PhD THESIS DECLARATION

I, the undersigned

FAMILY NAME	Giannetti
NAME	Verdiana
Student ID no.	1452325

Thesis title:

Three Essays on Product Innovation: from Launch to Recall

PhD in	Business Administration and Management
Cycle	29
Student's Advisor	Gaia Rubera
Calendar year of thesis defence	2018

DECLARE

under my responsibility:

1) that, according to Italian Republic Presidential Decree no. 445, 28th December 2000, mendacious declarations, falsifying records and the use of false records are punishable under the Italian penal code and related special laws. Should any of the above prove true, all benefits included in this declaration and those of the temporary "embargo" are automatically forfeited from the beginning;

2) that the University has the obligation, according to art. 6, par. 11, Ministerial Decree no. 224, 30th April 1999, to keep a copy of the thesis on deposit at the "Bilioteche Nazionali Centrali" (Italian National Libraries) in Rome and Florence, where consultation will be permitted, unless there is a temporary "embargo" protecting the rights of external bodies and the industrial/commercial exploitation of the thesis;

3) that the Bocconi Library will file the thesis in its "Archivio Istituzionale ad Accesso Aperto" (Institutional Registry) which permits online consultation of the complete text (except in cases of temporary "embargo");

4) that, in order to file the thesis at the Bocconi Library, the University requires that the thesis be submitted online by the student in unalterable format to Società NORMADEC (acting on behalf of the University), and that NORMADEC will indicate in each footnote the following information:

- PhD thesis: Three Essays on Product Innovation: from Launch to Recall
- by: Giannetti Verdiana
- defended at Università Commerciale "Luigi Bocconi" – Milano in the year 2018
- the thesis is protected by the regulations governing copyright (Italian law no. 633, 22nd April 1941 and subsequent modifications). The exception is the right of Università Commerciale "Luigi Bocconi" to reproduce the same, quoting the source, for research and teaching purposes;
- the thesis is subject to "embargo" for 36 months;

5) that the copy of the thesis submitted online to Normadec is identical to the copies handed in/sent to the members of the Thesis Board and to any other paper or digital copy deposited at the University offices, and, as a consequence, the University is absolved from any responsibility regarding errors, inaccuracy or omissions in the contents of the thesis;

6) that the contents and organization of the thesis is an original work carried out by the undersigned and does not in any way compromise the rights of third parties (Italian law, no. 633, 22nd April 1941 and subsequent integrations and modifications), including those regarding security of personal details; therefore the University is in any case absolved from any responsibility whatsoever, civil, administrative or penal, and shall be exempt from any requests or claims from third parties;

7) that the PhD thesis is subject to “embargo” as per the separate undersigned “PhD Thesis Temporary ″Embargo″ Request”.

Date: 20/03/2018

Abstract

The present thesis is made up of three essays.
In the first essay, I investigate the two interrelated phenomena of trickle-down (i.e., the diffusion of innovations from developed countries to emerging ones) and reverse innovation (i.e., the diffusion of innovations from emerging countries to developed ones). Using data on 127,782 food-products' launches in 51 countries in 2001-2014, the essay answers four questions: (1) Which diffusion process occurs faster: trickle-down or reverse innovation? (2) Which characteristics of innovations accelerate trickle-down and reverse innovation? (3) Is there heterogeneity in the effects of such characteristics across specific emerging (developed) countries? (4) Does the speed of trickle-down (reverse innovation) influence the performance of innovations? Results, which are robust, show that reverse innovation occurs faster than trickle-down; price, number of claims, and package size all play a role in accelerating these two diffusion processes; heterogeneity exists across emerging as well as across developed countries; a faster diffusion process results in better performance.
In the second essay, I look at cross-country innovation diffusion, as proxied by cross-country innovation launches, adopting a cultural lens. Using data on packaged food's launches in 40 countries in 2001-2014, the essay answers three questions: (1) What is the impact of Cultural distance on the number of innovation launches across a certain lead country (i.e., the first country in which an innovation is launched)–lag country (i.e., each country in which the innovation is subsequently launched) pair? (2) What is the impact of Cultural distance on the time it takes for an innovation to be launched across a certain lead country–lag country pair? (3) Are there better measures for Cultural distance than Hofstede-based ones? Results, which are robust, show that Cultural distance decreases the number of innovation launches across a lead country-lag country pair and decelerates cross-country innovation launches; Genetic distance is a valuable alternative to Hofstede-based measures as a proxy for Cultural distance. Additional analysis reveals that both Cultural distance and time to cross-country innovation launch decrease innovation performance in lag countries.
In the third and final essay, I focus on product-harm crises (also interchangeably termed as product recalls) and, in particular, on their leadership antecedents. Using data on 75 publicly-listed U.S. medical device firms between 2003 and 2015, I show that a Marketing CEO, i.e., one with prior marketing functional experience, along with powerful finance and R&D departments, decreases the number of product-harm crises. Further, a Marketing CEO also decreases the positive effect of CEO's stock option pay on the number of product-harm crises.

Product's Characteristics as Drivers of Trickle-Down and Reverse Innovation: Evidence from the Food Industry

Verdiana Giannetti[a]

Gaia Rubera[b]

[a] Verdiana Giannetti (verdiana.giannetti@phd.unibocconi.it) is a PhD Candidate in Business Administration and Management at Bocconi University, Via Roentgen 1, 20136 Milano, Italy.

[b] Gaia Rubera (gaia.rubera@unibocconi.it) is Full Professor of Marketing at Bocconi University, Via Roentgen 1, 20136 Milano, Italy.

Abstract

Nowadays, growth for multinationals comes largely from introducing innovations in emerging countries. However, this practice proves particularly challenging for firms traditionally operating in developed countries. Adding further complexity, such firms also have to defend their positions in developed countries from the rise of emerging countries' firms. Hence, it is now crucial to understand how to accelerate the diffusion of innovations from emerging countries to developed ones (i.e., reverse innovation) and vice versa (i.e., trickle-down). A faster diffusion would in fact unlock additional sources of cash flow by disclosing new markets for innovations. Using data on 127,782 food-products' launches in 51 countries in 2001-2014, the paper answers four questions: (1) Which diffusion process occurs faster: trickle-down or reverse innovation? (2) Which characteristics of innovations accelerate trickle-down and reverse innovation? (3) Is there heterogeneity in the effects of such characteristics across specific emerging (developed) countries? (4) Does the speed of trickle-down (reverse innovation) influence the performance of innovations? Results show that: reverse innovation occurs faster than trickle-down; price, number of claims, and package size all play a role in accelerating these two diffusion processes; heterogeneity exists across emerging as well as across developed countries; a faster diffusion process results in better performance.

Keywords: *Product Innovation, Trickle-Down, Reverse Innovation, Global Innovation Diffusion, Emerging Countries*

In the current scenario of economic stagnation in developed countries, growth for multinationals comes largely from launching innovations in emerging countries (Ernst, Kahle, Dubiel, Prabhu, and Subramaniam 2015). However, difficulties in understanding consumers in emerging countries make this practice particularly challenging for firms traditionally operating in developed countries (Ernst et al. 2015; Sheth 2011). Adding complexity to the picture, multinationals also have to defend their established positions in developed countries from the rise of emerging countries' firms like Chinese Huawei and Lenovo, Mexican Grupo Bimbo, or Brazilian Embraer, which are in fact threatening the positions of established multinationals in their own domestic markets (Ramamurti and Singh 2009; Sheth 2011). In this hypercompetitive environment, it is essential to understand how to accelerate the diffusion of innovations from developed countries to emerging ones (i.e., trickle-down) and vice versa (i.e., reverse innovation). A faster diffusion process would in fact unlock additional sources of cash flow for firms by opening up new markets for their innovations.

Although innovation in and for emerging countries has emerged as a fertile area of research in marketing (Zeschky, Winterhalter, and Gassmann 2014), the extant literature is still largely anecdotal (Ernst et al. 2015), with a primary focus on countries like India and China (e.g., Immelt, Govindarajan, and Trimble 2009; Prahalad 2004; Radjou, Prabhu, and Ahuja 2012). Hence, it neglects some of the largest (e.g., Brazil and Russia) and fastest-growing countries (e.g., Vietnam and Philippines) in the world. Despite recent calls to conduct more research on emerging countries (Banerjee, Prabhu, and Chandy 2015; Sheth 2011), a quantitative analysis based on a large sample of countries is still missing (Ernst et al. 2015). Further, the literature on trickle-down and reverse innovation suffers from the following limitations.

First, researchers disagree about which diffusion process occurs faster. Two opposite paradigms have been offered: trickle-down, in which innovations first introduced in developed countries are subsequently introduced in emerging countries (Vernon 1966), and reverse innovation, in which innovations first introduced in emerging countries are subsequently introduced in developed countries (Immelt et al. 2009). On one hand, the traditional trickle-down paradigm maintains that firms meet fewer resistances when introducing innovations from developed countries to emerging ones, suggesting that trickle-down occurs faster than reverse innovation. On the other hand, the reverse innovation literature challenges this assumption by providing numerous examples of successful innovations that were first introduced in emerging countries and only subsequently in developed ones (Von Zedtwitz, Corsi, Veng Søberg, and Frega 2015), suggesting that reverse innovation may occur at least as easily as trickle-down. Second, research is not conclusive about the characteristics of innovations that trickle down (up). So far, most contributions have focused on price as a key accelerator of both trickle-down and reverse innovation. The accepted assumption is that lower-priced innovations move faster from developed countries to emerging ones and vice versa (Govindarajan and Trimble 2012). However, the evidence concerning price is still essentially anecdotal in nature. On a more limited scale, the literature has hinted that other product characteristics, mainly package size (Prahalad 2004) and product's attributes and benefits (Govindarajan and Ramamurti 2011; Winter and Govindarajan 2015), may play a role. However, the roles of package size and product's attributes and benefits have not been tested yet in the literature. Third, the literature on trickle-down and reverse innovation still relies on the naïve distinction between emerging vs. developed countries. Yet, the emerging countries label simplistically includes fast-follower countries, least-developed countries, and newly industrialized countries (Von Zedtwitz et al.

2015). Similarly, substantial heterogeneity exists also among developed countries. Such heterogeneity calls for a finer-grained analysis of how innovations diffuse across specific emerging and developed countries. Fourth, the literature is silent about how well innovations that trickle down (up) perform and whether the speed at which trickle-down (reverse innovation) occurs affects subsequent performance. So far, the literature has assumed that a faster trickle-down (reverse innovation) is indeed good, as innovations trickle down (up) because they satisfy consumers' needs in the new countries. We test this assumption by examining the impact of speed of trickle-down (reverse innovation) on the subsequent performance of innovations.

Given these gaps in the literature, this paper aims to answer four key questions. First, which diffusion process occurs faster: trickle-down or reverse innovation? Answering this question would allow managers to allocate their resources to those innovations that diffuse faster, thereby accelerating the generation of additional cash flow. Second, what are the characteristics of innovations that accelerate trickle-down and reverse innovation? Answering this question would allow firms in developed countries to protect their positions by identifying those innovations from emerging countries that are more likely to be launched in developed countries. Similarly, it would allow multinationals to capitalize on the launch of innovations in developed countries by quickly introducing them also in emerging countries. Further, it would help new entrants from emerging countries to understand how to gain ground in developed countries by rapidly adapting emerging countries' innovations for launch in developed countries. Third, is there heterogeneity in the effects of such characteristics across emerging countries as well as across developed countries? In answering this question, we overcome the naïve distinction between developed and emerging countries and provide managers with finer-grained actionable insights. Fourth, does the speed of trickle-down and reverse innovation influence the subsequent performance of innovations? Showing that the speed at which innovations trickle down (up) actually benefits their performance is essential to justify the focus on such aspect of global innovation diffusion.

This paper contributes to the literature in the following ways. First, to the best of our knowledge, this is the first large-scale quantitative study on trickle-down and reverse innovation as it is based on a large sample of 127,782 food products' launches occurred in 51 countries in a 14-year period (from 2001 to 2014). Second, we are the first to show that, contrary to the assumption of the traditional trickle-down paradigm, reverse innovation actually occurs faster than trickle-down. Third, we identify the product characteristics that accelerate trickle-down by showing that, among those innovations initially introduced in developed countries, lower-priced innovations experience a faster trickle-down to emerging countries. Similarly, we identify the product characteristics that accelerate reverse innovation. In doing so, beyond price, we highlight the relevance of two overlooked product characteristics: package size and number of claims. Contradicting the assumption that lower-priced innovations from emerging countries diffuse faster in developed countries (Govindarajan and Ramamurti 2011), we find that higher-priced innovations trickle up faster. Further, we find that innovations with more claims and a smaller package size trickle up faster from emerging countries to developed ones. Fourth, we show that there is heterogeneity across developed countries and across emerging countries with regard to the effects of price, number of claims, and package size on speed of trickle-down and reverse innovation. Hence, we bring forth the necessity of overcoming the simplistic distinction between developed and emerging countries. Finally, we show that a faster diffusion process actually improves the subsequent performance of the innovation, thus supporting the idea that a faster trickle-down and a faster reverse innovation are indeed desirable outcomes.

Global Innovation Diffusion Patterns

The present section describes four alternative global innovation diffusion patterns, which we classify along two dimensions: (1) the first country in which the innovation is launched, distinguishing between developed and emerging countries, and (2) the subsequent countries in which the innovation is launched, distinguishing between innovations that remain in the same type of country or move to countries with a different level of development. Combining these two dimensions we identify the following four global innovation diffusion patterns:

I. *Developed-only*: Innovations initially launched in a developed country that are not subsequently launched in emerging countries;

II. *Emerging-only:* Innovations initially launched in an emerging country that are not subsequently launched in developed countries;

III. *Trickle-down*: Innovations initially launched in a developed country and subsequently in at least one emerging country;

IV. *Reverse innovations*: Innovations initially launched in an emerging country and subsequently in at least one developed country.

We now describe trickle-down and reverse innovations more in detail.

Trickle-Down

In the traditional view of global innovation, developed countries are scientific and technological leaders, host entrepreneurs and consumers, and are, as a result, the only sources of innovations worldwide. Vernon's Life-Cycle Theory (1966) well synthesizes this orthodoxy where emerging countries are relegated to be passive receivers of innovations at the end of their life-cycle: innovations diffuse first horizontally among developed countries and then downward to emerging countries. In pursuing trickle-down, firms remove expensive features from products and sell them in emerging countries at a lower price (Winter and Govindarajan 2015). Thus, an innovation that is eventually launched in emerging countries has lower price and fewer features than the equivalent innovation in developed countries. Such modifications are necessary to meet the needs of resource-constrained consumers in emerging countries.

Reverse Innovation

Immelt and colleagues (2009) coined the term reverse innovation to describe the diffusion pattern of innovations initially launched in emerging countries and then in developed countries. As evidenced by Williamson (2010), innovations launched in emerging countries may, at times, improve their performance to appeal also to consumers in developed countries and therefore trickle up, reversing the traditional cycle depicted in Vernon (1966). Emerging countries are in fact perfect cradles of innovations that may ultimately disrupt established markets by offering an improved price-performance level (Seely-Brown and Hagel 2005).

Hypotheses Development

We now introduce our hypotheses concerning the roles of price, number of claims, and package size in accelerating trickle-down and reverse innovation. We focus on these characteristics because the extant literature has identified three relevant drivers of both trickle-down and reverse innovation (see e.g., Govindarajan and Ramamurti 2011; Prahalad 2004; Winter and Govindarajan 2015): price, product’s attributes and benefits, here proxied by claims, and package size.

Price

Price is a crucial variable in determining the behaviors of consumers (Chandrasekaran, Art, Tellis, and Frambach 2013). We expect it to play a pivotal role in accelerating both trickle-down and reverse innovation.

Trickle-Down. We argue that innovations with lower price will trickle down faster for two main reasons. First, per capita income is a critical discriminant between consumers in emerging and developed countries, with the former having a much smaller disposable income than the latter (Chandrasekaran et al. 2013; Ernst et al. 2015; Govindarajan and Ramamurti 2011). It is hence not surprising that the literature has identified in price the key force behind the adoption of innovations in emerging countries (Hart and Christensen 2002; Williamson 2010). Thus, innovations that target consumers in emerging countries must find a way to dramatically reduce price while delivering an adequate level of performance. Second, independently from their income, consumers from emerging countries value price-consciousness and sophistication in money-handling more and are more price-sensitive than consumers from developed countries (Ackerman and Tellis 2001). Hence, we hypothesize:

> H_{1A}: Among innovations initially launched in developed countries, those characterized by a lower price trickle down faster.

Reverse Innovation. Past research has convincingly shown that consumers in developed countries use price to infer quality, as superior quality typically commands a higher price (Tellis 1986). Price-signaling of quality is common in the case of innovations, whose quality level is still unclear. The problem of quality becomes particularly salient when consumers in developed countries have to buy innovations originally launched in emerging countries, as they may be particularly suspicious about components and production standards (Auriol and Schilizzi 2015). Thus, a higher price associated with an innovation originally launched in emerging countries can make consumers in developed countries more confident about its quality. It is reasonable to hypothesize that consumers in developed countries will use price to infer quality and prefer, among innovations initially launched in emerging countries, those characterized by a higher price. Hence, we hypothesize:

> H_{1B}: Among innovations initially launched in emerging countries, those characterized by a higher price trickle up faster.

Number of Claims

Firms widely use product claims to signal the attributes and benefits of products. As a result, claims are likely to substantially influence consumers' purchase decisions (Chandon 2013; Kozup, Creyer, and Burton 2003). We expect them to play a pivotal role in accelerating both trickle-down and reverse innovation.

Trickle-Down. We argue that innovations characterized by fewer claims will trickle down faster for two main reasons. First, firms may use claims as mere communication tools, as consumers make inferences about products' benefits by generalizing from claims (Chandon 2013). However, many claims can lead to information overload, limiting consumers' ability to process information and increasing the risk of confusion (Malhotra 1982). This problem is particularly salient when consumers have low levels of functional literacy, where being functionally literate refers to having the language and numeracy competencies required to function adequately as adults in day-to-day life (Kirsch and Guthrie 1977). According to Unesco (2008), the vast majority of the functionally illiterate population in the world is today concentrated in emerging countries due to poverty and low educational levels[1]. Such difference impacts the way consumers in emerging countries react to claims. Hence, the marketing information that an innovation conveys via claims needs to be limited as low-literate consumers may have difficulties in processing it (Viswanathan, Rosa, and Harris 2005). Second, the literature emphasizes the need for innovations launched

[1] UNESCO Institute for Statistics. *International Literacy Statistics: A Review of Concepts, Methodology and Current Data*. 2008. Available at: http://unesdoc.unesco.org/images/0016/001628/162808e.pdf

in emerging countries to be defeatured (Govindarajan and Trimble 2012). Price reduction is in fact partially achieved by reducing product benefits at the bare minimum. Hence, as claims reflect product's attributes and benefits (Chandon 2013), we hypothesize that:

> H_{2A}: Among innovations initially launched in developed countries, those characterized by fewer claims trickle down faster.

Reverse Innovation. We argue that innovations with more claims will trickle up faster for two main reasons. First, Govindarajan and Trimble (2012) and Govindarajan and Ramamurti (2011) argue that innovations trickle up to developed countries through a process of progressive improvement. As claims reflect product's attributes and benefits (Chandon 2013), we can expect innovations with more claims, i.e., enriched innovations, to trickle up faster. Second, claims, just like price, may act as signals of quality (Kozup et al. 2003). As consumers in developed countries may be particularly skeptical of quality when innovations come from emerging countries, more claims associated with an innovation initially targeted at emerging countries can make them more confident. Hence, we hypothesize:

> H_{2B}: Among innovations initially launched in emerging countries, those characterized by more claims trickle up faster.

Package Size

The literature has frequently evidenced the crucial role of package size in innovating for emerging countries (see e.g., Prahalad 2004). We expect package size to play a pivotal role in accelerating both trickle-down and reverse innovation.

Trickle-Down. Consumers in emerging countries differ from those in developed countries with respect to their life habits. In particular, we expect two main differences to be essential when it comes to the role of package size in accelerating trickle-down: means of transportation and house size. First, in developed countries, the most common mean of transportation is by large the car while, in emerging countries, consumers usually move by motorcycle or bicycle[2]. Second, consumers in emerging countries live in much smaller houses than consumers in developed countries[3]. Consumers in emerging countries may therefore not have enough room to store large items in their houses. Similarly, they may not be able to transport them from the store to their house, being forced to buy small packages (Prahalad 2004). Further, lower disposable income implies that consumers in emerging countries cannot afford paying all at once for the same quantity of product as consumers in developed countries do. It is therefore accepted in the literature that innovations launched in emerging countries have to come in smaller size than innovations launched in developed countries (Prahalad 2004). Thus, we hypothesize:

> H_{3A}: Among innovations initially launched in developed countries, those characterized by a smaller package size trickle down faster.

Reverse Innovation. Consumers in developed countries usually own houses large enough to store products, cars to transport them, and enough incomes to afford the higher unitary prices associated with larger sizes. Hence, they can afford to buy large packages to avoid multiple trips to the store and, in the meantime, save money, as products in large packages typically cost less per unit volume (Granger and Billson 1972). According to Prahalad (2004), consumers in developed countries use their money to obtain more convenient prices. Thus, we can expect them to prefer, among innovations initially launched in emerging countries, those with a larger package size, which allows them to save both time and money:

> H_{3B}: Among innovations initially launched in emerging countries, those characterized by a larger package size trickle up faster.

---

[2] Pew Research Center. *Car, bike or motorcycle? Depends on where you live*. 2015. Available at: http://www.pewresearch.org/fact-tank/2015/04/16/car-bike-or-motorcycle-depends-on-where-you-live/
[3] United Nations Population Division. *Charting the Progress of Populations.* 2000. Available at: http://www.un.org/esa/population/pubsarchive/chart/2.pdf

Method

In this section, we describe the sample and measures used in the paper.

