to prospect theory (Kahnemann & Tversky, 1979) or mental accounting (Thaler, 1985), if a consumer encounters a brand (or a product) at a price that is lower than the reference price, the price is perceived as a gain, whereas a price that is higher than the reference price is perceived as a loss. Hence, consumers consider not the absolute price but gains or losses relative to a reference price. In new product research, a price is often considered relative to *introductory* price. As the price of a product decreases over time, it leads to an increase in the adoption of new products. This trend may occur for several reasons.

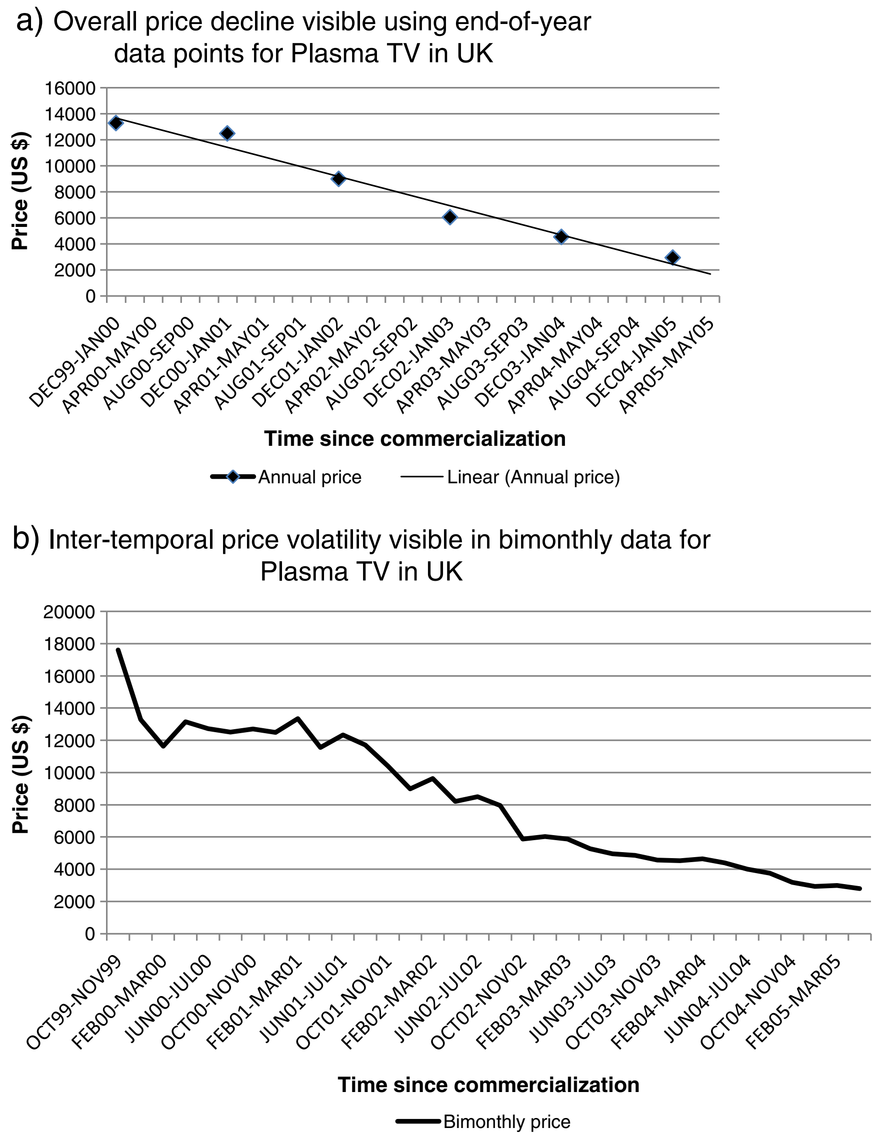


Fig. 2. a. Overall price decline visible using end-of-year data points for plasma TV in UK. b. Inter-temporal price volatility visible in bimonthly data for plasma TV in UK.

First, Bagwell and Riordan (1991) argue that for new products, initial high prices signify quality and subsequent decreasing prices reflect the diffusion of product information and the adaptation of the price signal to consumer learning about the quality of the product. As consumers gain experience with the product and information about its quality diffuses, firms may be able to efficiently signal quality at lower prices (Bagwell & Riordan, 1991).

Second, consumer heterogeneity in price sensitivity drives takeoff. As the price of the new product decreases over time, the product becomes attractive to more price-sensitive customers and, as a critical mass of those customers adopt, takeoff occurs (Golder & Tellis, 1997). Indeed, economic research has demonstrated that because the purchase of new products is risky and their demand is price sensitive, the optimal pricing strategy for new products is often considered to be the monotonic lowering of price (Krishnan, Bass, & Jain, 1999). Typically, during the introduction stage of a new product, innovators and early adopters are attracted to the new product. These consumers are more likely than later adopters to favorably evaluate the utility/price tradeoff (Kalyanaraman & Winer, 1995), thus driving sales during the early stage of the product life cycle, even at high prices. In subsequent periods of the early life cycle, firms may strategically lower price to price discriminate among successively more price-sensitive segments (although as production costs decrease, prices may also decrease in response to the decreasing costs (Wei & Xiao, 2012).

Consistent with the above, meta-analytic studies on the effect of price on new product sales reveal that price elasticity is stronger during the introduction/growth stage than after takeoff, during the mature/decline stage (Bijmolt, Van Heerde, & Pieters, 2005). The reasoning behind this tendency suggests the following hypothesis:

H1. A lower relative price increases the hazard of takeoff for a new product.

2.1.2. Inter-temporal pricing volatility

New product pricing is characterized by both upward and downward movements, as well as significant changes *within* a short period of time. Agarwal and Bayus (2002) suggest that crucial R&D expenditures during the early years of market evolution may increase costs and translate into innovations that consumers value. Accordingly, firms may choose to recover R&D costs or exploit superior valuations by temporarily increasing prices.

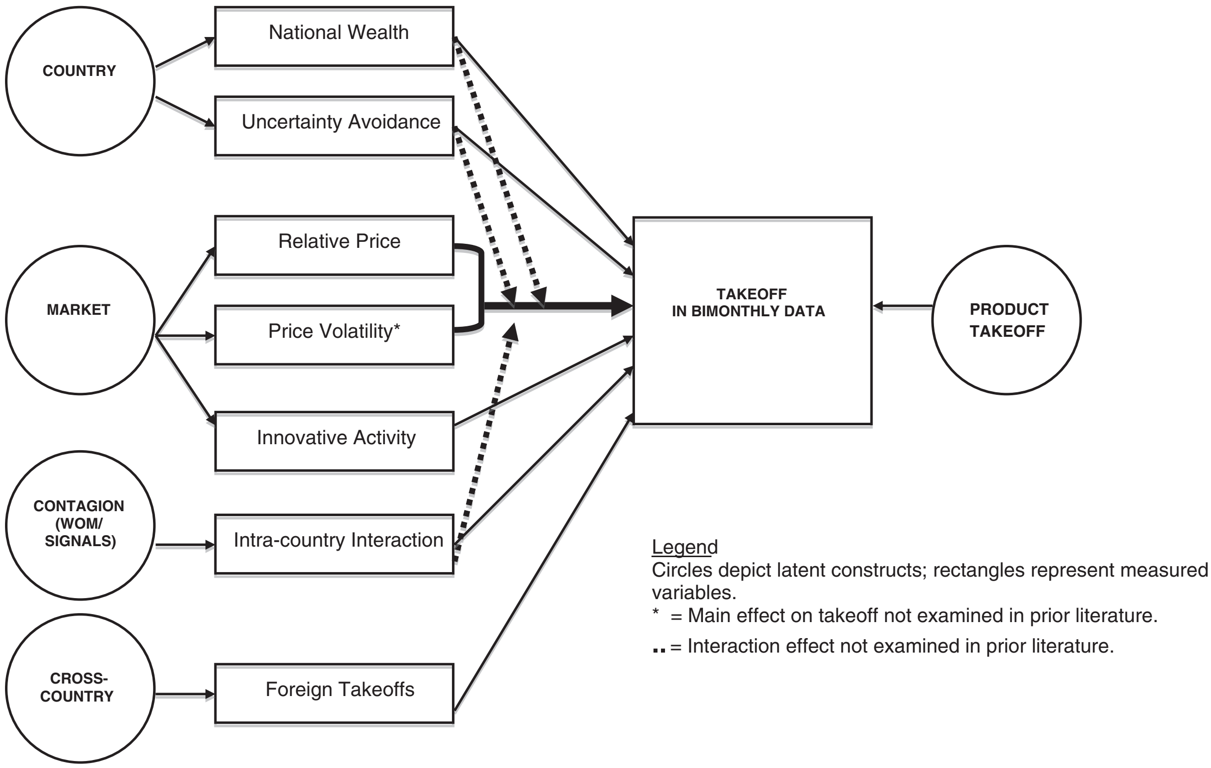


Fig. 3. A contingency framework for the influence of pricing on product takeoff.

How may short-term price volatility affect consumer behavior? Alba, Mela, Shimp, and Urbany (1999) show that consumers find it easier to estimate average prices in the case of consumer goods, where price differences tend to be small. However, price changes tend to be far greater for new consumer durables than for fast moving consumer goods. So, consumers experience greater difficulty in estimating an average price for new consumer durables (Marn, Roegner, & Zawada, 2003). Figs. 1a, b, and c and 2b illustrate price volatility situations that are typical with regard to the pricing of consumer electronics.