Sample

We test our hypotheses in the packaged food industry, a $1.8 trillion market that has grown at 4% between 2001 and 2011 (Howard, Hunter, and Wislo 2011). Innovation is endemic in this industry (Van Heerde, Mela, and Manchanda 2004) and several scholars have recently selected it as their setting in the study of innovation (see e.g., Moorman, Ferraro, and Huber 2012; Sorescu and Spanjol 2008). The growing relevance of emerging countries in the packaged food industry makes it a particularly appropriate context for our study. While in 2001 emerging countries were responsible for only 20% of sales in this industry, in 2011 they represented 34%, and are expected to contribute to 70% of growth in the next years (Howard et al. 2011), presumably taking on a crucial innovative role. Further, anecdotal evidence suggests that this industry is particularly appropriate for our study. For instance, Govindarajan and Trimble (2012) make the case of Pepsico's salted snack Kurkure as constituting an exemplary case of reverse innovation. On the other hand, Cheetos, another Pepsico's snack, after being initially launched in the U.S. market, are now massively distributed in China, India, and Brazil, thus constituting a clear example of trickle-down.

We collect data on innovation launches in 51 countries from Mintel GNPD, a database that records launches in the packaged food industry and provides a wide range of detailed information including, among others, ingredients, price, claims, and the date an innovation is launched in a specific country. Mintel GNPD categorizes launches in five categories: New Product, New Packaging, New Variety, New Formulation, and Re-launch. In order to capture launches that contain a sufficient degree of novelty in terms of benefits offered to consumers (Chandy and Tellis 1998), we focus on launches that are classified alternatively as “New Product” or “New Packaging”[4]. Further, as Mintel GNPD comprises more than one million launches in the period under study, in order to make our analysis feasible, we focus on three categories: bakery, baby food, and snacks. Collectively, these categories account for around 28% of the total number of food products introduced globally from 1996 to 2014.

As our analyses rely on tracking the diffusion of innovations across countries using the different launches associated with each innovation, we pay particular care in cleaning the data in order to ensure that the same innovation is correctly identified, even though it is reported with slightly different names across different launches. For instance, donuts are identified in the original database also as doughnuts. We consider these alternative labels as referring to the same innovation. Similarly, apple and carrot juice is originally identified also as apple-carrot Juice, apple & carrot juice, and so on.

We limit our analysis to the 2001-2014 period. This choice is due to the fact that we have data on launches from June 1996 on only. We could hence wrongly code an innovation as being introduced for the first time after June 1996, when instead it was launched before. As an example, in our database, potato chips appear for the first time in September 1996 in Belgium. It is very likely, however, that the innovation “potato chips” was launched for the first time way before 1996, therefore not being an innovation when it first appears in our database. In order to solve this issue and make sure that all the launches in our database represent real innovations when they first appear, we remove all those innovations that are introduced at least once before the end of 2000. It is in fact reasonable to assume that innovations that never appear in our database before January 2001 are real innovations when they first appear. As an example, bloody mary potato chips appear for the first time in

[4] We run our analyses also excluding launches that are classified as “New Packaging”. Results do not change.

October 2002 and hence are retained in our sample. Our final sample comprises 66,810 innovations for a total of 127,782 launches in 51 countries between 2001 and 2014. Of these innovations, 35,662 are developed-only (53%), 24,538 emerging-only (37%), 3,714 trickle-down (6%), and 2,896 reverse innovations (4%). An overview of the structure of our database, where launches are nested in innovations, is presented in Table 1.

---- Insert Table 1 here ----

Measures

This section explains the measures in our study, which we report in Table 2.

---- Insert Table 2 here ----

Descriptive statistics and correlations among variables are reported in Tables 1_A and 1_B in the Appendix. Variance Inflation Factors are all well below 10. Our unit of analysis is the single innovation (e.g., seafood samosa) for which we track the number of days that pass between the first launch in an emerging (developed) country and the first launch in a developed (emerging) country.

Trickle-down. We indicate trickle-down with a dummy variable taking on value 1 if the innovation is initially launched in a developed country and subsequently in at least one emerging country; 0 otherwise. We classify countries according to the World Economic Outlook, a report published twice a year by the International Monetary Fund. The WEO portrays the current condition of the world economy with projections for up to four years, including key macroeconomic indicators, such as GDP and fiscal balance. The only country undergoing a change in the classification in the period under study is Czech Republic, classified as developed from 2009 on.

Reverse Innovation. We use a dummy variable taking on value 1 if the innovation is initially launched in an emerging country and subsequently in at least one developed country; 0 otherwise.

Time to Trickle-down. It is the number of days between the first launch of the innovation in a developed country and its first launch in an emerging country.

Time to Reverse Innovation. It is the number of days between the first launch of the innovation in an emerging country and its first launch in a developed country.

Price. We measure price as the price in Euros of one unit of product.

Package Size. We measure package size as product's weight in grams.

Number of Claims. This is a count variable recording the number of distinct product claims associated with a given launch. Examples of claims are "gluten-free" or "sugar-free".

Control Variables. In order to reduce spuriousness of results, we include a number of control variables. First, we control for Previous Launches, by counting the number of times a given innovation is introduced in countries of the initial type (e.g., developed) before the current launch. In adding this covariate, we control for the fact that innovations that experience more launches in countries of the initial type may be more likely to be launched in another type of country. For the same reason, since an innovation may be introduced several times in the same country by different firms, we also control for the number of Previous Countries of the initial type in which an innovation has been introduced before the current launch. We also control for type of launch (i.e., new product vs. new packaging) with a dummy variable taking on value 1 if a specific launch is a package innovation and 0 otherwise. Further, we include year fixed effects for the year a specific innovation is first launched onto the market, country fixed effects, and category fixed effects, to control for possible heterogeneity across countries and across categories.

Results

In this section, we present analyses and results related to our four research questions.

Which Diffusion Process Occurs Faster?

Our first research question is about whether it takes shorter for trickle-down or to reverse innovation to occur. Figure 1 reports the incidence of trickle-down and reverse innovations over total yearly launches in 2001-2014 and shows that the incidence of both trickle-down and reverse innovations has increased in recent years, especially after 2006.

---- Insert Figure 1 here ----

We find that, on average, it takes 1,332 days for an innovation to trickle down and 1,177 days for an innovation to trickle up. The difference between the two time lags, i.e., 155 days, is statistically significant (t = 6.05, $p < 0.01$), thus suggesting that, on average, reverse innovation takes shorter than trickle-down to occur. Hence, our finding contradicts the traditional paradigm of global innovation diffusion rooted in Vernon (1966), according to which trickle-down occurs faster than reverse innovation.

Which Product Characteristics Accelerate Trickle-Down and Reverse Innovation?

We start presenting model-free evidence about differences in the average characteristics that trickle-down and reverse innovations take on when introduced in emerging and developed countries. We then run hazard models to test how product characteristics accelerate trickle-down and reverse innovation.

Model-free Evidence

Trickle-Down (3,714 innovations). We find that trickle-down innovations have a higher price (2.64 vs. 1.89, t = 22.41, $p < 0.01$), higher price per gram (0.03 vs. 0.02, t = 4.21, $p < 0.01$), more claims (1.88 vs. 1.69, t = 7.10, $p < 0.01$), and larger packages (237.06 vs. 223.44, t = 3.23, $p < 0.01$) when sold in developed countries than when sold in emerging countries, after trickle-down.

Reverse Innovation (2,896 innovations). We find that reverse innovations have a higher price (2.50 vs. 1.64, t = 25.42, $p < 0.01$), higher price per gram (0.03 vs. 0.02, t =

7.36, $p < 0.01$), more claims (1.93 vs. 1.40, t = 17.96, $p < 0.01$), and larger packages (235.62 vs. 221.44, t = 3.17, $p < 0.01$) when sold in developed countries, after reverse innovation, than when sold in emerging countries.

Hazard Models

In order to investigate the roles of price, number of claims, and package size in accelerating trickle-down and reverse innovation, we now estimate three parametric hazard models: (1) a model with time-invariant covariates, where product characteristics are averaged across launches for the same innovation before trickle-down (reverse innovation) or right-censoring; (2) a model with time-varying covariates, where we use the characteristics associated with consecutive launches to track the evolution of the innovation in the market over time; and (3) a model with time-varying covariates and a shared frailty effect at the innovation level to allow for intra-innovation correlation across launches. Figure 2 provides a graphical explanation of the difference between (1) and (2).

---- Insert Figure 2 here ----

Endogeneity Issues. Before discussing our hazard models analysis, we discuss possible biases in our results due to endogeneity. Specifically, we identify three potential sources of endogeneity. First, time effects may affect the speed at which innovations trickle up (down). For instance, there might be years during which consumers in developed (emerging) countries are particularly open to innovations from emerging (developed) countries. During these years innovations might trickle up (down) faster. If this were the case, then time effects rather than product characteristics would, at least partially, drive time to reverse innovation (trickle-down). To control for unobserved time effects, we include year fixed effects.

Second, consumers in developed (emerging) countries may be more open to innovations from emerging (developed) countries in some categories than in others. Hence, unobserved heterogeneity across categories might drive time to reverse innovation (trickle-down). We control for this with category fixed effects.

Third, consumers in developed (emerging) countries may be more open to innovations that were last introduced in a specific emerging (developed) country. We control for this with fixed effects for the last country in which the innovation was launched before the current launch.

Further, one may argue that some unobserved firm-level considerations might drive both the characteristics of innovations when they trickle up and time to reverse innovation, as the firm that decides to introduce an innovation from emerging countries for the first time in a developed country (i.e., trickle up) also sets the characteristics of the innovation in this new country. However, this is not a concern in our analysis because we do not look at the characteristics that innovations take on when they trickle up, but at their characteristics *before* reverse innovation. For instance, in the case depicted in Figure 2, the firm that introduces innovation *i* in India is not necessarily the same firm that has introduced the innovation in the U.K., Japan, or the U.S.. Hence, there is no endogeneity as the firm that decides to trickle up an innovation is not the same firm that sets the characteristics of the innovation before the event. Similar considerations hold for trickle-down.

Hazard Models with Time-Invariant Covariates. We present two models. Model 1_A in Table 3 compares developed-only and trickle-down innovations. Both types of innovations are first introduced in developed countries; the latter are eventually launched in emerging countries too. Model 1_B in Table 3 compares emerging-only and reverse innovations. Both types of innovations are first introduced in emerging countries; the latter are eventually launched in developed countries too.

Since our data are right censored, i.e., not all innovations trickle down (up) by the end of our observation period, we cannot use standard regression. In particular, in Model 1_A, only 3,714 innovations out of the 39,376 that are first introduced in a developed country trickle down by the end of 2014. Similarly, in Model 1_B, only 2,896 innovations out of the 27,434 that are first introduced in an emerging country trickle up by the end of 2014. Hence, we use a Hazard Model, which allows right-censored observations. The dependent variable is here made up of two parts: (1) the time to event, i.e., time to trickle-down or reverse innovation, and (2) the event status, which records if the event of interest has occurred or not at a certain date. For the sake of simplicity, we present Model 1_A only. Here, the failure indicator takes on value 1 if the innovation initially launched in a developed country is eventually launched in an emerging country and 0 if the innovation is right-censored. We treat innovation's characteristics as time-invariant and average price, number of claims, and package size across all launches for the innovation before trickle-down or right-censoring.

Let T be a non-negative continuous random variable with distribution $F(t)$ and density $f(t) = df(t)/dt$ that represents the time in days between the first launch of the innovation in a developed country and its first launch in an emerging country or right-censoring (Tellis, Stremersch, and Yin 2003). The survival function, or the probability that such time will be at least *t*, is:

$$S(t) = \Pr(T > t) = 1 - F(t) \quad (1)$$

Then, the hazard function, or the probability that such time will be interrupted after time *t*, given that it has lasted until time *t*, is:

$$h(t) = \lim_{\Delta t \to 0} \Pr[t \leq T < t + \Delta t | T \geq t] / \Delta t = f(t)/S(t) \quad (2)$$

In presence of time-invariant covariates, the hazard function becomes:

$$h(t|X) = \lim_{\Delta t \to 0} \Pr[t \leq T < t + \Delta t | T \geq t, X] / \Delta t = f(t)/S(t) \quad (3)$$

where X is the vector of time-invariant covariates. We test a Weibull Distribution, suitable for modeling data with monotone hazard rates, which can be written as:

$$h(t) = p\lambda t^{p-1} \quad (4)$$

while the survival function can be written as:

$$S(t) = e^{-\lambda t^{p}} \quad (5)$$

where *p* is a parameter to be estimated from the data. When *p* is greater than 1, the expected hazard rate increases over time; when *p* is smaller than 1, the expected hazard rate decreases over time. We provide results in the no-hazard rates metric and present coefficients rather than exponentiated coefficients. Positive *b* coefficients increase the speed of trickle-down (Model 1_A) or reverse innovation (Model 1_B) while negative *b* coefficients decrease the speed of trickle-down (Model 1_A) or reverse innovation (Model 1_B).

---- Insert Table 3 here ----

We report results in Table 3. We find that an increase in unitary price decelerates trickle-down (b = -0.03, $p < 0.01$), while accelerating reverse innovation (b = 0.03, $p < 0.01$), in support of H_{1A} and H_{1B}. In order to facilitate the interpretation of the estimated coefficients, we determine, via the transformation 100 (e^{b} - 1), the percentage change in the expected hazard rate for a one-unit increase in the focal variable. Thus, 100 ($e^{-0.03}$ - 1) = -2.96% indicates the percentage decrease in the expected hazard rate of trickle-down for each one-unit increase in unitary price, holding the other regressors constant. Similarly, a one-unit increase in unitary price increases the hazard rate of reverse innovation by 3.05%. Number of claims has no effect on the hazard rate of trickle-down (b = -0.01, $p > 0.05$). Hence, H_{2A} is not supported. We also find that an increase in number of claims accelerates reverse innovation (b

= 0.09, $p < 0.01$), in support of H_{2B}, indicating that an additional claim increases the hazard rate of reverse innovation by 9.42%. Package size has no effect on trickle-down (b = 0.00001, $p > 0.05$), not supporting H_{3A}. Contradicting H_{3B}, a larger package size decelerates reverse innovation (b = -0.0003, $p < 0.01$): an increase of 100g in package size decreases the hazard rate of reverse innovation by 3%. As for the control variables, we find that number of previous developed countries accelerates trickle-down (b = 0.25, $p < 0.01$); number of previous emerging countries (b = 0.41, $p < 0.01$) accelerates reverse innovation; number of previous launches in emerging countries decelerates reverse innovation (b = -0.04, $p < 0.01$).

Hazard Models with Time-Varying Covariates. We now change our initial model to take into account the evolution of innovation characteristics over consecutive launches before trickle-down (reverse innovation) or right-censoring. Let t_k be the time at which trickle-down (reverse innovation) or right-censoring takes place. Following Tellis et al. (2003), we divide t_k into K non-overlapping time intervals, which can have different durations. Let t_0 be the initial launch date and $t_0 < t_1 < \cdots < t_{j-1} < t_j < \cdots < t_k$. Each time interval starts and ends when a new launch takes place. More specifically, when a launch takes place at t_0, its characteristics are assumed to persist until t_1, when a new launch takes place, and so on. Further, each time interval is associated with a failure indicator that takes on value 1 if, eventually, the innovation experiences trickle-down or reverse innovation, 0 otherwise. Hence, if innovation *i* is launched at t_0 in the U.S., at t_1 in Japan, at t_2 in U.K., and at t_3 in India, the failure indicator takes on value 0 in correspondence of the $t_0 - t_1$ and the $t_1 - t_2$ time intervals, as the innovation does not experience trickle-down at t_1 and t_2, and value 1 in correspondence of the $t_2 - t_3$ time interval, because at the end of this period, at t_3, the innovation experiences trickle-down to India. For each right-censored innovation we add an observation that takes place at the end of our data collection period, as we know that such innovations have not trickled down by December 2014. Finally, when multiple launches for a given innovation take place the same day, we retain only one observation and average its characteristics across those simultaneous launches.

The hazard rate takes now the following form (Tellis et al. 2003):

$$h(t|X(t)) = \lim_{\Delta t \to 0} \Pr[t \leq T < t + \Delta t | T \geq t, X(t)] \, / \, \Delta t = f(t)/S(t) \qquad (6)$$

We estimate equation 6 in Models 2_A and 2_B by assuming a Weibull Distribution. We cluster launches at the innovation level to account for possible correlation among errors across different launches for the same innovation. This new specification allows us to control for additional variables related to each launch. In particular, we control for type of launch (1 for New Packaging, 0 otherwise) and for the country in which each launch takes place. Further, for each launch, we control for firm experience in the category, which we measure as the number of launches a firm has undertaken in a category before the current launch. For instance, for a launch in the snacks category by firm *i*, we code firm experience as the number of launches firm *i* has undertaken in the snacks category up to the current date, focal launch excluded. Similarly, we measure firm experience in the focal country as the number of launches a firm has undertaken in a country before the current launch.

In our data, launches are nested within innovations. Hence, in Models 3_A and 3_B we test a two-level model and introduce a shared frailty term at the innovation level to allow for intra-innovation correlation across launches. Across innovations, the frailties are assumed to be gamma-distributed unobserved random effects that act multiplicatively on the hazard rate. For each observation *l* (i.e., launch) in each group *i* (i.e., innovation), a shared frailty model defines:

$$h(t_{li} \mid g_i) = g_i \, h(t_{li}) \qquad (7)$$

where g_i is the random effect at the innovation-level, modeled for innovation *i* and shared by all the launches *l* pertaining to the same innovation *i*. The estimated variance of g_i, θ, measures the extent of within-group correlation.

We report results in Table 3. For brevity reasons and since results are consistent across Models 2 and 3, we comment on the results of Models 3_A and 3_B only as they are characterized by slightly lower AIC and BIC (Model 2_A: 23,007.58 and 23,449.63; Model 3_A: 22,491.84 and 22,942.56; Model 2_B: 19,900.78 and 20,317.56; Model 3_B: 19,710.07 and 20,135.36). Both Models 3_A and 3_B are significant (χ^2_a = 1,873.36, $p < 0.01$ and χ^2_b = 1,442.17, $p < 0.01$). The ancillary parameters (p_a = 0.90 and p_b = 0.89) indicate that the hazard rates decrease over time, i.e., the longer the innovation has been in the market without trickling down (up) the lower are its chances of doing it in the future. In both cases we find a significant frailty effect, meaning that the correlation within innovation cannot be ignored (θ_a = 3.45, $p < 0.01$ and θ_b = 2.72, $p < 0.01$). We find that unitary price decelerates trickle-down (b = -0.04, $p < 0.01$) while accelerating reverse innovation (b = 0.11, $p < 0.01$), in support of H_{1A} and H_{1B}. Number of claims has no effect on trickle-down (b = 0.002, $p > 0.05$). Hence, H_{2A} is not supported. Number of claims significantly accelerates reverse innovation (b = 0.11, $p < 0.01$), in support of H_{2B}. Package size has a non-significant impact on trickle-down (b = -0.00003, $p > 0.05$). Hence, H_{3A} is not supported. Finally, contrarily to H_{3B}, an increase in package size decelerates reverse innovation (b = -0.0004, $p < 0.01$). These findings are consistent with the findings from Models 2_A and 2_B. Looking at control variables, number of previous emerging countries (b = 0.99, $p < 0.01$) and number of previous launches in emerging countries (b = 0.06, $p < 0.01$) accelerate reverse innovation. Similarly, number of previous developed countries (b = 0.84, $p < 0.01$) and number of previous launches in developed countries (b = 0.24, $p < 0.01$) accelerate trickle-down.

Robustness Checks

We now test the robustness of our findings. We present the results in the Appendix.

Different Time Periods. In order to analyze only innovations that are really new-to-the-world when they first appear in the database, we removed from Models 3_A and 3_B all the innovations that had been introduced at least once between June 1996 and December 2000. We re-estimate Models 3_A and 3_B by 1) removing also innovations introduced at least once in 2001 and 2) removing only innovations introduced at least once between 1996 and 1999. Our results do not change (see Table 2 in the Appendix).

Price per Gram. We replicate Models 3_A and 3_B by adding price per gram to the set of regressors. Our results do not change (see Table 3 in the Appendix).

Covariates' Standardization. Recall that our sample contains substantially different innovations ranging from potato-based snacks to growing-up milk. In order to account for the fact that different innovations may be characterized by inherently different characteristics, we mean-center price, number of claims, and package size at the subcategory-country type level and replicate Models 3_A and 3_B. As an example, a positive unitary price indicates here that the product has a higher price than the average product launched in the same subcategory (e.g., potato-based snacks, corn-based snacks) and in the same type of country. Our results do not change (see Table 3 in the Appendix).

Alternative Distributional Assumptions. We check the sensitivity of results to alternative distributional assumptions. In Models 3_A and 3_B, we replace the Weibull distribution with Exponential and Gompertz Distributions. We find that our distributional assumption does not affect significantly our results (see Table 4 in the Appendix).

Relaxing the Proportionality Assumption. We replace the Hazard Model with an Accelerated Failure Time Model, which relaxes the proportionality assumption when distributions different from the Weibull one are assumed. The main difference between the two models is that the effect of covariates is multiplicative on time in the Accelerated Failure Time Model, while it is multiplicative on hazard in the Hazard Model. We use Exponential, Lognormal, and Log-logistic distributions to estimate the Accelerated Failure Time Models. As expected, point estimates take here the opposite signs with respect to the Hazard Models so that the interpretation of results is not affected (see Table 5 in the Appendix).

Is there Heterogeneity in the Effects of Product Characteristics Across Specific Developed and Emerging Countries?

So far we treated all emerging and developed countries alike. For instance, take two innovations: the first one is first launched in the U.S. and then in India; the second one is first launched in the U.S. and then in Brazil. In the previous sections, the two innovations were both considered examples of trickle-down. We now take our analyses one step further by focusing on trickle-down and reverse innovation to a specific country or from a specific country. In doing so, we select the top four developed countries, i.e., the countries that originate the highest number of innovations in our sample among developed countries: U.S. (7,852 innovations), U.K. (3,416 innovations), Germany (2,917 innovations), and Japan (2,584 innovations). Similarly, we select the top four emerging countries: China (5,875 innovations), India (4,077 innovations), Brazil (2,226 innovations), and Mexico (1,862 innovations). Collectively, these countries account for 46% of the innovations in our sample.

When focusing on the U.S., we investigate the roles of price, number of claims, and package size in driving (1) trickle-down in emerging countries of innovations initially introduced in the U.S. and (2) reverse innovation to the U.S. of innovations initially introduced in emerging countries. In this case, we drop all those innovations that are initially launched in a developed country other than the U.S.. Then, we re-estimate Models 3_A and 3_B

with this newly defined sample. We proceed analogously for other developed countries and for emerging countries. We graphically report the results of these analyses in Table 4.

---- Insert Table 4 here ----

Dots represent point estimates while horizontal bars represent the limits of the estimated confidence interval for each estimate. Confidence intervals that do not contain zero indicate that an increase in the variable of interest has a significant effect (whether positive or negative) on time to trickle-down or reverse innovation. Results from Model 4_A show that an increase in price decelerates trickle-down from Japan (b = -0.20, $p < 0.05$) and, marginally, from the U.S. (b = -0.03, $p = 0.08$). Results from Model 4_B show that an increase in number of claims decelerates trickle-down to China (b = -0.07, $p < 0.05$) while accelerating, marginally, trickle-down to Mexico (b = 0.05, $p = 0.056$). Further, we find that an increase in package size accelerates trickle-down to Brazil (b = 0.0001, $p < 0.05$). In Model 5_A, we find that an increase in price accelerates reverse innovation to the U.S. (b = 0.09, $p < 0.01$) and, marginally, to the U.K. (b = 0.06, $p = 0.06$) and Germany (b = 0.05, $p = 0.089$). Further, an increase in number of claims accelerates reverse innovation to both the U.S. (b = 0.11, $p < 0.01$) and the U.K. (b = 0.15, $p < 0.01$). We also find that an increase in package size marginally accelerates reverse innovation to Germany (b = 0.0001, $p = 0.066$). Finally, in Model 5_B, we find that an increase in price accelerates reverse innovation from India (b = 0.27, $p < 0.01$), Mexico (b = 0.14, $p < 0.01$), and Brazil (b = 0.11, $p < 0.01$). Similarly, an increase in number of claims accelerates reverse innovation from China (b = 0.25, $p < 0.01$) and Mexico (b = 0.08, $p < 0.05$), while an increase in package size decelerates reverse innovation from Brazil (b = -0.001, $p < 0.05$). Hence, we can conclude that, despite the general pattern of results is mostly consistent with results from Models 3_A and 3_B, heterogeneity subsists in the effects of product characteristics across specific developed and emerging countries. We note here that many non-significant coefficients are actually close to statistical significance at the 5% level or, at least, at the 10% level. We believe that part of this scant significance is due to the smaller sample sizes available to run these analyses if compared to Models 3_A and 3_B and, in particular, to the limited number of failure events, here ranging between 186 and 720.

Does the Speed of Trickle-Down and Reverse Innovation Influence the Subsequent Performance of Innovations?

Our fourth research question investigates whether speed of trickle-down (reverse innovation) influences the performance of innovations after they trickle down (up). Unfortunately, there is no sales data available to measure performance. Hence, we measure the performance of a trickle-down innovation using the number of launches in emerging countries after the innovation trickles down. We reason that, if an innovation is successful, many firms will try to imitate it and hence we will observe many launches. Our dependent variable is thus the average number of launches in emerging countries for the innovation in a year after trickle-down. We obtain this variable as follows: (1) for each innovation we count the overall number of launches in emerging countries after trickle-down, (2) we divide this number by the number of days elapsing between trickle-down and the end of our data collection period, i.e., December 31st 2014, in order to obtain the average number of launches in emerging countries for the innovation in a day, (3) we finally multiply the obtained number by 365 in order to get the average number of launches in emerging countries for the innovation in a year. Our data may suffer from selection bias as it might be that, among those innovations initially launched in developed countries, only the best ones trickle down. This superior quality may also influence subsequent performance in emerging countries. Hence, we employ a two-step Heckman's sample selection model. In the first-stage, we predict an innovation's individual probability to experience trickle-down by using the same regressors previously employed in Model 1_A. We then compute the Inverse Mills ratio and, in order to correct for selection bias, add it in the second-stage to estimate the impact of time to trickle-down on performance. We take the log of both time to trickle-down and performance in order to facilitate the interpretation of results. We proceed analogously for reverse innovations.

---- Insert Table 5 here ----

Results, reported in Table 5, show that the estimated selection coefficient, lambda, is significant in both Models 6_A ($\lambda = -0.33$, $p < 0.05$) and 6_B ($\lambda = -0.21$, $p < 0.01$), indicating that we are correcting for selection bias. The results of the first-stage equations are consistent with the results of our hazard models. As for the second-stage equations, Model 6_A shows that time to trickle-down has a negative effect on performance (b = -0.04, $p < 0.01$): a 1% increase in time to trickle-down decreases by 4% the average number of launches in a year for the innovation. Model 6_B shows that time to reverse innovation has a negative effect on performance (b = -0.05, $p < 0.01$): a 1% increase in time to reverse innovation decreases by 5% the average number of launches in a year for the innovation. Hence, we show that fast is indeed better and that innovations that trickle down (up) earlier experience greater success at later stages, after controlling for the fact that only innovations with certain characteristics trickle down (up). We estimate a similar model using OLS and dropping developed-only and emerging-only innovations. Results do not change.

Discussion

This study offers, to the best of our knowledge, the first large-scale empirical investigation of trickle-down and reverse innovation, an area where most contributions are anecdotal in nature and focused on a narrow set of countries, namely China and India. In doing so, we answer calls from marketing scholars to conduct more research on emerging countries (see e.g., Banerjee et al. 2015; Sheth 2011). Our analysis yields the following results:

- On average, trickle-down innovation takes longer than reverse innovation to occur;
- An increase in price and number of claims and a decrease in package size accelerate reverse innovation, while a decrease in price accelerates trickle-down;
- There is heterogeneity in the effects of these product characteristics even across specific emerging countries and across specific developed countries;
- The faster a product trickles down (up), the better its subsequent performance.

These results provide new and important insights to marketing academics and practitioners interested in better understanding the phenomena of trickle-down and reverse innovation.

First, our findings contradict the dominant perspective in the global innovation diffusion literature by showing that reverse innovation actually occurs faster than trickle-down. This result, combined with the numerous recent examples of successful reverse innovations across different industries, provides compelling evidence that reverse innovation indeed represents a viable alternative to trickle-down for multinationals traditionally operating in developed countries as well as a fruitful avenue for emerging countries' firms that aim to expand to developed countries. Second, by building on anecdotal evidence scattered across the literature (e.g., Govindarajan and Ramamurti 2011; Immelt et al. 2009; Prahalad 2004), this study highlights the role of three relevant product characteristics in accelerating global innovation diffusion. More specifically, the results indicate that price, number of claims, and package size all influence trickle-down and reverse innovation. These results provide evidence that, in order to unlock additional sources of cash flow by opening up new geographic markets for their innovations, firms need to carefully manage traditional marketing levers via the decisions concerning price, number of claims, and package size. As an example, if an emerging countries' firm aims to launch an innovation from emerging to developed countries, it may increase price and number of claims in order to signal superior quality to developed countries' consumers. Interestingly, some of our findings contradict previous contributions. In particular, our finding that higher-priced innovations from emerging countries diffuse faster to developed countries challenges the assumption that a key driver behind reverse innovation is the fact that low-priced innovations from emerging countries meet the needs of financially-constrained consumers in developed countries in periods of economic downturn. Similarly, our finding that innovations with a smaller package trickle up faster to developed countries runs contrary to the literature and may be rooted in recent trends toward snacking and in a health-conscious desire to keep portions small (Ordabayeva and Chandon 2013). Recent research suggesting that consumers associate smaller package sizes with superior quality (Yan, Sengupta, and Wyer 2013) could also contribute to explaining this unexpected finding. Third, we extend the extant literature by overcoming the simplistic distinction between emerging and developed countries. Thus, rather than simply distinguishing between two groups of countries, this research deepens our understanding of trickle-down and reverse innovation by taking into account each country's specificities with respect to the previously identified roles of price, number of claims, and package size. Consistent with the argument that the emerging country label, just like the developed country one, actually hides substantial heterogeneity (Von Zedtwitz et al. 2015), our results indicate that the same characteristics may display opposite effects in countries belonging to the same group. Managerially, the results from our study provide practitioners with finer-grained actionable insights, by offering them detailed guidelines necessary to accelerate trickle-down and reverse innovation to specific countries. As an example, a firm willing to accelerate its innovation diffusion to emerging countries should reduce its number of claims when targeting China and increase it when targeting Mexico. Fourth, we find that the speed at which innovation diffusion occurs significantly influences an innovation's subsequent performance. While most research in this area has been engaged in understanding the processes of trickle-down and reverse innovation, our study empirically establishes a linkage between diffusion process speed and innovation performance. In doing so, it confirms the relevance of our findings by making it clear that knowing how to accelerate trickle-down and reverse innovation is indeed a crucial takeaway for firms operating in today's hypercompetitive environment.

Limitations and Directions for Future Research

Although this study provides relevant insights, it has some limitations that should be considered fruitful avenues for future research. First, our analysis is limited to one industry. While the packaged food industry is obviously a substantive component of the overall global economy and, as such, has generated considerable research interest (e.g., Moorman et al. 2012; Sorescu and Spanjol 2008), empirical testing in other industries would be beneficial to demonstrate the generalizability of our findings. Second, apart from experience in a given category or in a given country, we do not have information on the characteristics of the firm that launches an innovation. Future contributions could investigate the role of firm's characteristics, beside product's characteristics, in accelerating both trickle-down and reverse innovation. Third, we do not have information on the location where innovations were initially conceptualized and developed, but just on where they were launched. Von Zedtwitz and colleagues (2015) recently proposed a broader typology of reverse innovation centered around four phases: (1) conceptualization, (2) development, (3) primary market launch, and

(4) secondary market launch. Acquiring information on the first two phases could help in better understanding the role of emerging countries in the global innovation diffusion process. Finally, future contributions could better investigate the role of package size in trickle-down and reverse innovation as our findings contradict most of the extant literature.

References

Ackerman, David and Gerard J. Tellis (2001), "Can Culture Affect Prices? A Cross-Cultural Study of Shopping and Retail Prices," *Journal of Retailing*, 77 (1), 57-82.

Auriol, Emmanuelle and Steven G.M. Schilizzi (2015), "Quality Signaling through Certification in Developing Countries," *Journal of Development Economics,* 116 (C), 105-121.

Banerjee, Sourindra, Jaideep C. Prabhu, and Rajesh K. Chandy (2015), "Indirect Learning: How Emerging-Market Firms Grow in Developed Markets," *Journal of Marketing,* 79 (1), 10-28.

Car, bike or motorcycle? Depends on where you live. 2015. Pew Research Center. Available at: http://www.pewresearch.org/fact-tank/2015/04/16/car-bike-or-motorcycle-depends-on-where-you-live/.

Chandon, Pierre (2013), "How Package Design and Packaged-based Marketing Claims Lead to Overeating," *Applied Economic Perspectives and Policy,* 35 (1), 7-31.

Chandrasekaran, Deepa, Joep W.C. Arts, Gerard J. Tellis, and Ruud T. Frambach (2013), "Pricing in the International Takeoff of New Products," *International Journal of Research in Marketing,* 30 (3), 249-264.

Chandy, Rajesh K. and Gerard J. Tellis (1998), "Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize," *Journal of Marketing Research,* 35 (4), 474-487.

Ernst, Holger, Hanna N. Kahle, Anna Dubiel, Jaideep C. Prabhu, and Mohan Subramaniam (2015), "The Antecedents and Consequences of Affordable Value Innovations for Emerging Markets," *Journal of Product Innovation Management,* 32 (1), 65-79.

Govindarajan, Vijay and Chris Trimble (2012), *Reverse Innovation, Create Far From Home, Win Everywhere*. Boston, MA: Harvard Business Review Press.

---- and Ravi Ramamurti (2011), "Reverse Innovation, Emerging Markets, and Global Strategy," *Global Strategy Journal*, 1 (3-4), 191-205.

Granger, Clive W.J. and Andrew Billson (1972) "Consumers' Attitudes toward Package Size and Price," *Journal of Marketing Research,* 9 (3), 239-248.

Hart, Stuart L. and Clayton M. Christensen (2002) "The Great Leap: Driving Innovation from the Base of the Pyramid," *MIT Sloan Management Review,* 44 (1), 51-56.

Howard, A, E. Hunter, S. Wislo (2011), *U.S. Food's Growing Pains: Challenges in the United States and Overseas*. New York, NY: Sanford C. Bernstein & Co.

Immelt, Jeffrey R., Vijay Govindarajan, and Chris Trimble (2009), "How GE is Disrupting Itself," *Harvard Business Review,* 87 (10), 56-65.

International Literacy Statistics: A Review of Concepts, Methodology and Current Data (2008). UNESCO Institute for Statistics. Available at: http://unesdoc.unesco.org/images/0016/001628/162808e.pdf.

Kirsch, Irwin and John T. Guthrie (1977), "The Concept and Measurement of Functional Literacy," *Reading Research Quarterly*, 13 (4), 485-507.

Kozup, John C., Elizabeth H. Creyer, and Scot Burton (2003), "Making Healthful Food Choices: The Influence of Health Claims and Nutrition Information on Consumers' Evaluations of Packaged Food Products and Restaurant Menu Items," *Journal of Marketing,* 67 (2), 19-34.

Malhotra, Naresh K (1982), "Information Load and Consumer Decision Making," *Journal of Consumer Research*, 8 (4), 419-430.

Moorman, Christine, Rosellina Ferraro, and Joel Huber (2012), "Unintended Nutrition Consequences: Firm Responses to the Nutrition Labeling and Education Act," *Marketing Science*, 31 (5), 717-737.

Ordabayeva, Nailya and Pierre Chandon (2013), "Predicting and Managing Consumers' Package Size Impressions," *Journal of Marketing*, 77 (5), 123-137.

Prahalad, Coimbatore K. (2004), *The Fortune at the Bottom of the Pyramid: Eradicating Poverty Through Profits*. New York, NY: Pearson Education.

Radjou, Navi, Jaideep C. Prabhu, and Simone Ahuja (2012), *Jugaad Innovation: Think Frugal, Be Flexible, Generate Breakthrough Growth*. San Francisco, CA: Jossey-Bass.

Ramamurti, Ravi and Jitendra V. Singh (2009), *Emerging Multinationals in Emerging Markets*. Cambridge, UK: Cambridge University Press.

Seely-Brown, John and John Hagel III (2005), "Innovation Blowback: Disruptive Management Practices from Asia," *McKinsey Quarterly*, 1 (1), 34-45.

Sheth, Jagdish N. (2011), "Impact of Emerging Markets on Marketing: Rethinking Existing Perspectives and Practices," *Journal of Marketing*, 75 (4), 166-182.

Sorescu, Alina B. and Jelena Spanjol (2008), "Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods," *Journal of Marketing*, 72 (2), 114-132.

Tellis, Gerald J., Stefan Stremersch, and Eden Yin (2003), "The International Takeoff of New Products: The Role of Economics, Culture, and Country Innovativeness," *Marketing Science*, 22 (2), 188-208.

---- (1986), "Beyond the Many Faces of Price: An Integration of Pricing Strategies," *Journal of Marketing*, 50 (4), 146-160.

Van Heerde, Harald J., Carl F. Mela, and Puneet Manchanda (2004), "The Dynamic Effect of Innovation on Market Structure," *Journal of Marketing Research*, 41 (2), 166-183.

Vernon, Raymond (1966), "International Investment and International Trade in the Product Cycle," *Quarterly Journal of Economics*, 80 (2), 190-207.

Viswanathan, Madhubalan, José A. Rosa, and James E. Harris (2005), "Decision Making and Coping of Functionally Illiterate Consumers and Some Implications for Marketing Management," *Journal of Marketing*, 69 (1), 15-31.

Von Zedtwitz, Max, Simone Corsi, Peder Veng Søberg, and Romeo Frega (2015), "A Typology of Reverse Innovation," *Journal of Product Innovation Management*, 32 (1), 12-28.

Williamson, Peter J. (2010), "Cost Innovation: Preparing for a 'Value-for-Money' Revolution," *Long Range Planning*, 43 (2-3), 343-353.

Winter, Amos and Vijay Govindarajan (2015), "Engineering Reverse Innovations," *Harvard Business Review*, 93 (7-8), 80-89.

World Economic Outlook. International Monetary Fund. Available at: http://www.imf.org/external/ns/cs.aspx?id=231.

Yan, Dengfeng, Jaideep Sengupta, and Robert S. Wyer (2014), "Package Size and Perceived Quality: The Intervening Role of Unit Price Perceptions," *Journal of Consumer Psychology*, 24 (1), 4-17.

Zeschky, Marco B., Stephan Winterhalter, and Oliver Gassmann (2014), "From Cost to Frugal and Reverse Innovation: Mapping the Field and Implications for Global Competitiveness," *Research-Technology Management*, 57 (4), 20-27.

Figure 1: Percentage of Trickle-Down and Reverse Innovations over yearly launches 2001-2014