The higher the price instability, the less likely consumers are to reliably estimate a new product's price. Lacking the ability to form realistic expectations, consumers may postpone purchase of the innovation. In this vein, Winer (1985) posits that price volatility and unanticipated inflation or deflation may have a negative effect on demand. In the case of new products, consumers have multiple alternatives, including postponing their purchase or never buying the new product (Jacobson & Obermiller, 1990). Postponing adoption may be particularly conspicuous for new products that have not yet taken off because their success prior to takeoff is unclear to both firms and consumers. If too many consumers wait, sales of the new product remain low and the hazard of takeoff decreases. The above reasoning suggests the following:

H2. Higher inter-temporal pricing volatility decreases the hazard of takeoff for a new product.

2.2. Country factors and pricing

Prior research emphasizes two important country variables, national wealth and uncertainty avoidance, that influence product takeoff. We control for the primary effects of these variables in the regression analysis. In this section, we focus on how these variables may moderate the influence of pricing on takeoff.

2.2.1. National wealth and pricing

National wealth relates to consumers' average spending power in a particular country (Talukdar, Sudhir, & Ainslie, 2002). The literature on international takeoff has supplied mixed evidence with regard to the role of national wealth in stimulating takeoff. Wealth was not found to have a significant effect on takeoff when a cluster of European countries were considered (Tellis et al., 2003) but was found to be a significant driver of takeoff when more heterogeneous sets of countries were considered (Chandrasekaran & Tellis, 2008; Van Everdingen et al., 2009).

How would national wealth influence the role of pricing in stimulating takeoff? We assume that on average, consumers in wealthier countries possess more disposable income than consumers in less wealthy countries. People are more price-sensitive when they have lower incomes and tighter budgets and less price-sensitive when they have higher incomes and greater spending power. Hence, wealthier consumers may be better able to afford new products early, when prices are relatively high. Moreover, wealthier consumers can better afford the risks of buying new products whose performance is uncertain. Hence, we posit the following:

H3. The effect of a lower relative price on the hazard of takeoff is weaker in more wealthy countries than it is in less wealthy countries.

Similarly, consumers in wealthier countries may be less price-sensitive and hence less impacted by temporary price fluctuations. Therefore, we posit the following:

H4. The effect of price volatility on the hazard of takeoff is weaker in more wealthy countries than it is in less wealthy countries.

2.2.2. Uncertainty avoidance and pricing

Uncertainty avoidance refers to the extent to which the members of a culture feel threatened by uncertain or unknown situations

(Hofstede, 2001). Uncertainty avoidance has been considered the most important cultural factor affecting consumer innovativeness and product takeoff (Steenkamp, Hofstede, & Wedel, 1999; Van Everdingen et al., 2009). Prior research argues that consumers from countries with high uncertainty avoidance are often likely to be less innovative per se (Steenkamp et al., 1999). Risk-averse consumers may also be less motivated to initially buy products when uncertainty surrounding the new product's performance makes it difficult to evaluate price–benefit trade-off. Hence, consumers in high uncertainty avoidance contexts may be more motivated than consumers in low uncertainty avoidance cultures to wait until the relative price is substantially lower than the launch price. Hence, we posit the following:

H5. The effect of a lower relative price on the hazard of takeoff is stronger in countries with high uncertainty avoidance than in countries with low uncertainty avoidance.

Furthermore, in cultures with high uncertainty avoidance, consumers will focus on reducing risk and avoiding ambiguous situations. Hence, during times of higher price volatility, consumers may be more likely to adopt a "wait-and-see approach" to the purchase of consumer electronics. This reasoning leads to the formulation of the following hypothesis:

H6. The effect of price volatility on the hazard of takeoff is stronger in countries with high uncertainty avoidance than in countries with low uncertainty avoidance.

2.3. Contagion and pricing

The vast marketing literature on product diffusion has examined the influence of inter-personal word-of-mouth communication (variously termed as imitation and internal influence) on sales (e.g., Bass, 1969; Mahajan, Muller, & Bass, 1990). The recent literature has addressed the influence of additional phenomena such as social signals or information cascades within the scope of consumer interactions that may impact product diffusion (Peres et al., 2010). We use the term contagion synonymously with consumer interactions, which may refer to word-of-mouth communication, signals, or imitation, as described above. Below, we examine the moderating role of contagion with regard to the two dimensions of pricing.

2.3.1. Contagion effects and relative price

One of the crucial influences driving consumers to purchase new products or services involves inter-personal communications or observations of the choices of others (e.g., Bass, 1969; Chevalier & Mayzlin, 2006; Ganesh & Kumar, 1996; Golder & Tellis, 2004; Mahajan et al., 1990; Peres et al., 2010; Putsis, Balasubramanian, Kaplan, & Sen, 1997; Tirunillai & Tellis, 2012; Van den Bulte & Stremersch, 2004). We use the term contagion to describe intra-country interactions among consumers.

How may contagion effects influence the role of relative price on the takeoff of new products? Anecdotal evidence suggests that when much conversation is generated about a product or if consumers are rushing to buy a product, some consumers may be motivated to buy the product immediately, irrespective of its price (Emigh, 2010; Heater, 2008). In fact, the literature on information cascades suggests that people converge in adopting a behavior with increasing momentum and declining individual evaluation because of their tendency to derive information from the behavior of prior adopters (Bikhchandani, Hirshleifer, & Welch, 1992; Golder & Tellis, 2004). For instance, Duan, Gu, and Whinston (2009) find that in the software adoption context, information cascades may lead to the adoption of inferior products by online users. Similarly, consumers may be more susceptible to higher-priced gadgets associated with higher levels of buzz, conversation and visible demand. Hence, we hypothesize the following:

H7. The effect of a lower relative price on the hazard of takeoff is weaker for a product with a high contagion effect than for a product with a low contagion effect.

2.3.2. Contagion effects and price volatility

We propose that there is a negative interaction effect between inter-temporal price volatility and contagion effects. When inter-temporal price volatility is high, the perceived riskiness of buying the product immediately, as opposed to waiting, may be enhanced. However, a strong demand for the product or enhanced buzz/conversations may alleviate some of the concerns that may arise from buying the product immediately as opposed to postponing the purchase decision. Hence, we hypothesize the following:

H8. The effect of price volatility on the hazard of takeoff is weaker for a product with a high contagion effect than for a product with a low contagion effect.

2.4. Control variables

We control for the effects of 3 other important factors that are likely to influence takeoff. These variables include foreign takeoffs, innovative activity, and seasonality.

Prior research has determined that foreign takeoffs may accelerate takeoffs in a focal country (Chandrasekaran & Tellis, 2008; Tellis et al., 2003; Van Everdingen et al., 2009). We therefore control for the influence of foreign takeoffs in our model.

Earlier research has examined the main effect of innovative activity. Agarwal and Bayus (2002) suggest that the sales of new products may be initially low because the first commercialized forms of new products are relatively primitive. Firm entry may subsequently stimulate innovative activity, which increases the appeal of new products, widens their market, and stimulates takeoff (Bayus et al., 2007). Hence, we control for the effects of innovative activity to isolate the influence of pricing on takeoff.

Most products display periodic patterns throughout the year, a process referred to as seasonality (Radas & Shugan, 1998). With respect to consumer goods, seasonality is often caused by holidays (Christmas and New Year and spring and summer breaks) and changes in the weather, such as the start of a new season (Hylleberg, 1992; Miron, 1996). Many firms adjust their strategies to suit seasonal sales patterns (Axarloglou, 2003; Radas & Shugan, 1998). The momentum gained from seasonal promotion strategies may boost new product sales, increasing the likelihood of takeoff during peak seasons. We therefore control for seasonality in our model.

3. Method

This section describes the data, measures, and model used in this study.

3.1. Data

We obtain data at the bimonthly level (2 consecutive months) from 1999 to 2005. The data cover the sale and prices of 7 new consumer durable products in 8 nations. Although limited by the nature of the disaggregate level of data, the number of unique product–country combinations in our data set is still higher than that in several prior studies examining the diffusion of new products (e.g., Agarwal & Bayus, 2002; Golder & Tellis, 1997, 2004; Helsen, Jedidi, & DeSarbo, 1993; Takada & Jain, 1991). The products include important innovations in the electronics industry introduced in the last 10 years and constitute innovations that have not been studied in the context of product diffusion. The products include the Digital Video Recorder (a device that records video in a digital format to a disk drive or other memory medium within a device), the DVD Recorder (also known as the DVDR, an optical disk recorder that records video onto blank writeable DVD media), the Surround Sound System (home theater), the LCD TV, the Plasma TV, the MP3 Hard Disk Player, and the MP3 Flash Player. Data are available for the United States and 7 European countries: France, Germany, Italy, the Netherlands, Spain, Sweden, and the United Kingdom.

We obtained the sales and price data from GFK International (www.gfk.com). In total, we obtained 1296 observations with regard to bimonthly sales and prices. GFK International collects the data based on actual sales at the retailer. We consider historical sales data from the time at which these products were commercialized. Countries are matched using time-origin for new product commercialization, in accordance with Dekimpe, Parker, and Sarvary (1998). The use of the term commercialization allows for the recognition that market research companies and databases include a product's sales or penetration only when it has achieved a low level of sales or penetration. We determine the earliest available commercialization date through an examination of our bimonthly data and estimate the validity of these start dates through an assessment of penetration rates and a comparison with annual data sources, as performed in prior takeoff research. After our bimonthly data's identification of the earliest start date, we begin our time count from the first data point. In 11 instances, annual sales and price data indicate that commercialization occurred 1 to 6 months earlier than the first available bimonthly data point and 10 instances in which the earliest commercialization occurred more than 6 months prior to our first bimonthly data point. For such cases, we consider the commercialization time to be the Dec–Jan period of the earliest available annual data point. In all of these cases, penetration at the first available data point is very low, with a mean of .05%.