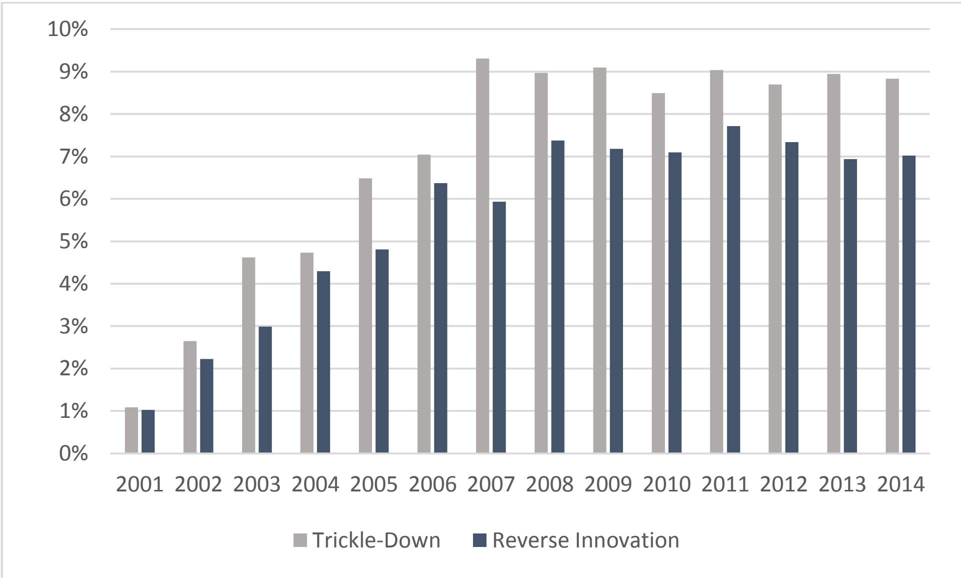


Figure 2: Graphical Overview of the Hazard Models Analysis

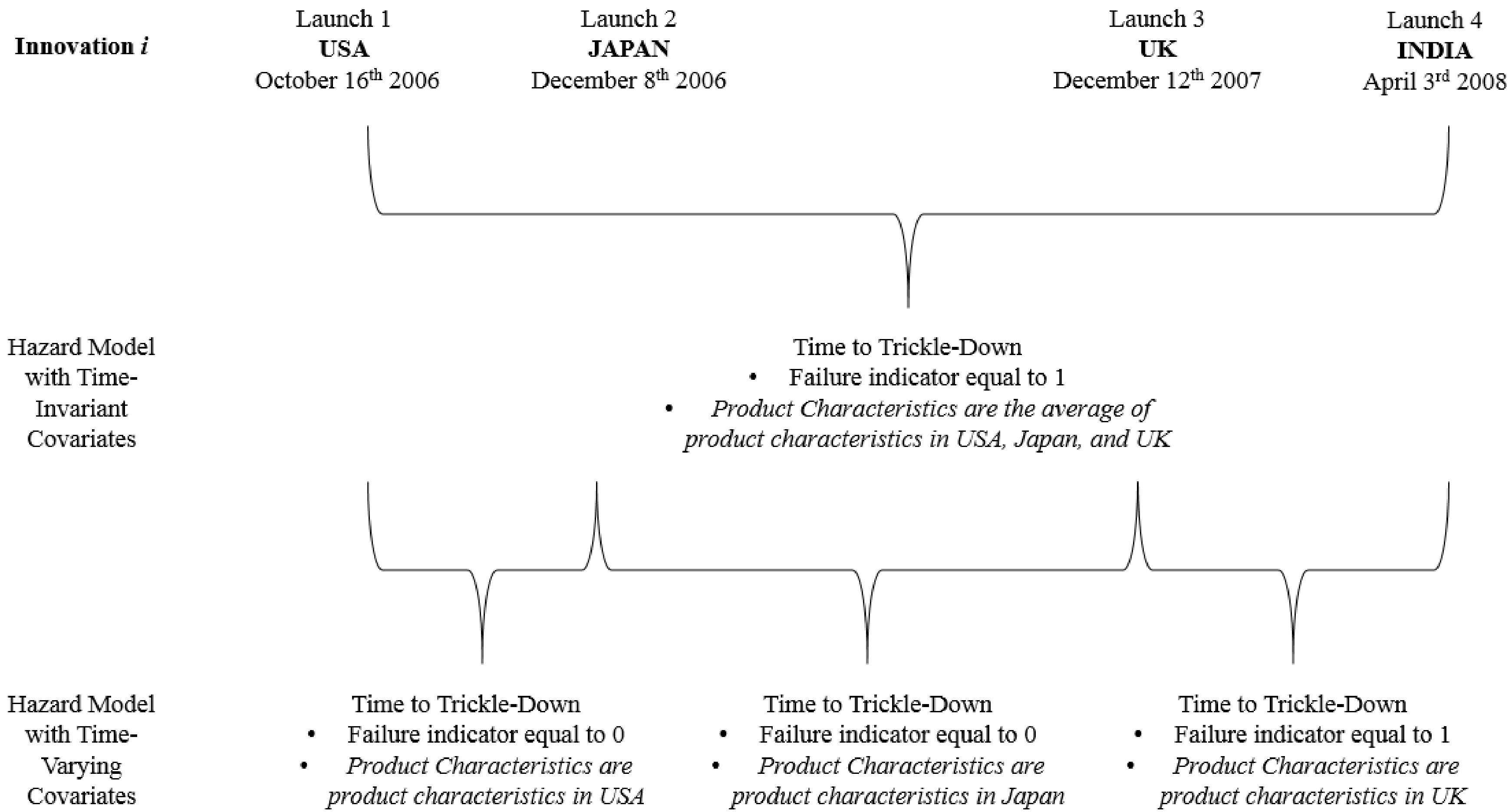


Table 1: Overview of Database Structure

Innovation	Innovation ID	Launch*	Country**	Country Type	Failure Indicator	Launch Date	Company	Price (€)	Package Size(gr)	Number of Claims	Diffusion
Glutinous Adzuki Bean and Rice Mochi	1	1	Singapore	Developed	0	February 4th 2010	Ajinomoto	1.09	160.00	1	Developed-only
	1	2	Taiwan	Developed	0	April 21st 2010	Taiwan Sham Chin Foods	1.81	300.00	0	
Gouda and Kaskaval Pastry Roll with Sesame	2	1	Turkey	Emerging	0	November 6th 2013	Iglo Group	2.79	500.00	3	Emerging-only
Scottish Shortbread Biscuit	3	1	USA	Developed	0	October 4th 2005	Christopher Brookes Distinctive Foods	2.31	198.44	1	Trickle-Down
	3	2	India	Emerging	1	December 14th 2005	Campbells Shortbread	2.02	124.96	1	
	3	3	South Africa	Emerging	0	February 16th 2010	National Brands	0.23	40.00	3	
	3	4	France	Developed	0	September 11th 2012	Aldi Group	1.69	200.00	1	
Seafood Samosa	4	1	India	Emerging	0	September 23rd 2010	Gadre Marine	1.67	250.00	0	Reverse Innovation
	4	2	Germany	Developed	1	June 26th 2012	Hamburger Feinfrost	3.99	240.00	0	

Notes: *127,782 launches nested in 66,810 innovations. ** Each innovation is associated with an Innovation ID and a diffusion type. Each launch is associated with a country, a launch date, a launching company, a price, a number of claims, and a package size.

Table 2: Variables, Measures, and Sources

Variable	Measure	Data Source
Trickle-Down	1 if the innovation trickles down, 0 otherwise	Mintel GNPD, our elaboration
Reverse Innovation	1 if the innovation trickles up, 0 otherwise	
Unitary Price	Price in Euros of one unit of product	Mintel GNPD
Package Size	Product's weight in Grams	
Number of Claims	Number of Claims associated with a product	
Previous Launches	Number of launches in countries of the initial type before the current date	Mintel GNPD, our elaboration
Previous Countries	Number of countries of the initial type where the product has been launched before the current date	
Type of Launch	1 for New Packaging, 0 otherwise	
Category Experience	Launching firm's number of launches in the category of interest before the current date	
Country Experience	Launching firm's number of launches in the country of interest before the current date	
Year of Introduction	Year during which the product's first launch took place	Mintel GNPD
Country	Country where a particular launch takes place	
Category	Baby Food, Bakery, or Snacks	

Table 3: Results of the Hazard Models Analysis

Dependent Variable	Hazard Rate of Trickle-Down Model 1_A	Hazard Rate of Reverse Innovation Model 1_B	Hazard Rate of Trickle-Down Model 2_A	Hazard Rate of Reverse Innovation Model 2_B	Hazard Rate of Trickle-Down Model 3_A	Hazard Rate of Reverse Innovation Model 3_B
Unitary Price	-.03 (.01)***	.03 (.004)***	-.03 (.01)***	.03 (.01)***	-.04 (.01)***	.11 (.01)***
Package Size	.00001 (.0001)	-.0003 (.0001)***	.00001 (.0001)	-.0003 (.0001)**	-.00003 (.0001)	-.0004 (.0001)***
Number of Claims	-.01 (.01)	.09 (.01)***	.01 (.01)	.09 (.01)***	.002 (.01)	.11 (.01)***
Previous Launches	.01 (.02)	-.04 (.01)***	.01 (.05)	-.01 (.01)	.24 (.05)***	.06 (.02)***
Previous Countries	.25 (.03)***	.41 (.03)***	.46 (.06)***	.68 (.04)***	.84 (.06)***	.99 (.05)***
Type of Launch			.17 (.05)***	-.18 (.06)***	.12 (.06)**	-.25 (.07)***
Category Experience			.0002 (.0001)**	.0003 (.0001)***	.0002 (.0001)*	.0003 (.0001)***
Country Experience			.001 (.0004)***	-.002 (.001)**	.0004 (.0004)	-.002 (.001)**
Year FEs	YES	YES	YES	YES	YES	YES
Country FEs			YES	YES	YES	YES
Category FEs	YES	YES	YES	YES	YES	YES
Observations	34,615	26,038	42,947	36,525	42,947	36,525
χ^2	393.86	444.57	601.24	1,125.87	1,873.36	1,442.17

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Table 4: Results of the Country-level Models

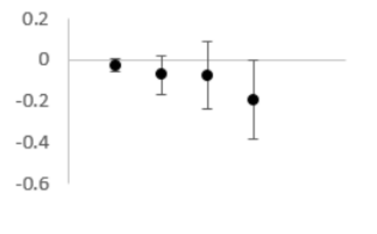
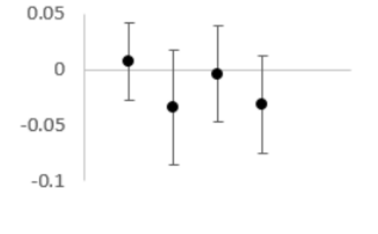
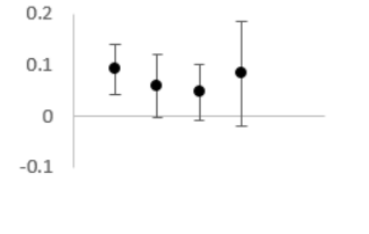
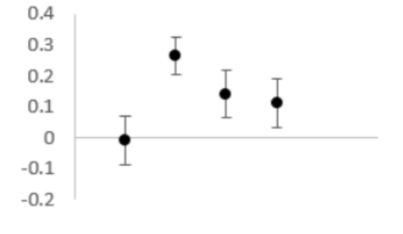
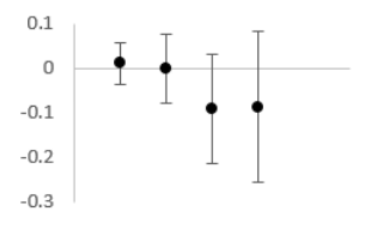
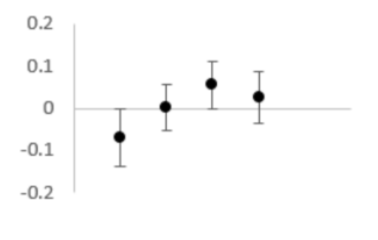
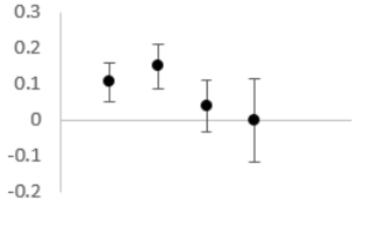
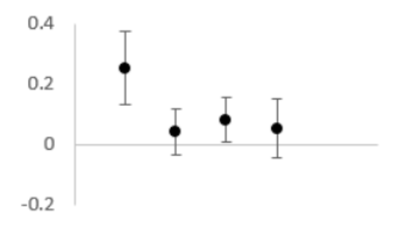
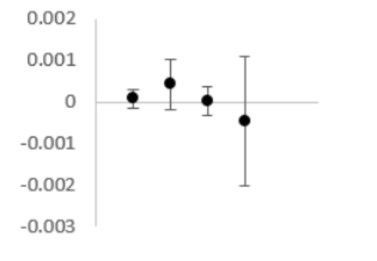
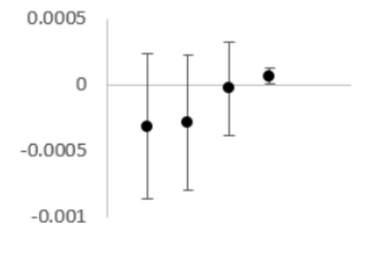
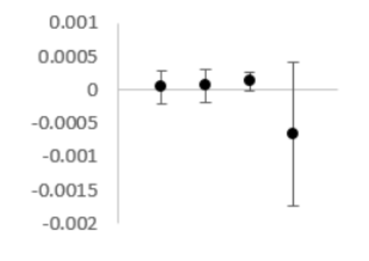
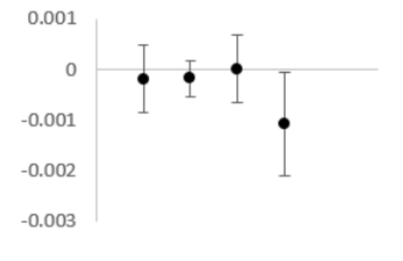
<table>
<tr><td></td><td colspan="8">Trickle-Down</td><td colspan="8">Reverse Innovation</td></tr>
<tr><td>Product Characteristics</td><td colspan="4">4_A. Developed Country-of-Origin</td><td colspan="4">4_B. Emerging Country-of-Destination</td><td colspan="4">5_A. Developed Country-of-Destination</td><td colspan="4">5_B. Emerging Country-of-Origin</td></tr>
<tr><td></td><td>USA</td><td>UK</td><td>Germany</td><td>Japan</td><td>China</td><td>India</td><td>Mexico</td><td>Brazil</td><td>USA</td><td>UK</td><td>Germany</td><td>Japan</td><td>China</td><td>India</td><td>Mexico</td><td>Brazil</td></tr>
<tr><td>Unitary Price</td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Number of Claims</td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td>Package Size</td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td></tr>
</table>

Table 5: Results of the Heckman's Sample Selection Model

(1) Likelihood of Trickle-Down or Reverse Innovation

Stage 1 Model		
Dependent Variable	Likelihood of Trickle-Down Model 6_A	Likelihood of Reverse Innovation Model 6_B
Unitary Price	-.02 (.004)***	.04 (.01)***
Package Size	-.000001 (.00003)	-.0002 (.0001)***
Number of Claims	-.01 (.01)	.05 (.01)***
Previous Launches	.03 (.01)**	-.02 (.01)***
Previous Countries	.22 (.02)***	.37 (.02)***
Year Fixed FEs	YES	YES
Category FEs	YES	YES

(2) Performance after Crossing the Development Gap

Stage 2 Model		
Dependent Variable	Performance in Emerging Countries Model 6_A	Performance in Developed Countries Model 6_B
Time to Trickle-Down	-.04 (.01)***	
Time to Reverse Innovation		-.05 (.01)***
Previous Launches	-.002 (.01)	.002 (.003)
Previous Countries	-.01 (.03)	.02 (.02)
Year FEs	YES	YES
Category Fixed FEs	YES	YES
Lambda	-.33 (.15)**	-.21 (.07)***
Observations	34,614	26,048
χ^2	80.72	132.29

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Appendix

Table 1_A: Correlations: Trickle-Down and Developed-Only

	Mean	Std.dev	1.	2.	3.	4.	5.	6.	7.	8.
1. Trickle-Down	.07	.26	1.00							
2. Unitary Price	2.78	3.11	-.02*	1.00						
3. Package Size	228.33	473.88	-.003	.16*	1.00					
4. Number of Claims	2.08	2.38	-.04*	.08*	-.04*	1.00				
5. Previous Launches	.53	1.47	.07*	.01*	.03*	.02*	1.00			
6. Previous Countries	.38	.87	.09*	.003	.01*	.03*	.84*	1.00		
7. Category Experience	107.70	290.29	-.02*	-.07*	-.02*	.03*	.04*	.04*	1.00	
8. Country Experience	35.32	81.35	-.03*	-.09*	-.01	.01	.05*	.03*	.46*	1.00

Notes: *p < .10. **p < .05. ***p < .01. All VIFs are well below 10.

Table 1_B: Correlations: Reverse Innovation and Emerging-Only

	Mean	Std.dev	1.	2.	3.	4.	5.	6.	7.	8.
1. Reverse Innovation	.07	.26	1.00							
2. Unitary Price	1.51	2.09	.04*	1.00						
3. Package Size	224.05	491.07	-.01*	.20*	1.00					
4. Number of Claims	1.50	1.99	-.002	.20*	.04*	1.00				
5. Previous Launches	1.29	4.16	-.03*	-.04*	.04*	-.02*	1.00			
6. Previous Countries	.43	.82	.02*	-.03*	.03*	-.02*	.62*	1.00		
7. Category Experience	73.48	293.36	-.003	.03*	-.03*	.08*	-.01*	.01*	1.00	
8. Country Experience	11.73	41.20	-.02*	-.02*	-.02*	.08*	.02*	.04*	.40*	1.00

Notes: *p < .10. **p < .05. ***p < .01. All VIFs are well below 10.

Table 2: Different Time Periods

Dependent Variable	Dropping 2001: Hazard Rate of Trickle-Down Model 3_A	Dropping 2001: Hazard Rate of Reverse Innovation Model 3_B	Adding 2000: Hazard Rate of Trickle-Down Model 3_A	Adding 2000: Hazard Rate of Reverse Innovation Model 3_B
Unitary Price	-.04 (.01)***	.11 (.01)***	-.04 (.01)***	.11 (.01)***
Package Size	-.00003 (.0001)	-.0004 (.0001)***	-.0001 (.0001)	-.0004 (.0001)***
Number of Claims	-.001 (.01)	.11 (.01)***	.00003 (.01)	.11 (.01)***
Previous Launches	.26 (.06)***	.05 (.02)***	.22 (.05)***	.06 (.02)***
Previous Countries	.85 (.07)***	1.00 (.05)***	.88 (.06)***	.99 (.05)***
Type of Launch	.12 (.06)*	-.27 (.07)***	.14 (.06)**	-.24 (.07)***
Category Experience	.0002 (.0001)**	.0003 (.0001)***	.0002 (.0001)*	.0003 (.0001)***
Country Experience	.0004 (.0004)	-.002 (.001)**	.0004 (.0004)	-.002 (.001)**
Year FEs	YES	YES	YES	YES
Country FEs	YES	YES	YES	YES
Category FEs	YES	YES	YES	YES
Observations	41,473	35,618	44,225	36,861
χ^2	1,665.09	1,342.76	2,061.87	1,523.07

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Table 3: Adding Price per Gram and Covariates' Standardization

	Adding Price per Gram		Covariates' Standardization	
Dependent Variable	Hazard Rate of Trickle-Down Model 3_A	Hazard Rate of Reverse Innovation Model 3_B	Hazard Rate of Trickle-Down Model 3_A	Hazard Rate of Reverse Innovation Model 3_B
Unitary Price	-.04 (.01)***	.11 (.01)***	-.05 (.01)***	.12 (.01)***
Package Size	-.00002 (.0001)	-.0004 (.0001)***	.0001 (.00004)	-.0004 (.0001)***
Price per Gram	.21 (.36)	.44 (.42)		
Number of Claims	.002 (.01)	.11 (.01)***	-.01 (.01)	.09 (.01)***
Previous Launches	.24 (.05)***	.06 (.02)***	.24 (.05)***	.06 (.02)***
Previous Countries	.84 (.06)***	.99 (.05)***	.84 (.06)***	.99 (.05)***
Type of Launch	.12 (.06)**	-.25 (.07)***	.12 (.06)**	-.24 (.07)***
Category Experience	.0002 (.0001)*	.0003 (.0001)***	.0002 (.0001)**	.0003 (.0001)***
Country Experience	.0004 (.0004)	-.002 (.001)**	.0003 (.0004)	-.002 (.001)**
Year FEs	YES	YES	YES	YES
Country FEs	YES	YES	YES	YES
Category FEs	YES	YES	YES	YES
Observations	42,946	36,525	42,947	36,525
χ^2	1,873.50	1,443.43	1,878.89	1,428.97

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Table 4: Alternative Distributional Assumptions

	Exponential		Gompertz	
	Hazard Rate of Trickle-Down Model 3_A	Hazard Rate of Reverse Innovation Model 3_B	Hazard Rate of Trickle-Down Model 3_A	Hazard Rate of Reverse Innovation Model 3_B
Unitary Price	-.04 (.01)***	.12 (.01)***	-.04 (.01)***	.11 (.01)***
Package Size	-.00003 (.0001)	-.0004 (.0001)***	-.00003 (.0001)	-.0004 (.0001)***
Number of Claims	.001 (.01)	.12 (.01)***	.004 (.01)	.11 (.01)***
Previous Launches	.28 (.05)***	.07 (.02)***	.24 (.05)***	.06 (.02)***
Previous Countries	.83 (.07)***	1.00 (.05)***	.82 (.06)***	.95 (.05)***
Type of Launch	.12 (.06)*	-.26 (.07)***	.12 (.06)**	-.24 (.07)***
Category Experience	.0002 (.0001)*	.0003 (.0001)***	.0002 (.0001)*	.0003 (.0001)***
Country Experience	.0003 (.0004)	-.002 (.001)**	.0004 (.0004)	-.002 (.001)**
Year FEs	YES	YES	YES	YES
Country FEs	YES	YES	YES	YES
Category FEs	YES	YES	YES	YES
Observations	42,947	36,525	42,947	36,525
χ^2	1,879.66	1,419.94	1,763.29	1,396.73

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Table 5. Relaxing the Proportionality Assumption

	Exponential		Lognormal		Log-logistic	
Dependent Variable	Time to Trickle-Down Model 3_A	Time to Reverse Innovation Model 3_B	Time to Trickle-Down Model 3_A	Time to Reverse Innovation Model 3_B	Time to Trickle-Down Model 3_A	Time to Reverse Innovation Model 3_B
Unitary Price	.04 (.01)***	-.12 (.01)***	.05 (.01)***	-.12 (.02)***	.05 (.01)***	-.13 (.02)***
Package Size	.00003 (.0001)	.0004 (.0001)***	.00003 (.0001)	.0005 (.0001)***	.00001 (.0001)	.0005 (.0001)***
Number of Claims	-.001 (.01)	-.12 (.01)***	-.003 (.02)	-.15 (.02)***	.001 (.01)	-.13 (.02)***
Previous Launches	-.28 (.05)***	-.07 (.02)***	-.89 (.16)***	-.15 (.05)***	-.46 (.11)***	-.07 (.03)**
Previous Countries	-.83 (.07)***	-1.00 (.05)***	-1.33 (.19)***	-1.77 (.12)***	-1.11 (.14)***	-1.34 (.09)***
Type of Launch	-.12 (.06)*	.26 (.07)***	-.18 (.08)**	.32 (.09)***	-.12 (.07)	.34 (.09)***
Category Experience	-.0002 (.0001)*	-.0003 (.0001)***	-.0003 (.0001)*	-.0004 (.0001)***	-.0002 (.0001)	-.0004 (.0001)***
Country Experience	-.0003 (.0004)	.002 (.001)**	-.0004 (.0005)	.002 (.001)**	-.0005 (.0005)	.002 (.001)**
Year FEs	YES	YES	YES	YES	YES	YES
Country FEs	YES	YES	YES	YES	YES	YES
Category FEs	YES	YES	YES	YES	YES	YES
Observations	42,947	36,525	42,947	36,525	42,947	36,525
χ^2	1,879.66	1,419.94	2,125.60	1,517.27	1,959.31	1,439.09

Notes: *p < .10. **p < .05. ***p < .01. All regressions include a constant. Unstandardized parameter estimates and standard errors in parenthesis.

Cultural (and Genetic) Distance and Its Impact on Cross-Country Innovation Launches: Insights from the Packaged Food Industry

Verdiana Giannetti[a]

Gaia Rubera[b]

[a] Verdiana Giannetti (verdiana.giannetti@phd.unibocconi.it) is a PhD Candidate in Business Administration and Management at Bocconi University, Via Roentgen 1, 20136 Milano, Italy.

[b] Gaia Rubera (gaia.rubera@unibocconi.it) is Full Professor of Marketing at Bocconi University, Via Roentgen 1, 20136 Milano, Italy.

Abstract

Firms willing to survive and succeed in periods of economic downturn need to expand beyond their domestic markets by launching innovations abroad. Further, they also need to defend their established positions by the disruptive potential of foreign innovations by being the first to launch such innovations in domestic markets. Hence, it is important for firms to understand which innovations from abroad are likely to be launched and succeed in their domestic markets, as well as which domestic innovations are likely to be launched and succeed abroad. Using data on packaged food's launches in 40 countries in 2001-2014, the paper answers three questions: (1) What is the impact of Cultural distance on the number of innovation launches across a certain lead country (i.e., the first country in which an innovation is launched)–lag country (i.e., each country in which the innovation is subsequently launched) pair?; (2) What is the impact of Cultural distance on the time it takes for an innovation to be launched across a certain lead country–lag country pair?; (3) Are there better measures for Cultural distance than Hofstede-based ones? Results, which are robust to alternative measures of Cultural distance and estimation approaches, show that Cultural distance decreases the number of innovation launches across a lead country-lag country pair and decelerates cross-country innovation launches; Genetic distance is a valuable alternative to Hofstede-based measures as a proxy for Cultural distance. Additional analysis reveals that both Cultural distance and time to cross-country innovation launch decrease innovation performance in lag countries. Implications for marketing academics and practitioners are presented.

Keywords*: Cultural distance, Genetic distance, Product Innovation, Innovation Diffusion, Packaged Food Industry.*

Firms willing to survive and succeed in periods of economic downturn like today need to expand beyond their domestic markets by launching innovations in foreign countries (Lee et al. 2011). Further, they also need to defend their established positions from the disruptive potential of foreign innovations by being the first to launch such innovations in their domestic markets. Globalization has, in fact, increased the speed of innovation launches across countries and many firms face now hypercompetitive global markets, where launch decisions are crucial (Harvey and Griffith 2007).

Hence, it is important for firms to understand which foreign innovations are likely to be launched and succeed in their domestic markets, as well as which domestic innovations are likely to be launched and succeed abroad. Understanding such processes would in fact allow firms to draw from additional sources of cash flow by disclosing new geographic outlets for innovations. In particular, understanding toward which countries a domestic innovation will diffuse faster (and more successfully) would allow firms to expand their geographic domain and unlock additional sources of cash flow earlier. On the other hand, understanding which countries' foreign innovations are most likely to enter their domestic markets would allow firms to protect their positions by anticipating competitors' moves. Despite the relevance of international launch decisions, research on this topic, the focus of our contribution, is still scarce in the literature (Verniers, Stremersch, and Croux 2011).

Hereinafter, we look at cross-country innovation diffusion, as proxied by cross-country innovation launches, adopting a cultural lens. Although culturally-rooted research on innovation diffusion is a fertile area, the extant literature suffers from the following limitations.

First, most extant contributions are based on small samples of innovations and countries (Helsen, Jedidi, and DeSarbo 1993; Yeniyurt, Townsend, and Talay 2007). Further, most investigations are conducted in the area of consumer durables, while fast-moving consumer goods, possibly due to data limitations, are neglected (see e.g., Chadrasekaran and Tellis 2008; Dekimpe, Parker, and Sarvary 2000; Gatignon, Eliashberg, and Rosen 1989; Rubera, Griffith, and Yalcinkaya 2012; Sundqvist, Lauri, and Puumalainen 2005; Tellis, Stremersch, and Yin 2003).

Second, most research focuses on innovation diffusion as proxied by heterogeneous innovation adoption rates within specific countries (Yeniyurt et al. 2007). As a result, despite the fact that launching innovations in the global marketplace has become an urgency for firms, cross-country innovation launches have received thus far limited attention in the literature (Subramaniam, Rosenthal, and Hatten 1998; Verniers et al. 2011; Yeniyurt et al. 2007).

Third, scholars in this stream of research have focused on the role that national culture plays in innovation diffusion by investigating the impact of specific cultural dimensions on heterogeneous innovation adoption rates within specific countries (see e.g., Chandrasekaran and Tellis 2008; Tellis et al. 2003). In doing so, they have neglected interactions in cross-country innovation diffusion as well as the role of cultural similarities in such process. These limitations, however, have been partly overcome by a stream of research that focuses on interactions across innovation adoption rates in different countries (see e.g., Albuquerque, Bronnenberg, and Corbett 2007; Kumar and Krishnan 2002; Putsis et al. 1997; Van Everdingen, Aghina, and Fok 2005; Van Everdingen, Fok, and Stremersch 2009). In these contributions, interactions are often captured through the so-called lead-lag effect (Eliashberg and Helsen 1996; Kalish, Mahajan, and Muller 1995; Takada and Jain 1991), where sales in the lead country (i.e., the first country where the innovation is launched) are expected to affect sales in the lag country (i.e., the country where the innovation is subsequently launched) and cross-country cultural similarity is expected to enhance the effect (Ganesh, Kumar, and Subramaniam 1997). However, the focus on cross-country interactions is still limited in the literature.

Fourth, most contributions in the culturally-rooted research on innovation diffusion recur to Hofstede's framework to operationalize national culture. Hofstede's framework, however, has been largely criticized (see e.g., McSweeney 2002; Steenkamp 2001), therefore calling for alternative and more reliable proxies of national culture.

Given these gaps in the literature, the present paper aims to answer three questions.

First, what is the impact of national culture and, more specifically, of Cultural Distance (CD), i.e., the extent to which a country's culture is different from another country's culture, on the number of innovation launches across a certain lead country-lag country pair?

Second, what is the impact of CD on the time it takes for an innovation to be launched across a certain lead country-lag country pair? Answering these questions would allow firms to decide where to launch the innovations initially targeted at consumers in their domestic countries. Similarly, it would allow them to understand which innovations are likely to be launched in their domestic countries from abroad in order to anticipate competitors' moves.

Third, is there an alternative measure for CD capable of overcoming the limitations of Hofstede-based measures? We propose here a new measure for CD, i.e., Genetic Distance (GD), which could be used to better grasp differences in culture across countries.

Our investigation is conducted on 20,613 packaged food's launches across 40 countries in 2001-2014, thus constituting a substantial improvement with respect to most extant studies, where samples have been small (Yeniyurt et al. 2007; Helsen et al. 1993). The paper contributes to the literature in the following ways.

First, we show that CD decreases the number of innovation launches across a certain lead country-lag country pair. Similarly, we find that it decelerates innovation launches across the country pair. Second, we bring for the first time, to the best of our knowledge, in the management and marketing literatures the notion of GD, a construct rooted in anthropology and widely used in the empirical economic literature, and show that GD is a valid alternative measure for CD. Our contribution provides scholars and practitioners with an easily available measure of CD across countries, i.e., GD, which could be used, along with the widely used Hofstede-based measures, to better grasp differences in habits and customs across countries. Additional analysis, reported in the discussion section, reveals that both CD and time to cross-country innovation launch decrease innovation performance in lag countries, therefore confirming the relevance of our research questions to practitioners that aim to maximize the market performance of their innovations.

The rest of the paper is organized as follows. We first introduce the theoretical background of the paper. We then describe the data and measures, the estimation approach, and results. We conclude with a discussion of theoretical contributions, implications for managerial practice, and limitations and opportunities for future research.

Theoretical Background

In the following sections, we briefly review the literature on the impact of Culture, in general, and CD, in particular, in innovation diffusion. We then present the notion of GD.

National culture and Cultural distance in Innovation Diffusion Research

According to Hofstede (2001, p.9), culture is “the collective programming of the mind which distinguishes the members of one group or category of people from another […]. Culture, in this sense, includes systems of values; and values are among the building blocks of culture”. In this paper, we use the word culture to refer to national culture, i.e., the way people in a country think, feel, and act.

Cultural differences across countries have been shown to have an impact on innovation adoption and diffusion (Chandrasekaran and Tellis 2008).

A key research stream in this area focuses on the differences between diffusion processes in distinct countries and on whether these differences can be ascribed to cultural heterogeneity (Kumar and Krishnan 2002). Most contributions in this stream thus focus on the role of specific cultural dimensions (Sundqvist et al. 2005) in stimulating or constraining the adoption rates of innovations within different countries (Chandrasekaran and Tellis 2008; Gatignon et al. 1989; Rubera et al. 2012; Takada and Jain 1991; Tellis et al. 2003; Yeniyurt and Townsend 2003).

Further, cultural differences are pivotal in explaining differences in consumers' expectations and consequent firm strategies across countries. Cultural differences prevent product standardization and must be cautiously considered when operating abroad (Jain 1989; Yalcinkaya 2008) as consumers in different countries react differently to the same innovation.

Another key research stream in innovation diffusion focuses on the interactions between innovation diffusion processes across countries (see e.g., Albuquerque et al. 2007; Kumar and Krishnan 2002; Putsis et al. 1997; Van Everdingen et al. 2009; Van Everdingen et al. 2005). Interactions are often captured through the so-called lead-lag effect (Eliashberg and Helsen 1996; Kalish et al. 1995; Takada and Jain 1991), where sales in the lead country affect sales in the lag country. The explanation is based on the learning effect (Ganesh and Kumar 1996; Kumar, Sunder, and Ramaseshan 2011) taking place between lead countries and lag countries. According to the learning effect theory, consumers in lag countries learn about the innovation from the experience of consumers in lead countries, and this results in faster adoption in lag countries than in lead countries. Ganesh et al. (1997) find that the learning effect is enhanced when lead and lag countries are culturally similar because culturally similar consumers are more likely to communicate as well as to share similar expectations and behaviors. Analogous results are present, among others, in Albuquerque et al. (2007) and Kumar and Krishnan (2002).

Criticism of Hofstede's Framework

So far, most studies in the culturally-rooted literature on innovation diffusion build upon Hofstede's framework to measure Cultural Distance (CD). Despite its popularity, Hofstede's framework has also been the subject of numerous critiques since its first publication. Triandis (1982), Sorge (1983), and Steenkamp (2001), even though acknowledging the relevance of Hofstede's work in dealing with the "overwhelming complexity of culture" (Sorge, p. 628), criticize its dimensions as being too narrow and therefore suitable only for modeling work-related values, which do not coincide with national values. Similarly, McSweeney (2002) emphasizes the intrinsic complexity of culture and argues that it cannot be easily grasped via a limited number of dimensions such as in Hofstede. Despite such amount of critiques, most measures of CD in innovation diffusion research are still derived from Hofstede's work. In the following pages, we introduce Genetic Distance as an alternative proxy for CD.

Genetic Distance

Genetic Distance (GD) can be defined as a synthetic measure of differences in allelic frequencies across populations (Giuliano, Spilimbergo, and Tonon 2014), where *alleles* are the particular forms that a *gene* can take. Recently, many economic analyses have used GD (e.g., Ashraf and Galor 2008; Desmet et al. 2007; Giuliano et al. 2014; Guiso, Sapienza, and Zingales 2009; Spolaore and Wacziarg 2013, 2009).

GD can be used as a proxy for CD as it is essentially a measure of time, being strongly related to how long the populations of two countries have been separated from each other. When populations split, in fact, the process of random drift takes them in different directions, increasing their distance in terms of allelic frequencies. GD can be used as a proxy for cultural differences as the longer the period of separation between two populations, the greater their differences in habits, values, expectations, and preferences - that develop and stratify over time – will be. More specifically, being strongly related to how long the populations of two countries have been separated from each other, GD can be used as a broad proxy for the cross-generational transmission of the whole complex of cultural traits, habits, and values within a country (Cavalli Sforza, Menozzi, and Piazza 1994; Stone and Lurquin 2007). It is worth mentioning that GD is computed starting from neutral genes (i.e., genes that are not affected by natural selection) and therefore does not capture differences in specific characteristics that directly matter for survival or fitness to the environment (Spolaore and Wacziarg 2013). Hence, using GD does not imply a direct effect of specific genes on tastes or preferences, nor on specific characteristics of consumers, i.e., *an effect of GD is not evidence of a genetic effect*. Rather, it signifies the importance of inter-generationally-transmitted cultural traits that develop and stratify over time, and that can be captured *via* differences in allelic frequencies.

In the following analyses, we introduce Hofstede's Cultural distance (HD) as well as GD among regressors in order to compare their effects on cross-country innovation launches. We use both measures contextually as no evidence of multi-collinearity emerges ($r = 0.12$, $p < 0.05$).

Hypotheses Development

In the following sections we introduce our hypotheses concerning the impact of CD on cross-country innovation launches.

Cultural Distance as a Source of Heterogeneous Consumers' Preferences

Both scholarly contributions and general wisdom posit that "some cultures are more distant than others" (Barkema, Bell, and Pennings 1996). Cultural differences have been shown to impede product standardization across countries and must be cautiously considered when operating abroad (Jain 1989). Despite globalization, in fact, cultural differences across countries remain substantial (Barkema, et al. 1996; Hofstede 2001; Leung et al. 2005; Yeniyurt and Townsend 2003) and substantially affect consumers' tastes, preferences, and resulting purchasing behaviors. As countries characterized by different cultures react differently to the same innovation, the key to a successful product launch is how well the product taps on heterogeneous expectations (Jain 1989; Kumar 2014; Subramaniam et al. 1998; Yalcinkaya 2008). In particular, Subramaniam and colleagues (1998) posit that firms must take into account "differences in culture, idiosyncratic tastes and buying habits" (p. 781) when launching innovations in the global marketplace. Cultural differences across countries are thus a key factor in explaining differences in consumption-related expectations.

Altogether, such contributions hint at the fact that innovations initially launched in a given country will better satisfy the needs of consumers in culturally close lag countries, being therefore more likely to be launched in culturally close countries than in culturally distant ones. More formally:

> H_1: The lower the Cultural distance within a certain lead country-lag country pair, the higher the number of innovation launches across it is.

Cultural Distance and the Learning Effect

The extant literature has emphasized the centrality of learning among consumers in lead and lag countries in facilitating cross-country innovation diffusion. According to the learning effect theory, in fact, an innovation introduced later in a certain lag country results in faster diffusion as consumers in the lag country have the opportunity to learn about the innovation by observing consumers in the lead country (Ganesh and Kumar 1996; Kalish et al. 1995; Kumar 2014). Ganesh et al. (1997) find that cultural similarity across countries accelerates the emergence of the learning effect and that, as a result, it enhances innovation diffusion rates within a certain country-pair. Dekimpe et al. (2000) and Van Everdingen et al. (2009) further argue the same. Also economists have pointed out a similar mechanism. Spolaore and Wacziarg (2013; 2009), in fact, argue that differences in vertically transmitted habits and norms create barriers to communication and imitation across countries. Hence, it is reasonable to hypothesize that consumers in culturally close countries will be more likely to learn from each other, therefore accelerating the diffusion of innovations across their countries. Further, as innovations originally intended for consumers in a certain country will best suit the needs of consumers in culturally close countries, we expect CD to decelerate cross-country innovation launches, as innovations will require time-consuming adaptations before being launched in culturally distant countries. Hence, we hypothesize:

> H_2: The lower the Cultural distance within a certain lead country-lag country pair, the faster innovation launches across it are.

Genetic Distance as a Comprehensive Synthesis of Cultural Dimensions

As already mentioned, CD is usually operationalized building on Hofstede’s dimensions (e.g., Kogut and Singh 1988). Culture is however an elusive concept and it is very challenging to grasp with a limited number of dimensions (Helsen et al. 1993; McSweeney 2002; Triandis 1982; Yeniyurt and Townsend 2003). We argue that GD will display a stronger effect on the number of innovation launches across a country pair, as well as on time to cross-country innovation launch, than HD. GD, reflecting the ancient history of populations, is in fact strongly correlated with a vast collection of differences in cultural dimensions (Spolaore and Wacziarg 2009), therefore constituting a substantial improvement with respect to Hofstede's dimensions, which cannot be considered the true and only factors responsible for CD (Barkema et al. 1996). Hence, we argue that GD, not being based on a limited set of dimensions, will display a stronger effect than HD on both cross-country number of launches and time to cross-country innovation launch. More formally:

> H_{3A}: The number of innovation launches across a certain lead country-lag country pair is more correlated with Genetic distance than with Hofstede's Cultural distance.
>
> H_{3B}: The innovation launch speed across a certain lead country-lag country pair is more correlated with Genetic distance than with Hofstede's Cultural distance.
> For an overview of our theoretical framework, see Figure 1.

---- Insert Figure 1 here ----

Data

We answer our research questions using data from the packaged food industry. We select this industry because product innovation is fundamental in this context (Van Heerde, Mela, and Manchanda 2004). Indeed, many recent studies on innovation have selected this industry as their setting (see e.g., Moorman, Ferraro, and Huber 2012; Sorescu and Spanjol 2008). Further, cultural differences across countries are crucial in informing firms' innovative efforts in the consumer packaged goods industry, making it an appropriate context for our investigation (Subramaniam et al. 1998). As an example, Jain (1989) posits that non-durable consumer goods are more likely than industrial or consumer durable goods to require adaptations across countries as they tap more on heterogeneous tastes, habits, and customs. The food industry, in particular, presents serious challenges for firms as tastes and preferences are heterogeneous and difficult to identify. For instance, Balut, a fertilised duck egg, with its partly developed embryo boiled alive, is quite popular in the Philippines, Vietnam, and Cambodia but would not easily find a market in Western countries.

We use Mintel GNPD to collect information on packaged food's launches in 40 countries between 1996 and 2014. We focus on the Bakery, Baby Food, and Snacks categories and on launches which are classified alternatively as "New Product" or "New Packaging".

As our analyses rely on tracking the launch history of innovations across countries, we carefully clean the database in order to ensure that the same innovation is properly identified as such, even though it is reported with somewhat different names across different launches. For instance, *Doughnuts* were identified in the original database also with their American English version *Donuts*. We consider these alternative labels as referring to the same innovation.

In order to make sure that all the launches represent products that are really new-to-the-world when they first appear – i.e., not mere launches for products already present in whatever country before 1996 – we remove all launches pertaining to products that appear at least once before 2001. We, in fact, assume that products never launched in this period are actually new when they first appear in the database. Our final sample comprises 20,613 cross-country innovation launches in 40 countries between 2001 and 2014. Examples of innovations in our database are *cranberry and pomegranate bar* and *seaweed-flavored fish-shaped biscuits.* We associate each launch with two different countries: (1) a lead country, i.e., the first country where the corresponding innovation is launched, and (2) a lag country, i.e., the country where the focal launch takes place.

Measures

In this section we describe our measures.

Dependent and Independent Variables

Number of Launches (Y). We use Mintel GNPD to collect yearly data on the cumulative number of launches in each lag country for innovations initially introduced in each lead country. As the same innovation may be launched multiple times by different firms in the same lag country, we retain, for each innovation, only the first launch in each specific lag country.

Time to Launch (T). Time to launch is the time lag in days between the first launch of the innovation in its lead country and its first launch in each lag country.

Genetic distance (GD). Data for GD are derived from Spolaore and Wacziarg (2009). Spolaore and Wacziarg (2009) derive GD data at the population level from Cavalli Sforza et al. (1994) and use countries' ethnic composition data from Alesina et al. (2003) as the starting point for constructing measures of cross-country GD. A detailed explanation of how this measure is built is presented in Spolaore and Wacziarg (2009, pp 524-525). GD equals zero if the allele distributions are the same across two countries' populations, whereas it is positive when the allele distributions differ. A higher GD is therefore associated with a longer period of separation, lower genealogical relatedness, and larger cultural differences. Following Chua, Roth, and Lemoine (2015), we examine sample scores for countries in our database and find them to have high face validity. For instance, the GDs between Germany and Switzerland (33.68), France (48.53), Canada (125.86), and Egypt (254.79) are in the expected order. GD data are bidirectional so that, as an example, GD between UK and India is the same as GD between India and UK.

Hofstede's Cultural distance (HD). We collect data on Power distance, Masculinity, Uncertainty avoidance, Individualism, Long-term orientation, and Indulgence for the countries in our sample manually from Geert Hofstede Center website. We then compute a synthetic measure of CD using Kogut and Singh (1988) indicator, which is as follows:

$$CD_P = \sum_{P=1}^{6} \{ \left(P_{pi} - P_{pj}\right)^2 / V_p \} / 6 \tag{1}$$

Where P_{pi} is the value for dimension *p* in country *i* and P_{pj} is the value for dimension *p* in country *j*. V_p is the variance of dimension *p* and 6 is the number of dimensions taken into consideration. V_p is computed using the scores on dimension *p* for all countries in our sample. The vast majority of CD studies follow this approach in operationalizing and measuring CD (Beugelsdijk et al. 2017; Kirkman, Lowe, and Gibson 2016; 2006). Most authors (e.g., Aggarwal, Kearney, and Lucey 2012; Barkema et al. 1996; Benito and Grisprud 1992; Mitra and Golder 2002; Yeniyurt et al. 2007) compute Kogut and Singh Index using four dimensions of culture while others (see e.g. Chua et al. 2015) use five dimensions. We use the same operationalization of culture but using all the six dimensions identified thus far by Hofstede and colleagues. Following Chua et al. (2015), we examine sample scores for countries in our database and find them to have high face validity. For instance, the HDs between Germany and Switzerland (0.30), France (0.90), Canada (1.20), and Egypt (3.42) are in the expected order. HD data are bidirectional so that, just like in the case of GD, HD between UK and India is the same as HD between India and UK.

Common Colonizer (COLONIZER_SAME). We use a dummy variable taking on value 1 if country *i* and *j* were colonized in the past by the same colonizer. We expect sharing a colonizer to facilitate the diffusion of innovations across a country pair. We collect this variable from the CEPII Geodist database, which has been already used by Spolaore and Wacziarg (2009), Aggarwal et al. (2012), and Giuliano et al. (2014).

Colony (COL). We use a dummy variable taking on value 1 if country *i* has ever been in a colonial relationship with country *j*. We expect this variable to facilitate the diffusion of innovations across a country pair. We collect this variable from the CEPII Geodist database.