We also collect information on different country characteristics from syndicated sources (Euromonitor Global Marketing Information Database and World Development Indicators Online) and publicly available sources (the Statistical Yearbook of the United Nations, World Bank Statistics, Eurostat Review, and Hofstede, 2001).

To assess innovative activity within the industry, we use patent statistics from the Delphion database (www.delphion.com). Delphion is a subscription-based database that contains detailed historical records on patents granted in the United States and other countries. Details on the measures used are provided in the next section.

3.2. Measures

This section describes the measure/operationalization of the DV, measures of the focal pricing constructs, measures of the moderator constructs, and measures of the remaining control variables.

3.2.1. Measure/operationalization of the DV-takeoff

Prior research uses threshold-based rules to guide the identification of takeoff adapted to suit the specific context (e.g., Golder & Tellis, 1997; Tellis & Stremersch, 2004; Tellis et al., 2003; Van Everdingen et al., 2009). In particular, Tellis et al. (2003) propose a measure of takeoff that is suitable for an international sample of countries. The authors define threshold as a standard plot of growth in sales for various levels of market penetration so that a more standard comparison of several countries can be obtained. Takeoff constitutes the first year in which an individual category's growth rate relative to the base sales crosses this threshold. However, this rule allows takeoff to be identified using annual data. We modify this rule to suit our more temporally disaggregate data in the following manner.

We use the principle of bimonthly compounding to derive the growth rate of sales to suit bimonthly data regarding the annual growth rates proposed in Tellis et al. (2003). Hence, we use the following formula for compounded bimonthly growth:

$$r_2 = \left[\left(1+\frac{r_1}{n_1}\right)^{\frac{n_1}{n_2}} - 1\right] n_2, \tag{1}$$

where

r_2	growth in sales at the bimonthly level
r_1	growth in sales at the annual level
n_2	6 (6 bimonthly periods = 1 year)
n_1	1 (to account for 1 year).

Fig. 4 displays the graph for the threshold for takeoff at the annual level, along with the corresponding bimonthly growth. Takeoff constitutes the first year in which the growth in sales for the new product exceeds the proposed growth threshold. Note that we consider takeoff to occur after a .5% threshold has been passed to avoid assessing takeoff at very low levels of market penetration.

We calculate the market penetration for all of the products in our database based on the following formula, where t refers to the bimonthly period:

$$Penetration_t = Penetration_{t-1} + sales_t/households_t * 100. \tag{2}$$

3.2.2. Measures of the focal pricing constructs

We calculate relative price as follows:

$$Relative\,price_t = price_t/price_{t=0}. \tag{3}$$

As prices vary among products, this measure allows for standardization across products. Furthermore, relative price incorporates the use of the initial price of a new product as a reference point (Golder & Tellis, 1997; Rajendran & Tellis, 1994). Firms may intentionally decrease or raise prices based on the expected sales path (Agarwal & Bayus, 2002; Golder & Tellis, 1997; Kalish, 1983). We use a 1 period lagged measure of relative price to account for the potential endogeneity of price. The prices of all products are in US dollars.

We operationalize inter-temporal price volatility as follows. Consumers may form price expectations of the current price based on a price trend, as well as the most recently observed price. We measure inter-temporal price volatility based on the deviation of the actual and the expected price. Similar to Winer (1986), we use an extrapolative expectation model to determine the course of predicted prices in a market defined by country and category. Thus,

$$P^r_t = \delta_0 + \delta_1 P^o_{t-1} + \delta_2 Time + \varepsilon_t, \tag{4}$$

where the subscript t refers to each bimonthly period. This equation is estimated separately for each group (product–country classification).

Eq. (4) assumes that a consumer's prediction of the current price of a product is based on the most recent observed price (1 bimonthly period prior) and a time trend. Time is a control variable, which tracks the time period for the estimation of any trends in prices.

For each category–country combination, we estimate Eq. (4) for each of a series of moving windows of 4 bimonthly periods. For each period, starting from the fifth bimonthly period, we compute the Root Mean Squared Error (RMSE) of estimating Eq. (4), which provides an estimate of the volatility of prices within the moving window from the consumer's perspective. We use a 1 period lagged measure in the regression.

3.2.3. Measures of moderator variables

Country-level macro-economic variables tend to be highly correlated (Dekimpe, Parker, & Sarvary, 2000). Hence, we operationalize wealth

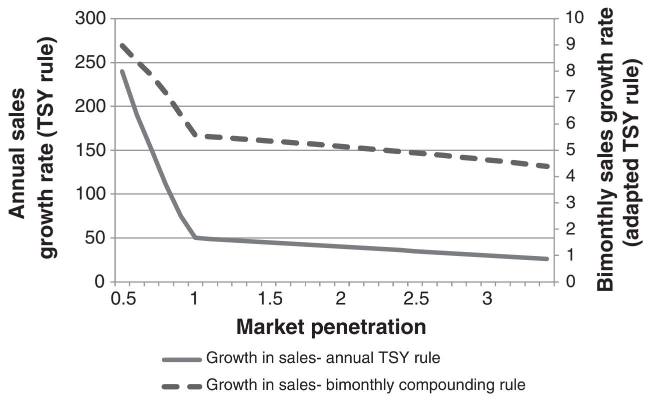


Fig. 4. Comparison of annual Tellis et al. (2003) rule and adapted bimonthly rule.

by simply using national GDP per capita (in US dollars). We obtain the data for Real GDP per capita (Laspeyres) (Heston, Summers, & Aten, 2002). We use a 1 period lag for this measure.

We use a measure of uncertainty avoidance proposed by Hofstede (2001). This measure is available for all countries at http://www.geert-hofstede.com/.

We use a 1 period lagged measure of cumulative sales for a product in a country to capture intra-country contagion effects.

3.2.4. Measures of other control variables

For foreign takeoffs, we calculate the sum of prior takeoffs in the other countries (in our sample) within each of 4 regions (North America, Mid-Western Europe, Mediterranean Europe, and Nordic Europe). This method is consistent with prior research that suggests the existence of a regional influence on the hazard of takeoff (Tellis et al., 2003; Van Everdingen et al., 2009). We use a 1 period lagged measure in the regression.

Multiple studies have used patenting level to capture the extent of innovative activity in an industry (e.g., Ahuja & Katila, 2001; Bayus et al., 2007; Prabhu, Chandy, Ellis, & Ellis, 2005).[2] Similarly, we use the cumulative number of patents granted for the product category until the start of the focal bimonthly period to capture the extent of innovative activity for each product. We assume that this measure, cumulative patents, is a good proxy for capturing the *cumulative* effect of innovative activity up to a particular point in time for each product. We use a 1 period lag of this measure to account for any potential endogeneity.

Delphion's European patent collection contains European patents published by the European Patent Office since 1991. The United States patent collection contains a list of all patents issued by the United States Patent and Trademark Office (USPTO) since 1974. For each product, we extract all United States- and European-granted patents by creating queries for the name of each product in Delphion's patent database. We assume that all large global manufacturers file either United States or European patents to protect their intellectual property.

We operationalize seasonality in the following manner. Although seasonal patterns are diminished in aggregate data, they are very visible in disaggregate data. Our data show seasonal peaks during the period of Dec–Jan of each year (see Fig. 5).

We derive seasonality indices directly from the sales data by applying the classical decomposition approach to estimate seasonality (Makridakis, Wheelwright, & McGee, 1983). This method derives an index of sales for each 2 month period during the year and separates the time series into 4 components: seasonality, trend, cycle, and randomness. This method involves the following steps. First, we compute the 6 (bimonthly) period moving average of sales (SMA) for each product–country combination during each bimonthly period (where the moving average is calculated in terms of the interval from 1 period before the current period to 4 periods after).

$$SMA_t = \sum_{j=-1}^{4} Bimonthly\,sales_{t+j}/6. \tag{5}$$

Second, we compute a centered moving average (CMA) using 2 consecutive bimonthly periods (the previous month and the current month) of the moving average calculated in the previous step. The centered moving average is the trend-cyclical component of the series.

$$CMA_t = \sum_{j=-1}^{0} SMA_{t+j}/2. \tag{6}$$

Third, for each product–country combination, during each bimonthly period, we isolate the seasonal factor by dividing the original sales series by the centered moving average to obtain the percent moving average (PMA), as follows:

$$PMA_t = Bimonthly\,sales_t/CMA_t. \tag{7}$$

Fourth, we compute the average of the percent moving average for all products and years of observation (for a total of j combinations) to obtain the seasonality index for each country and bimonthly period:

$$Seasonality\,index = \sum_{j=1}^{n} PMA_j/n. \tag{8}$$

We use the seasonality index as an independent variable in the regression analysis. A positive coefficient implies that the hazard of takeoff is higher during peak seasons than during off-peak seasons.

3.3. Model

Because takeoff is a time-dependent event, we use a discrete time hazard model to test the hypotheses. The discrete time hazard approach allows for great flexibility in specifying the time function and in the incorporation of time-varying explanatory variables (Allison, 1995). The event is the takeoff of product i in country j. The hazard of takeoff is the probability that product i in country j experiences takeoff during bimonthly period t, given the existence of no prior occurrences. If T is an integer random variable providing the time of the event occurrence, conditional probability P_{ijt} (the probability that the event occurs at time t, given that it has not already occurred) is computed as follows:

$$P_{ijt} = \Pr\left(T_{ij} = t/T_{ij} \geq t, x_{ijt}\right), \tag{9}$$

where x_{ijt} is a vector of explanatory variables observed for product i in country j for period t. The model for the dependence of P_{ijt} on x_{ijt} can be specified as follows:

$$P_{ijt} = 1/\left(1 + e^{-\alpha_t - \beta x_{ijt}}\right). \tag{10}$$

This model becomes the following:

$$\log\left(P_{ijt}/\left(1 - P_{ijt}\right)\right) = \alpha + \beta x_{ijt}. \tag{11}$$

[2] Although the use of patents as a measure of technological activity in an industry is somewhat problematic, as different firms may use different patenting strategies or exhibit varying levels of interest in obtaining patents, prior research has revealed a high correlation between level of patenting activity and the level of technological improvements in an industry (Bayus et al., 2007).

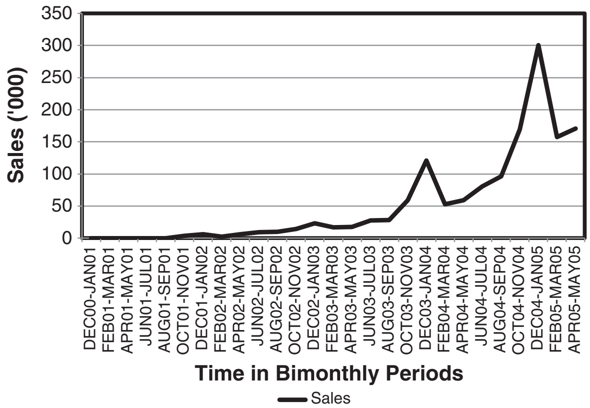


Fig. 5. Bimonthly sales of DVD recorder in the U.S.

For each product–country combination, there is a set of distinct observations, one for each unit of time until either the event (takeoff) occurs or the series is censored. For each of these observations, the dependent variable takes on a value of 1 if takeoff occurs during that time unit and a value of 0 otherwise. This method allows for the easy incorporation of time-varying covariates, corresponding to each period. Singer and Willet (1993) and Allison (1982) prove the equivalence between the likelihood of the discrete time hazard model and a sequence of N independent Bernoulli trials. Hence, maximum likelihood estimates can be derived using logistic regression in the discrete time framework. Thus, we pool these observations and estimate the following logistic regression model:

$$\begin{aligned}\log\left({}^{P_{ijt}}\Big/_{1}-P_{ijt}\right) &= \alpha+\beta_1 Relative\,Price_{ijt}+\beta_2 Price\,Volatility_{ijt}\\ &+\beta_3 National\,Wealth_{jt}+\beta_4 Uncertainty\,Avoidance_j\\ &+\beta_5 Intra-country\,Contagion_{ijt}+\beta_6 Foreign\,Takeoff_{ijt}\\ &+\beta_7 Innovative\,Activity_{it}+\beta_8 Seasonality_{it}.\end{aligned} \tag{12}$$

The proposed model (Eq. (12)) includes the main effects of both time-varying and time-invariant covariates. Time-varying covariates include relative price, price volatility, intra-country contagion effects, foreign takeoffs, innovative activity, seasonality, and national wealth (which is constant throughout a particular year but varies across years). The cultural dimension of uncertainty avoidance is time-invariant. Note that we do not include an effect for time because we capture the effect of contagion effects, measured as lagged cumulative sales.

We use the STATA logit procedure, allowing for the clustered robust standard error option, which specifies that the standard errors allow for intra-group (here, a product–country combination) correlation, relaxing the usual requirement that the observations be independent. That is, the observations are independent across groups (clusters) but not necessarily within groups.

4. Results

This section covers the identification of takeoff, other relevant descriptive statistics results obtained using our hazard model, and the robustness of the results.

4.1. Identification of takeoff

This section provides comparisons of the statistics on takeoff with regard to bimonthly and annual levels.

Table 2
Comparison of timing of bimonthly and annual takeoff.

Descriptions	%
Takeoff is not identified at either bimonthly level or annual level (product has not taken off)	12
Takeoff is identified at bimonthly level in the same year as rule identifies takeoff at annual level	73
Rule identifies takeoff at the bimonthly level in an earlier year than at annual level	15

We identify takeoff at the bimonthly level using the adapted Tellis et al. (2003) rule for 45 of the 51 product–country combinations. A visual inspection of penetration plots support the identification of takeoff for these product–country combinations. The average time until takeoff is 19.2 months, or roughly 2 years. This estimate is comparable to the 2 year interval for consumer electronics identified by Tellis et al. (2003) and the 3 year interval identified by Van Everdingen et al. (2009).

To assess the usefulness of measuring takeoff using bimonthly data, we apply the Tellis et al. (2003) rule using annual data and compare the results (Table 2). We obtain the annual sales data by aggregating across the 6 bimonthly periods. For instance, annual data for 1999 include the bimonthly periods of Feb–Mar, Apr–May, Jun–Jul, Aug–Sept, Oct–Nov, and Dec (99)–Jan (00). In some cases, bimonthly data end in Aug–Sept of the corresponding year. In all cases in which there are fewer bimonthly periods than would constitute one year, we estimate annual sales using proportional annualization.[3]

We identify takeoff at the annual level for 42 out of 51 product–country combinations. In 12% of the cases, we do not identify takeoff at either the bimonthly or the annual levels, suggesting that the product has not yet taken off. In 73% of the cases, we identify takeoff using both bimonthly and annual data for the same year (this includes the cases in which the bimonthly data enable the identification of takeoff before the Dec–Jan period of that year). This result indicates that our adaptations of the Tellis et al. (2003) rule to the more disaggregate data level have face validity.

In 45% of the cases, we identify takeoff using the bimonthly rule during a month prior to the Dec–Jan bimonthly period in the same year. For example, in Fig. 6, takeoff is identified using the adapted bimonthly rule in June–July 2003 and, using annual data and the Tellis et al. (2003) rule, takeoff is identified in 2003.

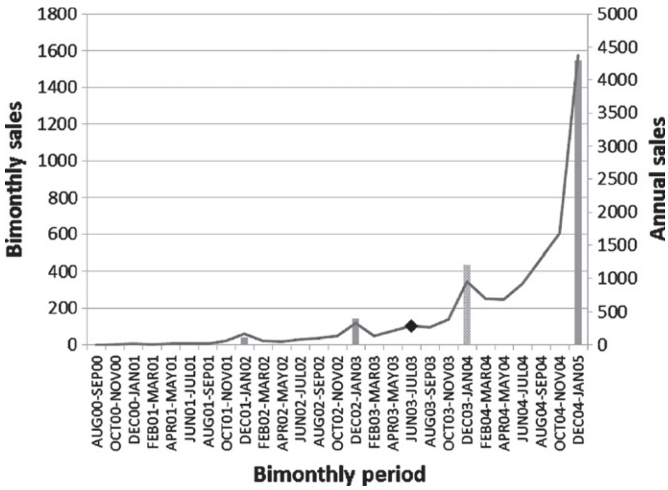
Furthermore, in 15% of the cases, we identify takeoff for an earlier year. The simple reason for this result is that there are 6 bimonthly data periods for every annual data period. This detail implies that with annual data, a greater number of observations is required for an accurate assessment and, although this type of data is more convenient to collect, we may not be able to pinpoint takeoff when it occurs over several months rather than several years.

4.2. Other key descriptive statistics for products and countries

On average and across countries, the least expensive products in our data are the MP3 player (audio) flash and audio HD. The most expensive products are the plasma TV and the LCD TV. Furthermore, audio flash and audio HD pricing are relatively less volatile than that for the plasma and the LCD TV (Table 3a).

On average, across products and countries, we find that prices decrease substantially during the early life cycles of new products

[3] That is, for each product–country combination, we first determine the proportion of total sales throughout the entire period of observation, which is contributed to by each bimonthly period (if for the year 2005, data for only 2 bimonthly periods are present, we estimate the annual sales in 2005 by dividing the total sales over the 2 bimonthly periods by the proportion of sales represented by the two bimonthly periods).



Notes:
Line refers to bimonthly sales; Column refers to corresponding annual sales
Takeoff identified with bimonthly data in Jun 03-July 03, corresponds to takeoff identified with annual data at the end of 2003 (Dec 03-Jan 04).

Fig. 6. Identification of takeoff-Audio HD sales in the US.

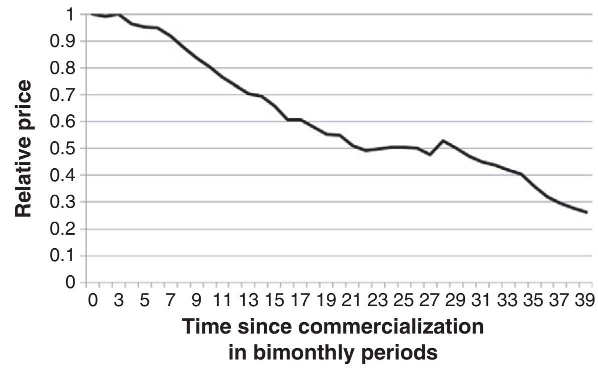


Fig. 7. Relative price averaged across products and countries.