Colony after 1945 (COL45). We use a dummy variable taking on value 1 if country *i* has ever been in a colonial relationship with country *j* after 1945. We expect this variable to facilitate the diffusion of innovations across a country pair and collect it from the CEPII Geodist database.

Migration Stock (MIG). We derive the 2000 bilateral migration stocks from lead country *i* to lag country *j* as well as from lead country *j* to lag country *i* for each pair of countries from the World Bank Global Bilateral Migration Database. Migration data are directional in nature. Hence, in the case of launches from country *i* to country *j*, we use the migration stock from country *i* to country *j* and vice versa. In doing so, we expect that the number of country *i*'s citizens living in country *j* will positively affect number of launches as well as launch speed from lead country *i* to lag country *j*, as international mobility of consumers leads to increasing similarity and easier communication (Jain 1989). The maximum number of migrants in our database is registered from Mexico to USA, for which 9.367.910 migrants are registered in 2000. Our measure is the log-transformed total number of migrants in 2000.

Common Legal System (LEGALSYSTEM_SAME). In order to account for similarities across countries' legal systems, we include a dummy variable that takes on value 1 if two countries' legal systems share the same origin (i.e., common law, civil/French, civil/German, civil/Scandinavian). We derive this variable from La Porta and colleagues (1998). We expect sharing the same legal system to increase the number of launches across a certain lead country-lag country pair as well as to accelerate innovation launch speed. Different regulations may in fact inhibit the diffusion of innovations from a country to another as innovations originally launched in a country may not satisfy legal requirements in other countries.

Physical Distance (DIST). Following Van Everdingen et al. (2009), we include the geodesic distance in kilometers between capital cities for each pair of countries. We collect this data from the CEPII Geodist database. The minimum distance is registered between Belgium and Netherlands while the maximum distance is registered between Colombia and Indonesia. We expect physical distance to hamper cross-country innovation launches. Related to this, Kumar et al. (2011) argue that geographical proximity accelerates learning across countries. Similarly, Rubera et al. (2012) posit that proximity facilitates the spread of advertising and word of mouth across countries. Hence, we expect geographic proximity to positively affect cross-country innovation diffusion by facilitating learning and preferences' convergence across countries.

Contiguity (CONT). Following Van Everdingen et al. (2009), we include a dummy variable taking on value 1 if country *i* and *j* share borders. We collect this data from the CEPII Geodist database. We expect contiguity to facilitate the diffusion of innovations across a country pair (Kumar et al. 2011).

GDP per Capita Difference (GDPDIFF). Building on Van Everdingen et al. (2009), we account for economic distance across countries by using the absolute value of the difference in the log of GDP per capita in U.S. $ between countries. We average the difference of logged GDPs across years and therefore keep it constant. We collect GDP data from the World Bank. Economic distance has received so far limited attention in the marketing literature and, more importantly, it has been rarely analyzed together with CD (Mitra and Golder 2002). We include Economic distance in order to prevent potential overestimation of the roles of HD and GD. Similar economic characteristics might in fact be associated with similarities in demand across countries (Mitra and Golder 2002).

Same Level of Development (DEVEL_SAME). In order to further account for economic distance across countries, we classify both lead and lag countries in terms of economic development between Emerging vs. Developed Countries. We generate a dummy variable taking on value 1 if the two countries share the same level of development, 0 otherwise. We derive this classification from the World Economic Outlook, published twice a year by the International Monetary Fund. Overall, we expect economic similarity to facilitate innovation diffusion. As an example, Jain (1989) argues that economic similarity among countries fosters homogeneity in terms of consumers' life habits, needs, and preferences. Similarly, Mitra and Golder (2002) argue that homogeneous economic conditions foster similarities in consumer demand across countries. Further, Kumar et al. (2011) argue that economic similarity facilitates learning across countries. Finally, Van Everdingen et al. (2009) find that economically distant countries exhibit weaker spillover effects than economically close countries when it comes to innovations' takeoff.

We add fixed effects for each lag country; similarly, we add fixed effects for each lead country. The lag country-fixed effects account for possible systematic differences in countries' likelihood to attract launches of innovations initially intended for consumers in other countries. The lead country-fixed effects capture possible systematic differences in countries' likelihood to generate innovations and, in particular, innovations which will be launched in other countries. Finally, we add year-fixed effects to account for possible unobserved heterogeneity across years. For an overview of all variables and their proxies, please see Table 1.

---- Insert Table 1 here ----

Does CD Affect Number of Cross-Country Innovation Launches and Time to Cross-Country Innovation Launch?

In the following sections we run two models. Model 1 is aimed at testing H_1, while model 2 is aimed at testing H_2. Descriptives and correlations are reported in Table 2. Correlation between GD and HD is positive and significant (r = 0.12, $p < 0.05$), but at a moderate level. All the variance inflation factors are below 10.

---- Insert Table 2 here ----

Random Effects Panel Model

In Model 1 we investigate the effects of HD and GD on number of cross-country innovation launches. The dependent variable is here the yearly cumulative number of launches in lag country *j* for innovations initially introduced in lead country *i*. The final database comprises 21,840 observations representing 1,560 lead country-lag country pairs, each one observed from 2001 to 2014. As covariates are time-invariant, we run a Random Effects Panel Model in order to account for potential individual-specific effects at the lead country-lag country pair level. Finally, it is worth mentioning that errors are here likely to be correlated by country pair independently of which country is the lead country and which country is the lag country. Failure to account for clustering in data with multiple levels of aggregation can result in biased standard errors (Moulton 1990). Hence, we specify a clustering variable that separately identifies each country pair independently of the direction of launch. Thus, we estimate the following model:

$$\mathrm{Ln}(Y_{ijt}) = \mu + \beta_1 GD_{ij} + \beta_2 HD_{ij} + \beta_3 COLONIZER\_SAME + \beta_4 COL_{ij} + \beta_5 COL45_{ij} + \beta_6 \ln(MIG_{ij}) + \beta_7 LEGALSYSTEM\_SAME_{ij} + \beta_8 DIST_{ij} + \beta_9 CONT_{ij} + \beta_{10} GDPDIFF_{ij} + \beta_{11} DEVEL\_SAME_{ij} + FEs + e_{ijt} \quad (2)$$

Where Y represents the yearly cumulative number of innovation launches, subscripts *i* represent lead countries, subscripts *j* represent lag countries, subscripts *t* represent years, and βs are the coefficients to be estimated. We normalize all non-dummy independent variables to obtain beta coefficients and perform effect comparison. Results are reported in Table 3.

Random Effects Panel Model: Results. We report results for the Random Effects Panel Model in Column 1 of Table 3. Both HD (b = -0.03, $p < 0.01$) and GD (b = -0.05, $p < 0.01$) have a negative impact on number of cross-country innovation launches, in support of H_1. Hence, the higher the HD or the GD between countries *i* and *j*, the lower the number of launches in country *j* for innovations initially introduced in country *i* is, and vice versa.

In order to test whether the effect of GD is stronger than the effect of HD, we conduct a Wald test on the null hypothesis that the coefficient of HD equals the coefficient of GD. As expected, we find that the effect of GD is significantly stronger than the effect of HD (χ^2 = 56.12, $p < 0.01$) in support of H_{3a}.

Looking at the control variables, we find that an increase in geographic distance reduces the number of cross-country innovation launches (b = -0.05, $p < 0.01$). Further, contiguity (b = 0.22, $p < 0.01$), sharing the same legal system (b = 0.07, $p < 0.01$), and migration stock (b = 0.02, $p < 0.05$) all increase the number of cross-country launches.

---- Insert Table 3 here ----

Accelerated Failure Time Model

In Model 2 we investigate the effects of HD and GD on the time it takes for innovations initially launched in lead country *i* to be launched in lag country *j* and vice versa. As our data are right censored, i.e., not necessarily an innovation initially launched in lead country *i* is eventually launched in lag country *j*, we cannot run a standard regression. Hence, we use the Accelerated Failure Time Model, which allows for right-censoring, to investigate the effect of CD on time to cross-country innovation launch. The dependent variable is here made up of two parts: (1) the failure indicator, i.e., 1 if the innovation launch in lag country *j* has occurred (0 otherwise), and (2) the time to event, i.e., the number of days between the first launch of the innovation in lead country *i* and its launch in country *j* (or right-censoring). Differently from hazard models, the effect of covariates is here multiplicative on time scale rather than on hazard scale (Srinivasan, Lilien, and Rangaswamy 2004).

In particular, we specify the following estimation equation:

$$\text{Ln}\,(T_{Kij}) = \mu + \alpha_1 GD_{ij} + \alpha_2 HD_{ij} + \alpha_3 COLONIZER\_SAME_{ij} + \alpha_4 COL_{ij} + \alpha_5 COL45_{ij} + \alpha_6 \ln(MIG_{ij}) + \alpha_7 LEGALSYSTEM\_SAME_{ij} + \alpha_8 DIST_{ij} + \alpha_9 CONT_{ij} + \alpha_{10} GDPDIFF_{ij} + \alpha_{11} DEVEL\_SAME_{ij} + FEs + \sigma e_{Kij} \quad (3)$$

Where T represents the number of days passing between the first launch of the innovation in lead country *i* and its launch in lag country *j*, subscripts *i* represent lead countries, subscripts *j* represent lag countries, subscripts *k* represent innovations, and αs are the coefficients to be estimated. The failure indicator takes on value 1 if the focal innovation initially launched in lead country *i* is eventually launched in lag country *j*. In applying the model, we retain each innovation initially launched in lead country *i* and specify its time to launch in each lag country *j* and whether the innovation is right-censored or not. Hence, the total number of observations is 385,164 as for each innovation (9,876 innovations) we have 39 observations corresponding to 39 possible lag countries. We set the time lag for right-censored innovations as the difference in days between the initial launch date of the innovation and the end of our data collection period, i.e., December 31st 2014. We use a Weibull distribution. In order to deal with the nested structure of data, we fit a shared frailty model by adding a shared frailty term at the pair level, as each innovation is nested in 39 country pairs, in order to allow for intra-pair correlation across innovations.

Accelerated Failure Time Model: Results. We report results for the Accelerated Failure Time Model in Column 1 of Table 4. GD (b = 0.16, $p < 0.01$) and HD (b = 0.13, $p < 0.01$) both decelerate cross-country innovation launches, in support of H_2. Hence, increases in GD or HD extend the time it takes for an innovation to be launched from lead country *i* to lag country *j*.

In order to test whether the effect of GD is stronger than the effect of HD, we conduct a Wald test on the null hypothesis that the coefficient of HD equals the coefficient of GD. We find that, once again, the effect of GD is stronger than the effect of HD ($\chi^2 = 74.80$, $p < 0.01$), in support of H_{3b}.

Looking at the control variables, physical distance (b = 0.24, $p < 0.01$) has a positive effect on the time it takes for an innovation initially introduced in country *i* to be launched in country *j*. Coherently, contiguity (b = -0.62, $p < 0.01$) has a significant negative effect on the time it takes for an innovation initially introduced in country *i* to be launched in country *j*. The effects of physical distance and contiguity seem to indicate that the learning effect between lead and lag countries is dependent also on geographic barriers. Migrations have a negative effect on the time it takes for an innovation initially introduced in country *i* to be launched in country *j* (b = -0.05, $p < 0.05$). Similarly, sharing the same legal system accelerates cross-country innovation launches (b = -0.28, $p < 0.01$). Further, having been in a colonial relationship after 1945 (b = - 0.25, $p < 0.10$) has a marginally significant negative effect on the time it takes for an innovation initially introduced in lead country *i* to be launched in lag country *j*. Finally, differences in GDP marginally decelerate cross-country innovation launches (b = 0.08, $p < 0.10$)

---- Insert Table 4 here ----

Robustness Checks

We now test the robustness of our results to alternative specifications.

Independent Variable. In order to make sure that our results are not driven by our measure of CD, we replace Hofstede dimensions with Schwartz dimensions of embeddedness, affective autonomy, intellectual autonomy, mastery, harmony, egalitarianism, and hierarchy (2008). Results, which are consistent, are reported in Columns 1 and 2 in Table 5.

---- Insert Table 5 here ----

Dependent Variable. In order to make sure that results are not driven by influential outliers, we winsorize the dependent variable (10%) in both Model 1 and Model 2. Results, which are consistent, are reported in Columns 3 and 4 in Table 5.

Estimator. We run Model 1 using Pooled OLS, between effects, and negative binomial estimators (without logging the dependent variable). Results, which are reported in Columns 2 to 4 of Table 3, are consistent with those obtained in the main model (see Column 1).

Distributional Assumption. Following Chandrasekaran and Tellis (2008), we replace the Weibull distribution in Model 2 with alternative distributions. In particular, we re-estimate Model 2 recurring to Exponential and Loglogistic distributions. Results, which are reported in Columns 2 and 3 of Table 4, are once again consistent with those obtained in the main model (see Column 1).

GD and HD. We run Models 1 and 2 using GD and HD separately. Once again, results are consistent with those obtained in the main analysis (See Table 6).

---- Insert Table 6 here ----

Category-fixed effects. In order to account for the fact that different innovations may be inherently less (more) likely to be launched across countries, we estimate Model 2 including product category (i.e., bakery, baby food, snacks) fixed effects. Results, available upon request from the authors, are consistent with those in Column 1 of Table 4.

Discussion and Implications

The focus of this study was to add to the innovation diffusion literature by providing a deeper examination of cross-country innovation launches via a large-scale empirical investigation in an area where research is scarce and most contributions are focused on a narrow set of countries and innovations. The results provide new and important insights.

First, we find that CD is correlated both to the number of launches between two countries and to the time it takes for an innovation to be launched from a country to another. More specifically, an increase in CD reduces the number of cross-country innovation launches while extending the time to cross-country innovation launch.

Second, as our effects hold for both HD and GD, our contribution provides Hofstede's framework with additional support while pointing out the relevance of GD (which displays a stronger effect) in capturing differences in habits, values, and customs across countries. To the best of our knowledge, GD data have never been used thus far in the management nor in the marketing literature. Our findings interestingly show that the remote history of populations, tracing back to Neolithic times, has a significant impact on today's marketing phenomena. Hence, findings from this paper provide both scholars and practitioners with a new ready-to-use measure of CD, which could be used, alongside traditional measures, to capture differences across consumers from different countries.

Third, we find that economic, geographic, and historic distances across countries all play a role in innovation diffusion. For what pertains to historic distance, we find that sharing a common recent colonial history accelerates cross-country innovation launches. Similarly, the number of migrants from a certain country living in another one as well as sharing similar legal systems facilitate innovation diffusion. Looking at economic distance, we find that differences in GDP per capita decelerate innovation diffusion across countries. Finally, geographic distance, here expressed in terms of contiguity and geodesic distance across capital cities, inhibits cross-country innovation diffusion. Hence, from a theoretical standpoint, our contribution fills a gap in the marketing literature which, to the best of our knowledge, has never taken into consideration such a comprehensive set of determinants of cross-country relationships.

We now investigate the impact of CD on innovation performance in lag countries. We measure the performance of an innovation in a given lag country as the number of launches for the innovation in the lag country after its first launch. Our dependent variable is thus the average number of launches in the focal lag country for the innovation in a year. We employ a Heckman's sample selection model with two-step estimation. In the first-stage equation we choose as covariates the same covariates that were previously employed in Model 2 to predict an innovation's individual probability to be launched in a given lag country. In the second-stage equation we correct for selection bias and estimate the impact of the same covariates along with time to launch, i.e., the number of days passing after the first launch of the innovation in lead country *i* before the innovation is ultimately launched in lag country *j*, on subsequent performance. We take the log of both time to launch and performance in order to facilitate the interpretation of results. Results are reported in Table 7. Looking at the second-stage equation, we see that time to launch has a negative effect on performance (b = -0.009, $p < 0.01$). Hence, we show that fast is indeed better and that innovations that are launched faster experience greater success at later stages, after controlling for the fact that only innovations with certain characteristics are actually launched in a given lag country. Further, GD (b = -0.03, $p < 0.01$) and HD (b = -0.03, $p < 0.01$) both have a negative effect on subsequent performance. Such results have important implications for practitioners willing to maximize their innovations' performance, as they show that launching innovations in culturally close countries has positive effects on innovation performance, both directly and indirectly, via reduced time to launch.

---- Insert Table 7 here ----

Limitations and Future Research Directions

The present research has limitations which represent fruitful directions for research. First, our model is tested in only one industry. While the packaged food industry has attracted significant research interest (see e.g., Moorman et al. 2012; Sorescu and Spanjol 2008; Van Heerde et al. 2004), empirical testing in other industries would contribute to assessing the generalizability of our findings beyond our context of investigation. Second, in our analyses, we control for country-specific characteristics via fixed effects. Despite this is out of our scope, such choice does not allow us to investigate the role of country-level characteristics in driving cross-country innovation launches. Future research could try to unveil the roles of variables such as, for instance, economic attractiveness, in the previously identified processes. Third, we do not investigate the characteristics of innovations that are launched across a specific lead country-lag country pair. Future contributions could try to investigate the role of product's characteristics, beside countries' characteristics, in driving cross-country innovation diffusion. Despite the previously identified limitations, we consider this contribution as a valuable one and wish it stimulates further research in this area.

References

Aggarwal, Raj, Colm Kearney, and Brian Lucey (2012), "Gravity and Culture in Foreign Portfolio Investment," *Journal of Banking and Finance*, 36 (2), 525-538.

Albuquerque, Paulo, Bart J. Bronnenberg, and Charles J. Corbett (2007), "A Spatiotemporal Analysis of the Global Diffusion of ISO 9000 and ISO 14000 Certification," *Management Science*, 53 (3), 1024-1041.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg (2003), "Fractionalization," *Journal of Economic Growth*, 8 (2), 155-194.

Ashraf, Quamrul and Oded Galor (2013) "The "Out of Africa" Hypothesis, Human Genetic Diversity, and Comparative Economic Development," *American Economic Review*, 103 (1), 1-46.

Barkema, Harry G., John H.J. Bell, and Johannes M. Pennings (1996), "Foreign Entry, Cultural Barriers and Learning," *Strategic Management Journal*, 17 (2), 151-166.

Benito, Gabriel R.G. and Geir Gripsrud (1992), "The Expansion of Foreign Direct Investments: Discrete Rational Location Choices or a Cultural Learning Process?," *Journal of International Business Studies*, 23 (3), 461-476.

Beugelsdijk, Sjoerd, Tatiana Kostova, Vincent E. Kunst, Ettore Spadafora, and Marc Van Essen (2017), "Cultural Distance and Firm Internationalization: A Meta-Analytical Review and Theoretical Implications," *Journal of Management*, 44 (1), 89-130.

Cavalli-Sforza, Luca L., Paolo Menozzi, and Alberto Piazza (1994), *The History and Geography of Human Genes.* Princeton, NJ: Princeton University Press.

Chandrasekaran, Deepa and Gerard J. Tellis (2008), "Global Takeoff of New Products: Culture, Wealth, or Vanishing Differences?," *Marketing Science*, 27 (5), 844-860.

Chua, Roy Y.J., Yannig Roth, and Jean-Francoise Lemoine (2015), "The Impact of Culture on Creativity: How Cultural Tightness and Cultural Distance Affect Global Innovation Crowdsourcing Work," *Administrative Science Quarterly*, 60 (2), 189-227.

Dekimpe, Marnik G., Philip M. Parker, and Miklos Sarvary (2000), ""Globalization'': Modeling Technology Adoption Timing Across Countries," *Technological Forecasting and Social Change*, 63 (1), 25-42.

Desmet, Klaus, Michel Le Breton, Ignacio Ortuno Ortin, and Shlomo Weber (2011), "The Stability and Breakup of Nations: A Quantitative Analysis," *Journal of Economic Growth*, 16 (3), 183-213.

Eliashberg Jehoshua and Kristiaan Helsen (1996), "Modeling Lead/Lag Phenomena in Global Marketing: The Case of VCRs," Working Paper, Wharton School.

Ganesh, Jaishankar, V. Kumar, and Velavan Subramaniam (1997), "Learning Effect in Multinational Diffusion of Consumer Durables: An Exploratory Investigation*,"* *Journal of the Academy of Marketing Science*, 25 (3), 214-228.

---- and V. Kumar (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.

Gatignon, Hubert, Jehoshua Eliashberg, and Thomas S. Robertson (1989), "Modeling Multinational Diffusion Patterns: An Efficient Methodology," *Marketing Science*, 8 (3), 231-247.

Giuliano, Paola, Antonio Spilimbergo, and Giovanni Tonon (2014), "Genetic Distance, Transportation Costs, and Trade," *Journal of Economic Geography*, 14 (1), 179-198.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2009), "Cultural Biases in Economic Exchange," *Quarterly Journal of Economics*, 124 (3), 1095-1131.

Harvey, Michael G. and David A. Griffith (2007), "The Role of Globalization, Time Acceleration, and Virtual Global Teams in Fostering Successful Global Product Launches," *Journal of Product Innovation Management*, 24 (5), 486-501.

Helsen, Kristiaan, Kamel Jedidi, and Wayne S. DeSarbo (1993), "A New Approach to Country Segmentation Utilizing Multinational Diffusion Patterns," *Journal of Marketing*, 57 (4), 60-71.

Hofstede, Geert H. (2001), *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations*. Thousand Oaks, CA: Sage Publications.

Jain, Subhash C (1989), "Standardization of International Marketing Strategy. Some Research Hypotheses," *Journal of Marketing*, 53 (1), 70-79.

Kalish, Shlomo, Vijay Mahajan, and Eitan Muller (1995), "Waterfall and Sprinkler New-Product Strategies in Competitive Global Markets," *International Journal of Research in Marketing*, 12 (2), 105-119.

Kirkman, Bradley L., Kevin B. Lowe, and Cristina B. Gibson (2017), "A Retrospective on Culture's Consequences: The 35-year Journey," *Journal of International Business Studies*, 48 (1), 12-29.