(Fig. 7). On average, prices are 5% lower than launch prices 1 year after commercialization. After 2 years, prices are 27% lower than the launch prices. After 3–4 years, prices are approximately 50% of the corresponding launch prices. On average, across products and countries, prices at takeoff are 52% of initial prices.

The countries represent a spectrum of uncertainty avoidance scores that range from low (Sweden, the United Kingdom and the United States) to high (Spain, France and Italy). Although our sample consists of only developed countries, the United States may be characterized as among the wealthier countries in the dataset, whereas Spain may be characterized as the least wealthy country in the dataset (see Table 3b).

We next examine the factors influencing the takeoff of new products using data at the disaggregate level and in an international context.

4.3. Estimates of the hazard model: main effects

The correlations among the independent variables are in Table 4. The estimates of the discrete time hazard model (Eq. (12)) are in Table 5. We cluster according to product–country combination and employ robust standard errors.

Model 1 is the base model without the interaction effects. We find that relative price has a negative and significant effect. Hence, lower relative prices increase the hazard of takeoff. These results support H1. Hence, across products and countries, we find that relative price affects the takeoff of new products.

We also find that price volatility has a negative and significant coefficient. Hence, we obtain support for H2, which holds that higher price volatility decreases the hazard of takeoff.

With regard to the non-price dimensions, we determine that higher levels of intra-country contagion levels and innovative activity and higher numbers of foreign takeoffs increase the hazard of takeoff. Higher uncertainty avoidance decreases the hazard of takeoff and, unexpectedly, higher wealth (GDP per capita) does as well.

The coefficient of seasonality is positive and significantly different from 0. Hence, the hazard of takeoff is higher during peak seasons.

To assess the models' fit, we use the pseudo R-square. Our results for Model 1, in Table 5, reveal a pseudo R-square of .34, which is consistent with prior research (Golder & Tellis, 1997, who report an R-square like measure of .31; Tellis et al., 2003 report .18 for the full model).

When independent variables are measured at different scales or in different units, beta coefficients must be standardized so that the relative effects of the independent variables can be compared. We derive the standardized estimates using the STB option in SAS Proc Logistic. The standardized coefficients for the main-effects only model are in Table 6. The interpretation of these standardized coefficients is as follows: A one-standard deviation increase in the independent variable (X) produces a b* standard deviation change in the logit of (Y). For example, an increase of one standard deviation in innovative activity is associated with an increase of .23 standard deviations in the logit of takeoff. A one-standard deviation increase in relative price leads to a decrease of .43 standard deviations in the logit of takeoff. Thus, in terms of the direct effects, we find that price volatility

Table 3a
Descriptive statistics on pricing dimensions and takeoff patterns by product.

	#[a]	# Takeoffs	Mean price at commercialization	Mean relative price at takeoff[b]	Mean price volatility at one period before takeoff (rank 1 = low, 7 = high)
DVD recorder	8	8	2206.66	.21	3
Digital video recorder	6	2	1427.90	.44	5
Home theater	8	8	906.44	.76	4
Plasma	7	6	14876.33	.22	7
LCD	8	8	2807.10	.54	6
Audio flash	7	7	219.71	.65	1
Audio HD	7	6	412.40	.75	2

Note: Prices in US $.
[a] Number of countries for which data on this category is available.
[b] Calculated for cases where takeoff has occurred.

Table 3b
Descriptive statistics on pricing dimensions and takeoff patterns by country.

	#[a]	# Takeoffs	Mean relative price at takeoff[b]	Uncertainty avoidance scores	Mean GDP per capita[c]
US	6	5	.52	46	34,544
UK	7	6	.56	35	23,297
Sweden	4	4	.41	29	24,733
Spain	7	6	.50	86	19,061
Netherlands	7	7	.66	53	25,525
Italy	7	5	.42	75	22,561
Germany	7	6	.49	65	23,488
France	6	6	.52	86	23,034

Note: Prices in US $.
[a] Number of categories for which data is available within each country.
[b] Calculated for cases where takeoff has occurred.
[c] Average GDPPC estimated across years for each country.

has the largest effect, followed by, in descending order, wealth, intra-country interactions, relative price, uncertainty avoidance, seasonality, innovative activity, and foreign takeoffs.

4.4. Estimates of the hazard model: interaction effects

We re-estimate Eq. (12) after including the interaction terms between the pricing dimensions and wealth, culture, and contagion. We sequentially include blocks of the interaction terms to facilitate interpretation.

Model 2 adds the interaction term between the pricing dimensions and national wealth. The results of this analysis are in Table 5. We do not find a significant effect for the interaction between relative price and national wealth. Hence, we do not obtain support for H3. However, we find that the interaction between price volatility and national wealth has a positive and significant effect. This result implies that in countries with high national wealth, the influence of price volatility on takeoff becomes less important. This finding supports H4.

Model 3 adds the interaction term between the pricing dimensions and uncertainty avoidance. We do not find a significant interaction effect between relative price and uncertainty avoidance. Hence, the results do not support H5. However, we find that the interaction between price volatility and uncertainty avoidance has a negative and significant effect. This result implies that the negative influence of price volatility on takeoff is enhanced in countries with high uncertainty avoidance, in support of H6.

Model 4 adds the interaction term between the pricing dimensions and intra-country contagion effects. We do not find a significant interaction between relative price and intra-country contagion effects. However, we find that the interaction between price volatility and intra-country contagion effects has a positive and significant effect. The results from Model 4 therefore do not support H7, but do support H8. This result implies that for products associated with high intra-country contagion effects, price volatility's effect on takeoff decreases.

4.5. Out-of-sample prediction

Can managers use our model to predict takeoff? We use a jackknife method to simulate the context of the manager of a target product in a target country. The jackknife method ascertains the out-of-sample predictive validity of the hazard model. We re-estimate Eq. (12) (plus the interaction terms) n times, excluding one market each time. Here, n is the number of markets (product–country combinations) in our sample. For each of these n runs, we use the estimated parameters of the model to predict the hazard of takeoff for the excluded target market. We compare predicted and actual takeoffs across these n iterations. We calculate the model's accuracy in predicting takeoff in terms of various hit rates. Specificity is the power of the model to detect true negatives, whereas sensitivity is the power of the model to detect true positives (see Eqs. (13) and (14)).

$$\textit{Specificity} = \frac{\text{True Negatives}}{\text{Actual Negatives}} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \quad (13)$$

$$\textit{Sensitivity} = \frac{\text{True Positives}}{\text{Actual Positives}} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}. \quad (14)$$

There is a trade-off between sensitivity and specificity. This distinction is sensitive to the relative size of the component groups and favors classification in the larger group (Hosmer & Lemeshow, 2004). In our case, there are many more occurrences of 0s than 1s and, thus, we choose an optimal cut-off point that maximizes both sensitivity and specificity. For the n iterations, model sensitivity is 61% and specificity is 91%, which is much higher than what could have been predicted by chance alone.

4.6. Robustness analysis

We next examine the robustness of the above analysis to the following: the inclusion of measures of industry level competition, additional pricing dimensions, an alternative hazard model specification, different control variables, a different price volatility specification, and the inclusion of different clustering specifications.

4.6.1. Impact of competitive activity

Competitive activity in the industry may affect product takeoff (Bayus et al., 2007). An increase in competitive activity denotes the entry of several new players into the market, who offer newer versions of the product, which may stimulate takeoff (Agarwal & Bayus, 2002). Research posits that tacit collusion to thwart new entrants is easier in markets characterized by high levels of concentration.

Table 4
Correlation matrix.

		1	2	3	4	5	6	7	8
1	Takeoff	1							
2	Relative price (lag 1)	−0.14	1						
3	Price volatility (lag 1)	−0.08	0.05	1					
4	Innovative activity (lag 1)	0.14	0.27	−0.13	1				
5	National wealth (lag 1)	0.04	−0.11	−0.11	0.01	1			
6	Uncertainty avoidance	−0.02	0.1	−0.09	0.01	−0.52	1		
7	Seasonality	0.09	−0.06	0	−0.01	−0.01	−0.01	1	
8	Foreign takeoff (lag 1)	0.33	−0.17	−0.09	0.17	−0.07	0.06	0.02	1
9	Contagion effects (lag 1)	0.32	−0.21	−0.15	0.11	0.50	−0.11	−0.00	0.18

Table 5
Results from hazard model (drivers of takeoff).

		(1)	(2)	(3)	(4)
Relative price (lag 1)	H1	−2.373***	−4.880*	−1.984	−1.320
		(−3.35)	(−1.67)	(−0.45)	(−0.14)
Price volatility (lag 1)	H2	−0.00692***	−0.0550***	−0.0352***	−0.0314**
		(−2.58)	(−5.32)	(−2.94)	(−2.01)
National wealth (lag 1)		−0.000308***	−0.000454***	−0.000402***	−0.000384*
		(−3.65)	(−4.47)	(−3.95)	(−1.73)
Uncertainty avoidance		−0.0278**	−0.0281**	0.00464	0.0151
		(−2.54)	(−2.43)	(0.23)	(0.59)
Contagion (lag 1)		1.38e−05***	1.55e−05***	1.51e−05***	1.36e−05*
		(5.72)	(5.70)	(5.24)	(1.95)
Foreign takeoffs (lag 1)		0.708**	0.633**	0.654**	0.633**
		(2.47)	(2.08)	(2.10)	(2.01)
Innovative activity (lag 1)		0.0106***	0.0117**	0.0129**	0.0125**
		(2.62)	(2.51)	(2.50)	(2.34)
Seasonality		1.274***	1.305***	1.249***	1.347***
		(3.06)	(3.13)	(3.00)	(3.28)
Relative price (lag 1) * National wealth (lag 1)	H3		9.47e−05	5.24e−05	5.55e−05
			(0.91)	(0.45)	(0.15)
Price volatility (lag 1) * National wealth (lag 1)	H4		2.01e−06***	1.76e−06***	1.75e−06***
			(5.22)	(3.84)	(2.95)
Relative price (lag 1) * Uncertainty avoidance	H5			−0.0344	−0.0426
				(−0.93)	(−1.06)
Price volatility (lag 1) * Uncertainty avoidance	H6			−0.000317***	−0.000470**
				(−2.60)	(−2.46)
Relative price (lag 1) * Contagion (lag 1)	H7				−2.44e−07
					(−0.02)
Price volatility (lag 1) * Contagion (lag 1)	H8				7.23e−08*
					(1.70)
Constant		5.253**	8.703***	5.757**	4.596
Pseudo R-square		0.339	0.353	0.366	0.373

Notes: Observations: 615, robust z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$, 2-sided significance levels.

Gielens and Steenkamp (2007) report that increasing concentration negatively impacts both first year purchases and trends in the purchase of new consumer packaged goods. Hence, the extent of competitive activity in an industry is an important control variable. To control for this effect, we develop a measure of the level of the concentration in the industry. We measure the Herfindahl–Hirschman Index of concentration in each product market. The Herfindahl–Hirschman Index is derived by calculating the sum of the squares of the market shares of every firm in the industry. The closer the market is to being a monopoly, the higher the market's concentration and the lower the level of competition are. For each of the 8 countries in our data set and for each product market, we obtain data on company market shares from the Euromonitor country reports (Euromonitor Global Marketing Information Database). We are able to obtain company market shares from 2002 to 2006 in terms of percentages of retail volume in the following product categories: home audio and video, portable media players, TV systems & projectors, and video/DVD systems.

We next run a separate hazard analysis by including this variable as an independent variable in the regression, along with 1 period lag, excluding the years before 2002. We find that the coefficient for the Herfindahl index is not significantly different from 0, whereas the other results remain substantially robust.

4.6.2. Additional pricing dimensions

We test the robustness of the model to the inclusion of additional pricing dimensions. We examine whether takeoff may be impacted by either the magnitude of the price increase or the magnitude of the price decrease during the previous period for each product in each country. We include a variable assessing price decrease

Table 6
Relative importance of main effects: standardized coefficients.

Parameter	Standardized estimate (1)	Standardized estimate (4)
Intercept		
Relative price (lag 1)	−0.43	−.24
Price volatility (lag 1)	−2.35	−10.69
National wealth (lag 1)	−0.70	−.87
Uncertainty avoidance	−0.31	.17
Contagion (lag 1)	0.60	.59
Foreign takeoffs (lag 1)	0.17	.15
Innovative activity (lag 1)	0.23	.27
Seasonality	0.24	.25
Relative price (lag 1) * National wealth (lag 1)		.25
Price volatility (lag 1) * National wealth (lag 1)		13.47
Relative price (lag 1) * Uncertainty avoidance		−.59
Price volatility (lag 1) * Uncertainty avoidance		−7.89
Relative price (lag 1) * Contagion (lag 1)		−.01
Price volatility (lag 1) * Contagion (lag 1)		.19

(increase), 1 period lagged, in the regression. We find that there is no significant increase (decrease) in the hazard of takeoff for this additional pricing dimension, whereas the other results remain robust.

We also consider the robustness of the analysis to the inclusion of absolute prices rather than relative prices. When absolute price is considered in Model 1, either the pricing dimensions are not significant or only the absolute price is significant (at the 10% level). There are issues with considering the absolute price. First, the reference price literature, as well as the underlying rationale based on economic theory, suggests that price relative to some threshold rather than absolute price, plays a role. Second, we obtain high correlations of .41 with the price volatility measure (as well as the measure we use in our robustness checks), whereas the correlation between our relative price measure and price volatility is only .05.

4.6.3. Alternative hazard model specification

We examine the robustness of our analysis to an alternate complementary log–log hazard specification. We find that our analysis is robust to all of the results for the hypotheses, with the exception of H4, on the interaction between price volatility and national wealth, for which we find no support.

4.6.4. Additional control variables

We test the robustness of our analysis to the inclusion of additional control variables tested in the literature on takeoff. Models 1 and 2 in Table A of the Appendix A show the impact of the addition of income inequality, as well as the three other dimensions of Hofstede's dimensions of culture. Our key findings remain robust. Models 3 and 4 show the inclusion of time since commercialization. Our results remain substantially robust (the results do not support the interaction of price volatility and GDP per capita).

4.6.5. Alternate price volatility measure

We consider a different specification of the price volatility measure to capture the impact of an exponentially decreasing price, such as the following:

$$P_t^r = \delta_0 + \delta_1 Time + \delta_2 Time^2 + \varepsilon_{ijt}, \tag{15}$$

where subscript t refers to the time period. Eq. (15) assumes that a consumer's prediction of the current price of a product is based on an exponential specification of Time, where Time tracks the time period, beginning at commercialization. This equation is estimated separately for each group (product–country classification). Our results remain robust, with the exception of the interaction effect between price volatility and uncertainty avoidance, which is no longer significantly different from 0 (see Appendix Table B).

4.6.6. Alternate clustering specifications

We allow for clustered error terms in small clusters (same product and same cluster). We determine the robustness to 2 other clustering specifications. One specification allows for the clustering of all observations addressing the same product across countries (Models 1 and 2 in Appendix Table C). The other specification allows for correlations among all observations across products belonging to the same country (Models 3 and 4 in Appendix Table C). The results are robust to these alternate specifications.

5. Discussion

New product takeoff is a critical event in the life cycle of new products, potentially signaling mass adoption and ultimate success. Managing the drivers that may affect takeoff is therefore of crucial importance for managers. Pricing is one of the most important marketing variables that practitioners use to manage new products (e.g., Gijsbrechts, 1993). However, various dimensions of price have not been considered in-depth with regard to the international takeoff of new products. This study focuses on the effect of two dimensions of price (relative price and price volatility) on the international takeoff of new products using a novel data set of bimonthly observations of 7 new consumer electronics products in 8 countries. This section discusses the key results, implications, and limitations of the study.

5.1. Key results

The key results of the study are as follows:

- Both relative price and price volatility significantly impact the hazard of takeoff. Price volatility may be one of the strongest factors driving (or hindering) takeoff.
- However, although the influence of price decreases relative to introductory price is stable across contexts, the effect of price volatility is moderated by wealth, culture, and contagion. The effect of price volatility is enhanced in countries with high uncertainty avoidance and diminished in countries with greater wealth. Moreover, for products that have high intra-country contagion effects, price volatility has a reduced impact.
- Greater data granularity leads to the identification of inter-temporal effects such as price volatility, which is a critical determinant of takeoff.

5.2. Implications

Our results have the following implications.

First, managers must carefully monitor prices to manage and accelerate takeoff. For takeoff, prices must eventually be substantially lower than introductory prices, strongly suggesting the need for a skimming strategy. Thus, managers should carefully consider the level of the introductory price and plan for regular price decreases.

Second, higher price volatility significantly lowers the hazard of takeoff. In fact, our analysis reveals that price volatility may be one of the important variables hindering takeoff, and an inability to obtain data at a disaggregate level may be seriously impacting our understanding of volatility's effects on takeoff. While executing a price skimming strategy, managers must plan to use this strategy judiciously, implementing steady rather than erratic price drops. Utilizing a steady price decrease strategy is particularly relevant in less wealthy or less venturesome countries, which are more sensitive to price volatility. In addition, although cost and competitive pressures may cause price volatility, managers must minimize such volatility to avoid the delay or abortion of a new product takeoff.

Third, earlier studies highlight the importance of managing social contagion during the growth and maturity stages (e.g., Chandrasekaran & Tellis, 2011; Goldenberg, Libai, & Muller, 2002; Peres et al., 2010; Van den Bulte & Stremersch, 2004). Our results highlight the importance of social contagion to the stimulation of takeoff at an earlier stage of the product life cycle. Furthermore, although some reviews speculate regarding a trade-off in terms of managerial time in which there is a focus on pricing rather than contagion (e.g., Peres et al., 2010), we find evidence of a positive interplay between pricing and contagion: increased social contagion may diminish price volatility's influence on takeoff.

Fourth, managers must know as early as possible whether takeoff occurs, a necessity that has gained importance in recent times, as takeoff appears to occur quickly, within months. This study provides a method for assessing takeoff at the bimonthly level through the adaptation of the Tellis et al. (2003) rule. Thus, in the context of bimonthly data, a manager can determine at the end of each 2 month period whether takeoff has occurred. Assessing takeoff using temporally disaggregate data can enable the pinpointing of takeoff within the year. This method will provide firms with control and flexibility for managing new products.

5.3. Limitations

This study has several limitations that suggest opportunities for future research. First, our research focuses on product categories, not individual brands. Thus, we consider average price for a category rather than the prices of individual brands. This practice is common in research on takeoff and diffusion because of the difficulty of procuring brand-level data across countries. Second, although this study is based on a set of multiple products and countries, using a more comprehensive set of products and countries will produce more generalizable findings. Third, we measure firm entry across countries according to industry concentration, which reflects the number of sellers in a market. Data on numbers of entrants would be very useful. Fourth, although our data are bimonthly, they are aggregated at the country level. Assessing takeoff using cross-sectional disaggregate data would be advantageous. Fifth, we do not consider the effects of the prices of competing products. All of these issues remain promising areas for future research.