----, ----, and ---- (2006), "A Quarter Century of Culture's Consequences: A Review of Empirical Research Incorporating Hofstede's Cultural Values Framework," *Journal of International Business Studies*, 37 (3), 285-320.

Kogut, Bruce and Harbir Singh (1988), "The Effect of National Culture on the Choice of Entry Mode," *Journal of International Business Studies*, 19 (3), 411-432.

Kumar, V. (2014), "Understanding Cultural Differences in Innovation: A Conceptual Framework and Future Research Directions," *Journal of International Marketing*, 22 (3), 1-29.

----, Sarang Sunder, and B. Ramaseshan (2011), "Analyzing the Diffusion of Global Customer Relationship Management: A Cross-Regional Modeling Framework," *Journal of International Marketing*, 19 (1), 23-39.

----- and Trichy V. Krishnan (2002), "Multinational Diffusion Models: an Alternative Framework," *Marketing Science*, 21 (3), 318-330.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny (1998), "Law and Finance," *Journal of Political Economy*, 106 (6), 1113-1155.

Lee, Yikuan, Bou-wen Lin, Yim-Yu Wong, and Roger J. Calantone (2011), "Understanding and Managing International Product Launch: A Comparison between Developed and Emerging Markets," *Journal of Product Innovation Management*, 28 (S1), 104-120.

Leung, Kwok, Rabi S. Bhagat, Nancy R. Buchan, Miriam Erez, and Cristina B. Gibson (2005), "Culture and International Business: Recent Advances and their Implications for Future Research," *Journal of International Business Studies*, 36 (4), 357–378.

McSweeney, Brendan (2002), "Hofstede's Model of National Cultural Differences and their Consequences: A Triumph of Faith - a Failure of Analysis," *Human Relations*, 55 (1), 89-118.

Mitra, Debanjan and Peter N. Golder (2002), "Whose Culture Matters? Near-Market Knowledge and Its Impact on Foreign Market Entry Timing," *Journal of Marketing Research*, 39 (3), 350-365.

Moorman, Christine, Rosellina Ferraro, and Joel Huber (2012), "Unintended Nutrition Consequences: Firm Responses to the Nutrition Labeling and Education Act," *Marketing Science,* 31 (5), 717-773.

Moulton, Brent R. (1990), "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables in Micro Units," *Review of Economics and Statistics*, 72 (2), 334-338.

Putsis, William P. Jr, Sridhar Balasubramaniam, Edward H. Kaplan, and Subrata K. Sen (1997), "Mixing Behavior in Cross-Country Diffusion," *Marketing Science,* 16 (4), 354-369.

Rubera, Gaia, David A. Griffith, and Goksel Yalcinkaya (2012), "Technological and Design Innovation Effects in Regional New Product Rollouts: A European Illustration," *Journal of Product Innovation Management*, 29 (6), 1047-1060.

Schwartz, Shalom H. (2008), *The 7 Schwartz Cultural Value Orientation Scores for 80 Countries*. Available at: https://www.researchgate.net/publication/304715744_The_7_Schwartz_cultural_value_orientation_scores_for_80_countries.

Sorescu, Alina and Jelena Spanjol (2008), "Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods," *Journal of Marketing*, 72 (2), 114-132.

Sorge, Arndt (1983), "Culture's Consequences: International Differences in Work-Related Values by Geert Hofstede," *Administrative Science Quarterly,* 28 (4), 625-629.

Spolaore, Enrico and Romain Wacziarg (2013), "How Deep Are the Roots of Economic Development?", *Journal of Economic Literature*, 51 (2), 325-369.

---- and ---- (2009), "The Diffusion of Development," *Quarterly Journal of Economics*, 124 (2), 469-529.

Srinivasan, Raji, Gary L. Lilien, and Arvind Rangaswamy (2004), "First in, First out? The Effects of Network Externalities on Pioneer Survival," *Journal of Marketing*, 68 (1), 41-58.

Steenkamp, Jan-Benedict E. M. (2001), "The Role of National Culture in International Marketing Research," *International Marketing Review*, 18 (1), 30-44.

Stone, Linda and Paul F. Lurquin. 2007. *Genes, Culture, and Human Evolution: A Synthesis*. Malden, MA: Wiley-Blackwell.

Subramaniam, Mohan, Stephen R. Rosenthal, and Kenneth J. Hatten (1998), "Global New Product Development Processes: Preliminary Findings and Research Propositions," *Journal of Management Studies*, 35 (6), 773–796.

Sundqvist, Sanna, Frank Lauri, and Kaisu Puumalainen (2005), "The Effects of Country Characteristics, Cultural Similarity and Adoption Timing on the Diffusion of Wireless Communications," *Journal of Business Research*, 58 (1), 107-110.

Takada, Hirokazu and Dipak Jain (1991), "Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries," *Journal of Marketing*, 55 (2), 48-54.

Tellis, Gerard J., Stefan Stremersch, and Eden Yin (2003), "The International Takeoff of New Products: The Role of Economics, Culture, and Country Innovativeness," *Marketing Science*, 22 (2), 188-208.

Triandis, Harry C. (1982), “A Model of Choice in Marketing,” in *Research in Marketing*, ed. J. Sheth, Vol. 6, Supplement 1, 145-162. Greenwich, CT: JAI Press.

Van Everdingen, Yvonne, Dennis Fok, and Stefan Stremersch (2009), “Modeling Global Spillover of New Product Takeoff,” *Journal of Marketing Research*, 46 (5), 637-652.

----, Wouter B. Aghina, and Dennis Fok (2005), “Forecasting Cross-Population Innovation Diffusion: A Bayesian Approach,” *International Journal of Research in Marketing*, 22 (3), 293-308.

Van Heerde, Harald J., Carl F. Mela, and Puneet Manchanda (2004), “The Dynamic Effect of Innovation on Market Structure,” *Journal of Marketing Research*, 41 (2), 166-183.

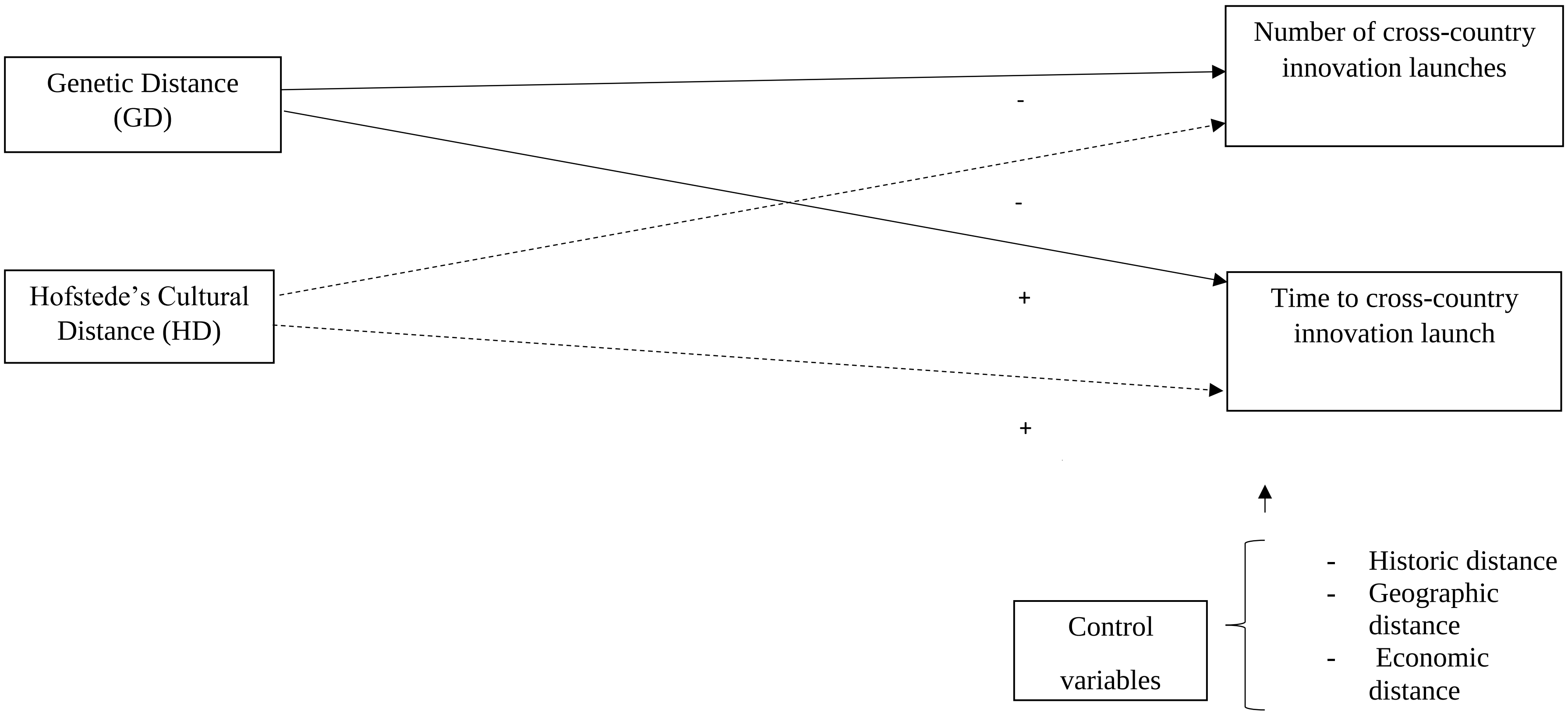
Verniers, Isabel, Stefan Stremersch, and Christophe Croux (2011), “The Global Entry of New Pharmaceuticals: A Joint Investigation of Launch Window and Price,” *International Journal of Research in Marketing*, 28 (4), 295-308.

Yalcinkaya, Goksel (2008), “A Culture-Based Approach to Understanding the Adoption and Diffusion of New Products across Countries,” *International Marketing Review,* 25 (2), 202-214.

Yeniyurt, Sengun, Janell D. Townsend, and Mehmet B. Talay (2007), “Factors Influencing Brand Launch in a Global Marketplace,” *Journal of Product Innovation Management,* 24 (5), 471-485.

---- and Janell D. Townsend (2003), “Does Culture Explain Acceptance of New Products in a Country? An Empirical Investigation,” *International Marketing Review*, 20 (4), 377-396.

Figure 1: Cultural Distance and its Impact on Cross-Country Innovation Launches



Notes: The dashed lines of HD's effects represent the expected weaker effects of HD (vs. GD) on both number of cross-country innovation launches and time to cross-country innovation launch.

Table 1: Variables, Measures, and Sources

	Variable	Measure	Data Source
Dependent variables	Number of Launches	Yearly cumulative number of innovation launches in lag country *j* for innovations initially introduced in lead country *i*	Mintel GNPD, Our Elaboration
	Time to Launch	Time-lag in days between the first launch of the innovation in lead country *i* and its first launch in lag country *j*	
Cultural distance	Genetic distance (GD)	See Spolaore and Wacziarg (2009)	Spolaore and Wacziarg (2009)
	Hofstede's Cultural distance (HD)	A composite index based on the averaged sum of the deviations corrected for their variances along each Hofstede's cultural dimension for each country pair (Kogut and Singh 1988)	Hofstede Center Website, Our Elaboration
Historic distance	Common Colonizer (COLONIZER_SAME)	1 if countries *i* and *j* were colonized in the past by the same colonizer, 0 otherwise	CEPII Geodist database
	Colony (COL)	1 if countries *i* and *j* have ever been in a colonial relationship, 0 otherwise	
	Colony after 1945 (COL45)	1 if countries *i* and *j* have ever been in a colonial relationship after 1945, 0 otherwise	
	Migration Stock (MIGLOG)	Total number of migrants from lead country *i* living in lag country *j* in 2000	World Bank Global Bilateral Migration Database
	Common Legal System (LEGALSYSTEM_SAME)	1 if countries *i* and *j*'s legal systems share the same origin, 0 otherwise	La Porta et al. (1998)
Geographic distance	Physical distance (DIST)	Physical (great circle) distance in kilometers between the capital cities of two countries	CEPII Geodist database
	Contiguity (CONT)	1 if countries *i* and *j* share borders, 0 otherwise	
Economic distance	GDP Per Capita difference (GDPDIFF)	Absolute value of the difference of logged GDPs per capita, averaged across years	World Bank GDP Per Capita Database
	Same Level of Development (DEVEL_SAME)	1 if countries *i* and *j* share the same level of development (i.e., emerging vs. developed)	IMF WEO, Our Elaboration

Table 2: Descriptives and Correlations

	Mean	Std.	.1	.2	.3	.4	.5	.6	.7	.8	.9	.10	.11
1. Genetic distance	778.23	535.82	1.00										
2. Hofstede's Cultural distance	1.97	1.09	.12*	1.00									
3. Common Colonizer	.01	.11	.06*	-.08*	1.00								
4. Colony	.04	.19	-.04*	-.10*	-.02*	1.00							
5. Colony after 1945	.01	.10	.04*	.03*	-.01	.51*	1.00						
6. Ln (Migration Stock)	7.13	2.96	-.39*	-.18*	.01	.23*	.11*	1.00					
7. Common Legal System	.32	.47	-.01	-.32*	.17*	.21*	.12*	.16*	1.00				
8. Physical Distance	8,342.72	5,002.73	.41*	.11*	-.06*	-.02*	.01	-.38*	-.03*	1.00			
9. Contiguity	.04	.20	-.17*	-.23*	.03*	.06*	-.02*	.25*	.19*	-.30*	1.00		
10. Same Level of Development	.51	.50	-.20*	-.25*	-.02*	-.03*	-.03*	.06*	.03*	-.17*	.17*	1.00	
11. GDP per Capita Difference	1.38	1.07	.22*	.26*	.08*	-.01	.07*	-.10*	-.04*	.11*	-.18*	-.79*	1.00

Notes: * p<0.05. Variance Inflation Factors are well below 10. The correlation between GD and HD reaches 0.20 ($p<0.05$) in the dataset for Model 2.

Table 3: Model 1 Estimation: Results

	Dependent variable: Number of Cross-country Innovation Launches			
	Random Effects^ Column 1	Pooled OLS^ Column 2	Between-Effects Column 3	Negative Binomial Column 4
GD	-.05 (.01)***	-.05 (.01)***	-.05 (.01)***	-.11 (.02)***
HD	-.03 (.01)***	-.03 (.01)***	-.03 (.01)***	-.11 (.02)***
COLONIZER_SAME	-.02 (.05)	-.02 (.05)	-.02 (.04)	-.24 (.09)**
COL	.06 (.04)	.06 (.04)	.06 (.03)**	.02 (.05)
COL45	.001 (.10)	.001 (.10)	.001 (.05)	.16 (.09)*
MIGLOG	.02 (.01)**	.02 (.01)**	.02 (.01)**	.09 (.02)***
LEGALSYSTEM_SAME	.07 (.02)***	.07 (.02)***	.07 (.01)***	.22 (.02)***
DIST	-.05 (.01)***	-.05*** (.01)	-.05 (.01)***	-.19 (.02)***
CONT	.22 (.06)***	.22 (.06)***	.22 (.02)***	.48 (.04)***
DEVEL_SAME	.01 (.02)	.01 (.02)	.01 (.02)	.08 (.05)*
GDPDIFF	-.01 (.01)	-.01 (.01)	-.01 (.01)	-.05 (.03)
Lead Country FEs	YES	YES	YES	YES
Lag Country FEs	YES	YES	YES	YES
Year FEs	YES	YES		YES
Sample Size	21,840	21,840	21,840	21,840
R-Sq	.47	.47	.30	
Log-likelihood				-20,879.66

Notes: *p<.10; **p<.05; ***p<.01. Country and Year Fixed Effects are included in the analysis but not reported here for brevity. All regressions include a constant. ^Robust Standard Errors.

Table 4: Model 2 Estimation: Results

	Dependent variable: Time to Cross-country Innovation Launch		
	Weibull Column 1	Exponential Column 2	Loglogistic Column 3
GD	.16 (.03)***	.14 (.03)***	.16 (.03)***
HD	.13 (.02)***	.11 (.02)***	.13 (.02)***
COLONIZER_SAME	.18 (.15)	.15 (.12)	.14 (.15)
COL	-.08 (.08)	-.07 (.07)	-.03 (.08)
COL45	-.25 (.14)*	-.21 (.12)*	-.29 (.14)**
MIGLOG	-.05 (.02)**	-.04 (.02)**	-.06 (.02)**
LEGALSYSTEM_SAME	-.28 (.04)***	-.24 (.03)***	-.29 (.04)***
DIST	.24 (.02)***	.21 (.02)***	.24 (.02)***
CONT	-.62 (.07)***	-.53 (.06)***	-.76 (.07)***
DEVEL_SAME	-.10 (.07)	-.09 (.06)	-.10 (.07)
GDPDIFF	.08 (.05)*	.07 (.04)*	.08 (.05)*
Lead Country FEs	YES	YES	YES
Lag Country FEs	YES	YES	YES
Year FEs	YES	YES	YES
Sample Size	385,164	385,164	385,164
$\chi 2$	5,214.87	4,966.54	5,257.20

Notes: *p<.10; **p<.05;***p<.01. Country and Year Fixed Effects are included in the analysis but not reported here for brevity. All regressions include a constant.

Table 5: Robustness checks

	Model 1^	Model 2	Model 1^	Model 2
	Schwartz CD		Winsorized DV (10%)	
	Column 1	Column 2	Column 3	Column 4
GD	-.05 (.02)***	.15 (.03)***	-.05 (.01)***	.12 (.02)***
HD			-.03 (.01)***	.10 (.02)***
Schwartz CD	-.02 (.01)***	.10 (.02)***		
COLONIZER_SAME	-.06 (.05)	.25 (.13)*	-.01 (.04)	.13 (.11)
COL	.08 (.04)*	-.14 (.08)*	.03 (.03)	-.06 (.06)
COL45	-.05 (.10)	-.13 (.14)	.01 (.08)	-.18 (.10)*
MIGLOG	.02 (.01)**	-.05 (.02)**	.02 (.01)***	-.04 (.02)**
LEGALSYSTEM_SAME	.08 (.01)***	-.32 (.04)***	.06 (.01)***	-.21 (.03)***
DIST	-.05 (.01)***	.24 (.02)***	-.05 (.01)***	.18 (.02)***
CONT	.22 (.06)***	-.63 (.07)***	.14 (.04)***	-.46 (.05)***
DEVEL_SAME	.01 (.02)	-.07 (.07)	.02 (.02)	-.08 (.05)
GDPDIFF	-.01 (.01)	.10 (.05)**	-.01 (.01)	.06 (.03)*
Lead Country FEs	YES	YES	YES	YES
Lag Country FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Sample Size	22,960	399,200	21,840	385,164
R-Sq	.47		.45	
$\chi 2$		5,361.73		4,780.86

Notes: *p<.10;**p<.05;***p<.01. Country and Year Fixed Effects are included in the analysis but not reported here for brevity. All regressions include a constant.

Table 6: Models with GD/HD only: Results

	Model 1^	Model 2	Model 1^	Model 2
	GD only		HD only	
	Column 1	Column 2	Column 3	Column 4
GD	-.06 (.01)***	.21 (.03)***		
HD			-.04 (.01)***	.16 (.02) ***
COLONIZER_SAME	-.04 (.04)	.17 (.13)	.001 (.06)	.11 (.15)
COL	.07 (.04)	-.12 (.08)	.06 (.04)	-.10 (.08)
COL45	-.04 (.10)	-.14 (.14)	-.0004 (.10)	-.23 (.14)
MIGLOG	.02 (.01)**	-.05 (.02)**	.02 (.01)**	-.06 (.02)**
LEGALSYSTEM_SAME	.08 (.01)***	-.33 (.04)***	.06 (.01)***	-.26 (.04)***
DIST	-.05 (.01)***	.24 (.02)***	-.07 (.01)***	.29 (.02)***
CONT	.22 (.06)***	-.64 (.07)***	.22 (.06)***	-.61 (.07)***
DEVEL_SAME	.01 (.02)	-.07 (.07)	.01 (.02)	-.10 (.07)
GDPDIFF	-.03 (.01)**	.15 (.04)***	-.01 (.01)	.08 (.05)*
Lead Country FEs	YES	YES	YES	YES
Lag Country FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Sample Size	22,960	399,200	21,840	385,164
R-Sq	.47		.47	
$\chi 2$		5,343.59		5,188.99

Notes: *p<.10; **p<.05;***p<.01. Country and Year Fixed Effects are included in the analysis but not reported here for brevity. All regressions include a constant.

Table 7: Heckman's Sample Selection Model: Results

Dependent Variable	Stage 1: Likelihood of being launched in the focal lag country	Stage 2: Number of launches in the focal lag country
GD	-.05 (.01)***	-.03 (.01)***
HD	-.06 (.01)***	-.03 (.01)***
Time to Launch°		-.009 (.002)***
COLONIZER_SAME	-.12 (.03)***	-.06 (.03)*
COL	-.03 (.02)	-.004 (.01)
COL45	.14 (.03)***	.07 (.03)**
MIGLOG	.05 (.01)***	.03 (.01)***
LEGALSYSTEM_SAME	.12 (.01)***	.07 (.02)***
DIST	-.10 (.01)***	-.05 (.01)***
CONT	.34 (.02)***	.20 (.05)***
DEVEL_SAME	.03 (.02)*	.04 (.02)**
GDPDIFF	-.03 (.01)***	-.02 (.01)
Lead Country FEs	YES	YES
Lag Country FEs	YES	YES
Year FEs	YES	YES
Λ		.64 (.17)***
χ2		321.92

Notes: *p<.10; **p<.05;***p<.01. Country and Year Fixed Effects are included in the analysis but not reported here for brevity. °Coefficient x 10^3. All regressions include a constant.