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Appendix A

Table A
Robustness checks — inclusion of additional control variables.

	(1)[a]	(2)[a]	(3)[b]	(4)[b]
Relative price (lag 1)	−3.468***	4.875	−2.474**	7.393
	(−3.04)	(0.38)	(−2.46)	(0.61)
Price volatility (lag 1)	−0.00766***	−0.114**	−0.0112***	−0.0829
	(−3.13)	(−2.28)	(−3.16)	(−1.10)
Income inequality (lag 1)	0.0853	0.0917	0.112	0.133
	(0.70)	(0.62)	(0.86)	(0.86)
National wealth (lag 1)	−0.00126***	−0.00139***	−0.00140***	−0.00143***
	(−4.85)	(−3.19)	(−4.81)	(−2.68)
Uncertainty avoidance	0.0513	0.106	0.0663	0.133*
	(1.01)	(1.57)	(1.40)	(1.89)
Power distance	−0.0496	−0.0489	−0.0782	−0.0897
	(−0.58)	(−0.46)	(−0.92)	(−0.83)
Masculinity	−0.134***	−0.155***	−0.148***	−0.171***
	(−4.96)	(−4.49)	(−5.29)	(−4.68)
Individualism	0.245***	0.274***	0.267***	0.297***
	(4.77)	(4.23)	(4.84)	(4.17)
Contagion (lag 1)	3.68e−05***	3.94e−05***	3.97e−05***	4.04e−05***
	(4.99)	(3.31)	(5.08)	(2.95)
Foreign takeoff (lag 1)	1.160**	1.283**	0.947**	1.076*
	(2.29)	(2.03)	(1.99)	(1.71)
Innovative activity (lag 1)	0.0110**	0.0115**	0.0122**	0.0125**
	(2.23)	(2.42)	(2.39)	(2.36)
Seasonality	1.682***	1.960***	1.608***	1.774***
	(3.08)	(3.28)	(2.92)	(3.01)
Relative price (lag 1) * National wealth (lag 1)		−0.000219		−0.000298
		(−0.48)		(−0.69)
Price volatility (lag 1) * National wealth (lag 1)		5.20e−06**		3.91e−06
		(2.38)		(1.26)
Relative price (lag 1) * Uncertainty avoidance		−0.0495		−0.0474
		(−1.04)		(−1.03)
Price volatility (lag 1) * Uncertainty avoidance		−0.000699***		−0.000769***
		(−3.14)		(−3.12)
Relative price (lag 1) * Contagion (lag 1)		−3.97e−07		1.36e−06
		(−0.03)		(0.12)
Price volatility (lag 1) * Contagion (lag 1)		1.74e−07***		1.67e−07***
		(3.20)		(2.76)
Time since commercialization			0.0895***	0.0876***
			(3.36)	(2.92)
Constant	9.311***	7.286	9.106**	4.318
	(2.76)	(0.92)	(2.40)	(0.43)
Pseudo R-square	0.474	0.522	0.500	0.542

Notes: Observations: 615, Robust z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$, 2-sided significance levels.
[a] Model shows inclusion of income inequality and cultural variables.
[b] Model shows inclusion of additional variable-time since commercialization.

Table B
Robustness checks — inclusion of a different specification of price volatility.

	(1)[a]	(2)[a]
Relative price (lag 1)	−2.286***	2.258
	(−3.26)	(0.27)
Price volatility (lag 1) — exponentially declining prices	−0.00555**	−0.0672**
	(−2.03)	(−2.25)
National wealth (lag 1)	−0.000300***	−0.000308
	(−3.64)	(−1.44)
Uncertainty avoidance	−0.0257**	0.000592
	(−2.39)	(0.03)
Contagion (lag 1)	1.42e−05***	9.14e−06
	(5.89)	(1.27)
Foreign takeoffs (lag 1)	0.715**	0.527
	(2.39)	(1.49)
Innovative activity (lag 1)	0.0103**	0.0108**
	(2.58)	(2.11)
Seasonality	1.269***	1.305***
	(3.06)	(3.21)
Relative price (lag 1) * National wealth (lag 1)		−0.000103
		(−0.30)
Price volatility (lag 1) — exponentially declining prices * National wealth (lag 1)		2.43e−06***
		(3.31)
Relative price (lag 1) * Uncertainty avoidance		−0.0407
		(−1.19)
Price volatility (lag 1) — exponentially declining prices * Uncertainty avoidance		−0.000105
		(−0.48)
Relative price (lag 1) * Contagion (lag 1)		5.23e−06
		(0.51)
Price volatility (lag 1) — exponentially declining prices * Contagion (lag 1)		1.76e−07**
		(1.96)
Constant	4.674**	3.639
	(2.12)	(0.68)
Psuedo R-square	0.333	0.364

Notes: Observations: 662, Robust z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$, 2-sided significance levels.
[a] Model shows inclusion of a different price volatility measure.

Table C
Robustness checks — inclusion of alternate clustering specifications.

	(1)[a]	(2)[a]	(3)[b]	(4)[b]
Relative price (lag 1)	−2.373***	−1.320	−2.373***	−1.320
	(−3.98)	(−0.15)	(−3.47)	(−0.16)
Price volatility (lag 1)	−0.00692***	−0.0314*	−0.00692**	−0.0314**
	(−4.20)	(−1.92)	(−1.98)	(−2.48)
National wealth (lag 1)	−0.000308***	−0.000384**	−0.000308*	−0.000384
	(−5.68)	(−2.16)	(−1.75)	(−1.48)
Uncertainty avoidance	−0.0278***	0.0151	−0.0278	0.0151
	(−3.58)	(0.53)	(−1.63)	(0.42)
Contagion (lag 1)	1.38e−05***	1.36e−05***	1.38e−05***	1.36e−05
	(8.48)	(2.85)	(2.80)	(1.47)
Prior takeoff (lag 1)	0.708***	0.633**	0.708	0.633
	(3.16)	(2.34)	(1.45)	(1.33)
Innovative activity (lag 1)	0.0106***	0.0125***	0.0106***	0.0125**
	(4.89)	(4.64)	(2.75)	(2.39)
Seasonality	1.274***	1.347***	1.274***	1.347***
	(4.39)	(3.53)	(3.15)	(4.06)
Relative price (lag 1) * National wealth (lag 1)		5.55e−05		5.55e−05
		(0.18)		(0.20)
Price volatility (lag 1) * National wealth (lag 1)		1.75e−06**		1.75e−06***
		(2.27)		(3.40)
Relative price (lag 1) * Uncertainty avoidance		−0.0426		−0.0426
		(−1.01)		(−1.13)
Price volatility (lag 1) * Uncertainty avoidance		−0.000470***		−0.000470**
		(−3.66)		(−2.05)
Relative price (lag 1) * Contagion (lag 1)		−2.44e−07		−2.44e−07
		(−0.03)		(−0.03)
Price volatility (lag 1) * contagion (lag 1)		7.23e−08**		7.23e−08
		(2.03)		(1.04)
Constant	5.253***	4.596	5.253	4.596
	(2.84)	(0.87)	(1.17)	(0.68)
Psuedo R-square	0.339	0.373	0.339	0.373

Notes: Observations: 615, Robust z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$, 2-sided significance levels.
[a] Model includes clustering of all observations dealing with same product across countries.
[b] Model includes clustering of all observations across products belonging to same country.

References

Agarwal, R., & Bayus, B. L. (2002). The market evolution and sales takeoff of product innovations. *Management Science*, *48*(8), 1024–1041.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197–220.

Alba, J. W., Mela, C. F., Shimp, T. A., & Urbany, J. E. (1999). The effect of discount frequency and depth on consumer price judgments. *Journal of Consumer Research*, *26*(2), 99–114.

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. In S. Leinhardt (Ed.), *Sociological methodology* (pp. 61–98). San Francisco: Jossey-Bass.

Allison, P. D. (1995). *Survival analysis using SAS: A practical guide.* Cary, NC: SAS Institute Inc.

Axarloglou, K. (2003). The cyclicality of new product introductions. *Journal of Business*, *76*(1), 29–48.

Bagwell, K., & Riordan, M. H. (1991). High and declining prices signal product quality. *American Economic Review*, *81*(1), 224–239.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, *15*(5), 215–227.

Bayus, B. L., Kang, W., & Agarwal, R. (2007). Creating growth in new markets: A simultaneous model of firm entry and price. *Journal of Product Innovation Management*, *24*(2), 139–155.

Bijmolt, T. H. A., Van Heerde, H. J., & Pieters, R. G. M. (2005). New empirical generalizations on the determinants of price elasticity. *Journal of Marketing Research*, *42*(2), 141–156.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom and cultural change as information cascades. *Journal of Political Economy*, *100*(5), 992–1026.

Chandrasekaran, Deepa, & Tellis, Gerard J. (2007). Diffusion of new products: A critical review of models, drivers, and findings. *Review of Marketing Research*, *39–80*.

Chandrasekaran, D., & Tellis, G. J. (2008). Global takeoff of new products: Culture, wealth or vanishing differences? *Marketing Science*, *27*(5), 844–860.

Chandrasekaran, D., & Tellis, G. J. (2011). Getting a grip on the saddle: Chasms or cycles? *Journal of Marketing*, *75*(4), 21–34.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.

Clarke, D. G. (1976). Econometric measurement of the duration of advertising effect on sales. *Journal of Consumer Research*, *13*(4), 345–357.

Dekimpe, M. G., Parker, P. M., & Sarvary, M. (1998). Staged estimation of international diffusion models: An application to global cellular telephone adoption. *Technological Forecasting and Social Change*, *57*(1), 105–132.

Dekimpe, M. G., Parker, P. M., & Sarvary, M. (2000). Multimarket and global diffusion. In V. Mahajan, E. Muller, & Y. Wind (Eds.), *New product diffusion models* (pp. 49–73). Boston: Kluwer Academic Publishers.

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational cascades and software adoption on the internet: An empirical investigation. *MIS Quarterly*, *33*(1), 23–48.

Emigh, J. (2010). Apple and analysts: ipad demand keeps soaring, Tabletpcreview.com. last accessed 7/12/2011, url: http://www.tabletpcreview.com/default.asp?newsID=1535&news=apple+ipad+tablet+computer

Ganesh, J., & Kumar, V. (1996). Capturing the cross-national learning effect: An analysis of an industrial technology diffusion. *Journal of the Academy of Marketing Science*, *24*(4), 328–337.

Geron, T. (2011). Decide.com brings price prediction to gadgets, Forbes.com. last accessed 4/7/2011, url: http://blogs.forbes.com/tomiogeron/2011/06/20/decide-com-brings-price-prediction-to-gadgets/

Gielens, K., & Steenkamp, J. -B. E. M. (2007). Drivers of consumer acceptance of new packaged goods: An investigation across products and countries. *International Journal of Research in Marketing*, *24*(2), 97–111.

Gijsbrechts, E. (1993). Prices and pricing research in consumer marketing: some recent developments. *International Journal of Research in Marketing*, *10*(2), 115–151.

Goldenberg, J., Libai, B., & Muller, E. (2002). Riding the saddle, how cross-market communications creates a major slump in sales. *Journal of Marketing*, *66*(2), 1–16.

Goldenberg, J., Lowengart, O., & Shapira, D. (2009). Zooming in: Self-emergence of movements in new product growth. *Marketing Science*, *28*(2), 274–292.

Golder, P. N., & Tellis, G. J. (1997). Will it every fly? Modeling the takeoff of really new consumer durables. *Marketing Science*, *16*(3), 256–270.

Golder, P. N., & Tellis, G. J. (2004). Growing, growing, gone: Cascades, diffusion, and turning points in the product life cycle. *Marketing Science*, *23*(2), 207–218.

Heater, B. (2008). Amazon's Kindle sold out through Christmas, PCMag.com. last accessed 7/12/2011, url: http://www.pcmag.com/article2/0,2817,2335700,00.asp

Helsen, K., Jedidi, K., & DeSarbo, W. S. (1993). A new approach to country segmentation utilizing multinational diffusion patterns. *Journal of Marketing*, *57*(4), 60–71.

Heston, A., Summers, R., & Aten, B. (2002). *Penn world table version 6.1.* Center for International Comparisons at the University of Pennsylvania (CICUP).

Hofstede, G. (2001). *Culture's consequences, comparing values, behaviors, institutions, and organizations across nations.* Thousand Oaks: Sage Publications.

Honisch, M., Pittnauer, S., & Stauffer, D. (2008). A percolation-based model explaining delayed takeoff in new-product diffusion. *Industrial and Corporate Change*, *17*(5), 1001–1017.

Hosmer, D. W., & Lemeshow, S. (2004). *Applied logistic regression* (2nd ed.). New York: Wiley.

Hylleberg, S. (1992). *Modeling seasonality.* New York: Oxford University Press.

Islam, T., & Meade, N. (2011). Detecting the impact of market factors on sales takeoff times of analog cellular telephones. *Marketing Letters*, *22*(2), 197–212.

Jacobson, R., & Obermiller, C. (1990). The formation of expected future price — A reference price for forward-looking consumers. *Journal of Consumer Research*, *16*(4), 420–432.

Judge, G., Griffiths, W. E., Carter Hill, R., Lütkepohl, H., & Lee, T. (1985). *The theory and practice of econometrics.* New York: Wiley.

Kahnemann, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291.

Kalish, S. (1983). Monopolist pricing with dynamic demand and production cost. *Marketing Science*, *2*(2), 135–159.

Kalyanaraman, G., & Winer, R. S. (1995). Empirical Generalizations from Reference Price Research. *Marketing Science*, *14*(3), G161–G169.

Krishnan, T. V., Bass, F. M., & Jain, D. C. (1999). Optimal pricing strategy for new products. *Management Science*, *45*(12), 1650–1663.

Mahajan, V., Muller, E., & Bass, F. M. (1990). New product diffusion models in marketing, a review and directions for research. *Journal of Marketing*, *54*(1), 1–26.

Makridakis, S., Wheelwright, S. C., & McGee, V. E. (1983). *Forecasting methods and applications.* New York: John Wiley and Sons.

Markovitch, D. G., & Golder, P. N. (2008). Using stock prices to predict market events: Evidence on sales takeoff and long-term firm survival. *Marketing Science*, *27*(4), 717–729.

Marn, M. V., Roegner, E. V., & Zawada, C. C. (2003). Pricing new products. *The McKinsey Quarterly*, *1*(3), 40–46.

Miron, J. A. (1996). *The economics of seasonal cycles.* Massachusetts: Mit Press.

Muller, E., Peres, R., & Mahajan, V. (2009). *Innovation diffusion and new product growth. Management Science Institute: Relevant Knowledge Series.*

Needleman, R. (2011). Decide.com: For gadget buyers, timing is everything. last accessed 4/7/2011, url: http://news.cnet.com/8301-19882_3-20072141-250/decide.com-for-gadget-buyers-timing-is-everything/

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing*, *27*(2), 91–106.

Prabhu, J. C., Chandy, R. K., Ellis, C., & Ellis, M. E. (2005). The impact of acquisitions on innovation: Poison pill, placebo or tonic? *Journal of Marketing*, *65*(1), 114–130.

Putsis, W. P., Jr., Balasubramanian, S., Kaplan, E. W., & Sen, S. K. (1997). Mixing behavior in cross-country diffusion. *Marketing Science*, *16*(4), 354–369.

Radas, S., & Shugan, S. M. (1998). Seasonal marketing and timing new product introductions. *Journal of Marketing Research*, *35*(3), 296–315.

Rajendran, K. N., & Tellis, G. J. (1994). Contextual and temporal components of reference price. *Journal of Marketing*, *58*(1), 22–34.

Simon, H. (1992). Pricing opportunities and how to exploit them. *Sloan Management Review*, *33*(2), 55–65.

Singer, J. D., & Willet, J. B. (1993). It's about time: Using discrete-time survival analysis to study duration and the timing of events. *Journal of Educational Statistics*, *18*(2), 155–195.

Steenkamp, J. -B. E. M., Hofstede, F. t., & Wedel, M. (1999). A cross-national investigation into the individual and national cultural antecedents of consumer innovativeness. *Journal of Marketing*, *63*(2), 55–69.

Stremersch, S., Tellis, G., Franses, P. H., & Binken, J. L. G. (2007). Indirect Network Effects in New Product Growth. *Journal of Marketing*, *71*(3), 52–74.

Takada, H., & Jain, D. (1991). Cross-national analysis of diffusion of consumer durable goods in Pacific Rim countries. *Journal of Marketing*, *55*(2), 48–54.

Talukdar, D., Sudhir, K., & Ainslie, A. (2002). Investigating new product diffusion across products and countries. *Marketing Science*, *21*(1), 97–114.

Tellis, Gerard J. (1986). Beyond the many faces of price: An integration of pricing strategies. *Journal of Marketing*, *50*(October), 146–160.

Tellis, Gerard J. (2013). *Unrelenting innovation: How to create a culture of market dominance.* Jossey-Bass.

Tellis, G. J., & Franses, P. H. (2006). Optimal data interval for estimating advertising responses. *Marketing Science*, *25*(3), 217–229.

Tellis, G. J., & Stremersch, S. (2004). Understanding and managing international growth of new products. *International Journal of Research in Marketing*, *21*(4), 421–438.

Tellis, G. J., Stremersch, S., & Yin, E. (2003). The international takeoff of new products: The role of economics, culture, and country innovativeness. *Marketing Science*, *22*(2), 188–208.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing Science*, *4*(3), 199–214.

Tirunillai, Seshadri, & Tellis, Gerard J. (2012). Does chatter really matter? The dynamics of user-generated content on stock performance. *Marketing Science*, *3*(2), 198–215.

Van den Bulte, C., & Stremersch, S. (2004). Social contagion and income heterogeneity in new product diffusion: A meta-analytic test. *Marketing Science*, *23*(4), 530–544.

Van Everdingen, Y., Fok, D., & Stremersch, S. (2009). Modeling global spill-over in new product takeoff. *Journal of Marketing Research*, *46*(5), 637–652.

Wei, L., & Xiao, J. (2012). Factors affecting the take-off of innovative technologies: Evidence from digital cameras. *Applied Economics*, *44*(32), 4143–4152.

Winer, R. S. (1985). A price vector model of demand for consumer durables: Preliminary developments. *Marketing Science*, *4*(1), 74–90.

Winer, R. S. (1986). A reference price model of brand choice for frequently purchased products. *Journal of Consumer Research*, *13*(2), 250–256.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22.