Chief Customer Advocate: The Role of Marketing CEOs in Reducing Product-Harm Crises

Raji Srinivasan[a]

Verdiana Giannetti[b]

[a] Raji Srinivasan (raji.srinivasan@mccombs.utexas.edu) is Sam Barshop Centennial Professor of Marketing Administration at the Red McCombs School of Business, The University of Texas at Austin, USA.

[b] Verdiana Giannetti (verdiana.giannetti@phd.unibocconi.it) is a PhD Candidate in Business Administration and Management at Bocconi University, Via Roentgen 1, 20136 Milano, Italy.

Abstract

Product-harm crises caused by product failures, which harm consumers and hurt firm performance, are, unfortunately, very common. Yet, there are few insights on whether a CEO with a marketing background in a firm can influence its product-harm crises. We hypothesize that a Marketing CEO in a firm will play a facilitating role, along with powerful marketing, finance, operations, and R&D departments in the top management team and CEO's stock option pay, in reducing the number of product-harm crises. We test the hypotheses using data on 75 publicly-listed U.S. medical device firms between 2003 and 2015. We measure the number of product-harm crises by the number of product recalls. We account for endogeneity of explanatory variables using a control function approach. The results, which are robust, indicate that a Marketing CEO along with powerful finance and R&D departments decreases the number of product-harm crises. Further, a Marketing CEO also decreases the positive effect of CEO's stock option pay on the number of product-harm crises. The findings, which identify the novel role of Marketing CEOs in reducing product-harm crises, generate actionable guidelines for business practice.

Keywords: *Product-Harm Crises, Product Recalls, Marketing CEO, Top Management Team, Medical Devices*

Product-harm crises, which occur when products fail to meet safety standards or are defective, are harmful for consumers and costly for firms. For firms, product-harm crises entail costs of repair, restitution, and/or liability, loss of customers, and resultant lower brand equity, profit, and valuations (Daughety and Reinganum 1995). While there are insights in the marketing literature on the negative effects of product-harm crises, we know much less about their antecedents, more generally, and, specifically, whether a firm's Marketing CEO, one with marketing functional experience, will affect its product-harm crises, the focus of this research.

From a theoretical perspective, there is a large body of work on product-harm crises (also interchangeably termed as product recalls) triggered by product failures. Such work has primarily focused on their negative effects on consumers' responses (Germann et al. 2014), product sales (Liu and Shankar 2015), category sales (Cleeren, Dekimpe, and Helsen 2008; Cleeren, Van Heerde, and Dekimpe 2013; Van Heerde, Helsen, and Dekimpe 2007), and firms' intangible value (Chen, Ganesan, and Liu 2009; Eilert et al. 2017). See Cleeren, Dekimpe, and Van Heerde (2017) for a very comprehensive review of the product-harm crises literature.

In Table 1, we summarize the literature on the antecedents of product-harm crises, about which we know much less. Antecedents examined in extant work include founding family presence (Kashmiri and Brower 2016), firms' experience with product recalls (Haunschild and Rhee 2004; Kalaignanam, Kushwaha, and Eilert 2013), R&D intensity and product scope (Kashmiri and Brower 2016; Thirumalai and Sinha 2011), and firms' leadership characteristics, including CEO's stock option pay, tenure, and founder status, the presence of a Chief Marketing Officer (CMO), and marketing department power in the top management team (TMT) (Kashmiri and Brower 2016; Kashmiri, Nicol, and Arora 2017; Wowak, Mannor, and Wowak 2015). Despite the evidence for customer advocacy of a

Marketing CEO in the firm (Homburg, Workman, and Krohmer 1999; Paşa and Shugan 1996), the literature has overlooked whether a Marketing CEO will affect its product-harm crises.

---- Insert Table 1 here ----

It is not a priori clear whether a Marketing CEO will affect product-harm crises. At first blush, it may appear that the CEO, who is responsible for meeting revenue targets, may encourage senior colleagues in the different departments (i.e., marketing, finance, operations, and R&D) to speed products to market without adequate product quality checks, increasing the number of product-harm crises. However, we propose an alternative view. The CEO's functional background is an indicator of the firm's emphasis on different functions in securing competitive advantage (Bertrand and Schoar 2003; Miller and Shamsie 2001). Hence, a Marketing CEO in a firm reflects the importance of the marketing function in its strategy and resource decisions. Accordingly, a Marketing CEO will reflect the firm's focus on brands and customers as valuable market-based assets. We propose that a Marketing CEO will consider the firm's brands and customers as strategic market-based assets and advocate for their well-being with powerful colleagues in the different departments who are responsible for introducing and managing products. We propose that a Marketing CEO will advocate lower risk-taking by colleagues in the different departments, emphasizing product quality and safety, therefore reducing the number of product-harm crises. Thus, we develop hypotheses about the facilitating role of the Marketing CEO, in conjunction with other firm characteristics, in reducing product-harm crises.

Applying upper echelons theory (Hambrick and Mason 1984), which argues that executives in different departments (Feng, Morgan, and Rego 2015; Finkelstein 1992) have different mindsets and goals, we consider the power of different departments on the firm's

TMT, specifically, the marketing, finance, operations, and R&D departments. Applying agency theory, we also consider the moderating role of the Marketing CEO on the effect of CEO's stock option pay, the CEO's compensation in the form of the firm's stock, which aligns the CEO's incentives and risk-taking with those of its shareholders (Jensen and Murphy 1990; Sanders and Hambrick 2007) and which has been shown to increase product harm-crises (Wowak et al. 2015), on the number of product-harm crises.

To test the hypotheses, we seek an industry where product-harm crises are voluntary, i.e., firms' strategic choices, ensuring its relevance for studying the role of CEOs in product-harm crises. One such industry is the U.S. medical device industry where product recalls are largely voluntary actions of medical device firms. The U.S. Food and Drug Administration (FDA, hereinafter) monitors and maintains records of all product recalls, providing comprehensive data for hypotheses testing.

This research's insights have high managerial relevance as product-harm crises hurt firms' reputations, market performance (Rhee and Haunschild 2006), and valuations (Chen et al. 2009). The findings are especially useful to reduce product-harm crises in the U.S. medical device industry. According to the FDA, recalls of defective medical devices nearly doubled from 2003 (604) to 2012 (1,190). Product-harm crises cost the U.S. medical device industry U.S. $2.5-5 billion per year and, on average, a product-harm crisis results in a 13% decline in the stock prices of medical device firms (Fuhr, George, and Pai 2009).

We collect data from multiple sources including the U.S. FDA Medical Device Recalls database, Standard and Poor's Compustat, ExecuComp, and online biographies of senior executives. The final sample consists of a panel of 75 firms (557 firm-years) between 2003 and 2015. We measure the number of product-harm crises of U.S. medical device firms by the annual count of their product recalls. We measure a Marketing CEO by whether the

CEO had prior marketing and/or sales functional experience before being appointed CEO and the power of different departments using the measure proposed by Feng et al. (2015). As some firms have no product recalls in this time period, there is over-dispersion and many zeros in the dependent variable. Hence, we estimate a zero-inflated negative binomial regression model. We correct for endogeneity of explanatory variables using a control function approach (Petrin and Train 2010).

The findings, which are robust to alternative model specifications, samples, and measures of variables, indicate that a Marketing CEO plays a facilitative role in reducing the number of product-harm crises. More specifically, a Marketing CEO in a firm, in conjunction with powerful finance and R&D departments, helps reduce the number of product-harm crises. Further, a Marketing CEO weakens the positive effect of CEO's stock option pay on the number of product-harm crises.

The paper's findings make several theoretical contributions. First, the findings extend the literature on product-harm crises by showing the top-down, beneficial influence of a Marketing CEO on product-harm crises. Second, by identifying a new mechanism, fewer product-harm crises, the findings identify yet another way, through the Marketing CEO, by which marketing leadership improves firm performance. To the best of our knowledge, this is the first study to provide empirical evidence of the role of Marketing CEOs in influencing firms' outcomes. In doing so, the findings extend the marketing literature, which has hitherto focused on the CMO, whose effects on product-harm crises, we find, are different from those of a Marketing CEO. Third, the findings also suggest a key role for C-suite executives in decreasing the number of product-harm crises and, albeit indirectly, in new product development, which has been typically studied at the project and middle-management levels.

For managerial practice, the findings generate actionable guidance on how corporate governance decisions—appointing a Marketing CEO in conjunction with powerful finance and R&D departments and high CEO's stock option pay—can reduce the number of product-harm crises. The research's insights, generated in the U.S. medical device industry, are also useful to various industry stakeholders (e.g., senior management, investors, shareholders, and regulators) in reducing product-harm crises.

The rest of the paper is organized as follows. We first develop the hypotheses. We then describe the data and measures, following which we discuss the estimation approach and results. We conclude with a discussion of the paper's theoretical contributions, implications for managerial practice, and limitations and opportunities for future research.

Hypotheses

We extend three developments in the management literature on firms' senior leadership to develop the hypotheses relating a Marketing CEO to product-harm crises.

First, building on the concept of bounded rationality (Cyert and March 1963), Hambrick and Mason (1984) proposed the upper echelons theory, that executives in firms' TMTs perceive situations and opportunities through personalized lenses, which are informed by their functional experiences, personalities, and values. Viewed this way, firms' strategic choices and outcomes are reflections of their senior executives' backgrounds.

Second, upper echelons theory further posits that the characteristics of CEOs shape firms' actions and outcomes. Empirical evidence (see Finkelstein, Hambrick, and Cannella 2009 for a summary) identifies effects of CEOs' experiences (e.g., Miller and Shamsie 2001), personalities, and values on firms' strategy and outcomes (e.g., Agle, Mitchell, and Sonnenfeld 1999; Bertrand and Schoar 2003). In other words, senior executives, including CEOs with different functional experiences, differ in their knowledge, values, and perspectives (Dearborn and Simon 1958), coherently affecting their firms' strategy and outcomes (Bertrand and Schoar 2003).

Third, upper echelons theory further argues that the characteristics of firms' TMTs (as a unit) explain the variance in firms' strategy and outcomes. In a review of upper echelons theory, Hambrick (2007, p. 341) notes "we can conclude that CEOs affect organizational outcomes … we anticipate that TMTs matter even more." A key demographic characteristic of the TMT is the power of different departments (Finkelstein 1992), which is determined by the extent to which the firm depends on the department to deliver performance. Recently, Feng et al. (2015) report the positive effect of marketing power in the TMT on the firm's valuation through long-run market-based-asset-building and short-run market-based-asset-leveraging capabilities.

Integrating these ideas, we propose that a Marketing CEO, by virtue of his/her marketing experience, will influence the decisions concerning product quality and safety of different departments on the firm's TMT, therefore affecting the number of product-harm crises. Departments with more scarce and valuable resources for the firm have more power. As Day (1997, p. 89) noted "some functions will be relatively more powerful than others, that is, they will control resources and have more influence in the strategy dialogue". Hence, we hypothesize interaction effects between a Marketing CEO and powerful departments on the firm's TMT, specifically marketing, finance, operations, and R&D departments, all of which influence new product decisions, including those related to product quality and safety.

Further, extending developments in agency theory (Jensen and Meckling 1976), we propose that a Marketing CEO will interact with the CEO's stock option pay, which aligns his/her risk-taking propensity with that of the firm's shareholders (Jensen and Murphy 1990), increases risk-taking (Sanders and Hambrick 2007) and the occurrence of product-harm crises

(Wowak et al. 2015), to reduce product-harm crises. We provide the theoretical framework in Figure 1.

---- Insert Figure 1 here ----

A pertinent question here is whether a Marketing CEO will directly affect the number of product-harm crises (i.e., main effect). As noted, the CEO has the most influence on the firm's strategy and resource allocation decisions and is responsible for delivering revenue and profit growth to shareholders (Bertrand and Schoar 2003). Hence, a CEO (including a Marketing CEO) may encourage senior colleagues to speed products to market without adequate quality and safety checks. This suggests that a Marketing CEO may directly increase the number of product-harm crises.

However, other developments suggest the opposite. A Marketing CEO in a firm reflects the importance of brands and customers in securing competitive advantage. Evidence in managerial decision-making (Wiseman and Gomez-Mejia 1998) indicates that, when decision-makers have something to lose, they perceive risk and are cautious. Hence, a Marketing CEO (cognizant of the firm's valuable market-based assets) may be risk-averse and advocate to senior colleagues that customers and brands (which are negatively affected by product-harm crises) are crucial assets to be treated with abundant care and caution. Hence, a Marketing CEO may emphasize product quality and safety, decreasing the number of product-harm crises. Given these opposing effects, on net, we do not anticipate a direct role of a Marketing CEO in a firm on the number of product-harm crises, but argue instead for a facilitative role (i.e., interaction effects).

Interaction Effects: Marketing CEO and Departmental Power

As discussed, CEOs (including Marketing CEOs), by virtue of their rank and functional experience (in marketing for example), influence the decision-making of executives in different departments. Hence, a marketing CEO may influence decisions on product quality and safety in new product development (Hickson et al. 1971), issues that are central to customers, with whom the CEO may have had experience working with, prior to being appointed CEO. Moreover, because of their oversight authority, CEOs have high structural power, which may take the form of "pulling rank" on the members of the TMT and/or controlling resources for crucial strategic decisions (Bertrand and Schoar 2003), suggesting a facilitative role for Marketing CEOs in influencing senior departmental colleagues.

Marketing department power. As with a Marketing CEO, high marketing department power signifies that there is substantial and relevant marketing expertise (Feng et al. 2015) in the firm and that resources related to marketing (i.e., products, customers, and brands) are important to securing competitive advantage (Verhoef and Leeflang 2009). Through their customer-connecting role, a high-powered marketing department (Moorman and Rust 1999) will stress the importance of brands and customer relationships to other colleagues, including the CEO. All else being equal, increasing marketing department power will improve the firm's responsiveness to customers and channel partners and result in the firm treating its brands and customer relationships with abundant caution.

Moreover, product-harm crises reduce the effectiveness of marketing programs, lowering the return on marketing spending (Cleeren et al. 2017), a key metric for the performance assessment of senior marketing executives. As noted above, when decision-makers have something to lose, they are more risk-averse (Wiseman and Gomez-Mejia 1998). Inputs from powerful marketing departments who have something to lose, in this case valuable market-based assets of brands, customer relationships, and channel relationships, may be risk-averse, emphasizing product quality and safety, therefore suggesting a negative main effect of marketing department power on product-harm crises.

Our interest is in the interaction effect between a Marketing CEO and marketing department power on the number of product-harm crises. Will the redundancy of perspectives of powerful marketing departments and Marketing CEOs have no effect on product-harm crises? We propose not. The “common knowledge effect” in group decision-making (Gigone and Hastie 1993), in fact, indicates that the influence of an item of information is positively related to the number of group members who have “common” knowledge of it. Such shared information among group members has an undue influence on group decision-making as it is a common reference point, as a result of which it is discussed extensively and weighted more in the group’s judgments. Thus, we propose that a Marketing CEO in a firm will reiterate the importance of protecting brands and customer relationships (the common knowledge that he/she shares with a powerful marketing department) to colleagues in powerful marketing departments, weighting these criteria over relevant others (e.g., time to market, lower costs) in product development and introduction decisions. Accordingly, increasing marketing department power when there is a Marketing CEO in the firm will heighten emphasis on product quality and safety, decreasing the number of product-harm crises. Thus, we propose H_1:

> H_1: Having a Marketing CEO in the firm, when there is high marketing department power, decreases the number of product-harm crises.

Finance department power. Senior finance executives manage the firm’s finances and serve as its primary link to investors, banks, regulators, and financial analysts. When the finance department is powerful, senior finance executives have a critical role in strategic decisions including identifying ways to leverage capital, managing revenues and profits, managing acquisitions and divestitures, and fending off hostile takeover attempts (Fligstein

1987). Given the importance of new products to the firm's revenue and profit growth, powerful finance executives may influence, albeit indirectly, new product decisions. However, as finance executives are not directly involved in new product decisions, we do not anticipate a main effect of finance department power on the number of product-harm crises.

Following the passage of the Sarbanes-Oxley (SOX) Act of 2002 (our data starts in 2003), which requires joint certification of the firm's annual reports by the Chief Finance Officer (CFO) and the CEO, senior finance executives, because of the fear of punitive action, have become more risk-averse in their earnings management practices (Bargeron, Lehn, and Zutter 2010). Indeed, this increasing risk aversion of senior finance executives, following the SOX Act, appears to extend to firms' discretionary spending, including on R&D (Lobo and Zhou 2006).

Again, our interest is in the interaction effect between a Marketing CEO and a powerful finance department on the number of product-harm crises. The common knowledge effect suggests that, when a Marketing CEO who, as discussed above, is averse to taking risks with new products, works in conjunction with a risk-averse, powerful finance department, there may be an increased emphasis on product quality and safety, therefore decreasing the number of product-harm crises. Thus, we propose H_2:

> H_2: Having a Marketing CEO in the firm, when there is high finance department power, decreases the number of product-harm crises.

Operations department power. Operations departments are tasked with the design and management of processes that effectively transform inputs into products (Krajewski, Ritman, and Malhotra 2013, p. 22). Performance metrics for senior operations executives include cost-efficiency, quality standards, and timely product delivery. Firms with powerful operations departments are likely to secure competitive advantage not only through innovative products, but also through lower costs, creating a focus among senior operations executives on efficiency and cost reduction (Bass 1990). With respect to new products, powerful operations departments may be focused on manufacturing and commercialization, following product development. Hence, powerful operations department may speed products to market without consideration of quality and safety issues, which may cause delays and costs, suggesting a positive main effect of operations department power on the number of product-harm crises. We next discuss the interaction effect between operations department power and a Marketing CEO on the number of product-harm crises.

First, senior operations executives are responsible for ensuring that the firm's operations are streamlined and cost-effective, an objective which is achieved when products are launched without delays. Hence, powerful operations executives may proceed with the efficient sourcing and manufacturing of new products without a complete assessment of all their risks. However, a Marketing CEO, who is an advocate for product quality and safety, may persuade senior operations colleagues to slow down and focus on product quality, reducing the number of product-harm crises.

Second, senior operations executives consider their firm's efficient operations processes to be strong intangible assets. When these executives have wealthy positions, they may be risk-averse (Wiseman and Gomez- Mejia 1998) and reluctant to take shortcuts in materials and product quality, which can create bottlenecks and lower the value of the operations processes, and, therefore, emphasize product quality and safety. This suggests that, when there is a Marketing CEO, who is concerned about the health of the firm's brands and customer relationships, increasing operations department power may further increase the firm's risk aversion, strengthening the focus on product quality and safety, and decreasing the number of product-harm crises. Given these arguments, we propose H_3:

> H_3: Having a Marketing CEO in the firm, when there is high operations department power, decreases the number of product-harm crises.

R&D department power. The R&D department is responsible for developing new technologies and products (Gupta, Raj, and Wilemon 1986). The higher the R&D department power, the higher the firm's innovation rate and the greater the importance of new products in achieving superior performance. R&D executives, who are trained in professional basic scientific fields (e.g., engineering, medicine), have a long-term orientation compared to administration and marketing executives (Ruekert and Walker 1987). Compared to executives in other departments, R&D executives are more committed to the development of their technical skills (Diaz and Gomez-Mejia 1997). Moreover, R&D executives are more interested in developing technical reputations with members of their professional communities outside the firm than with colleagues from other departments within the firm (Badawy 1971; Gerpott, Domsch, and Keller 1988). Product failures are high-profile events, which may spread through professional communities and potentially hurt the professional reputations and career prospects of senior R&D executives, suggesting a negative main effect of R&D department power on the number of product-harm crises. Our interest, again, is in the effect of R&D department power on the number of product-harm crises, when there is a Marketing CEO.

As professional reputations are important to senior R&D executives, they may not only be focused on developing innovative new products with superior benefits, but they may also be concerned about rushing new products to market without adequate quality checks. The responsibility for such product failures, in fact, may be pinned on the R&D department, decreasing the influence of R&D executives both within the firm and among the external professional community. Hence, we anticipate that powerful R&D executives and a Marketing CEO will work together to advocate for product quality and safety, reduce product defects, and decrease the number of product-harm crises. Thus, we propose H_4:

H_4: Having a Marketing CEO in the firm, when there is high R&D department power, decreases the number of product-harm crises.

Interaction Effect: Marketing CEO and CEO's Stock Option Pay

Stock option pay gives the CEO the right to purchase a share of the firm's stock within a period of time for a fixed price, providing considerable upside potential with limited downside risk (Jensen and Meckling 1976). Hence, increasing CEO's stock option pay (vs. fixed salary pay) reduces agency problems between the risk-averse CEO (manager) and risk-seeking shareholders (owners). Compensating CEOs with a high proportion of equity pay aligns their risk-taking tendencies with those of the firm's shareholders, which increases the firm's engagement in risky endeavors such as acquisitions (Sanders and Hambrick 2007). As Sanders and Hambrick (2007, p. 1073) note, CEO's stock option pay would "cause CEOs to not be attuned to early signs of project failure and generally care less about risk mitigation." Supporting this view, CEO's stock option pay increases the occurrence of product-harm crises (Wowak et al. 2015). Our interest is in the effect of CEO's stock option pay on the number of product-harm crises, when there is a Marketing CEO.

CEOs vary in their experiences, values, and motives, resulting in their heterogeneous responses to incentives (Finkelstein et al. 2009). We propose that the Marketing CEO's marketing experience will provide the CEO with a long-term perspective of the shareholder wealth benefits of customers and brands as intangible market-based assets, weakening the risk-taking tendencies induced by increasing CEO's stock option pay. Thus, we anticipate that the Marketing CEO's recognition of the firm's brands and customers as valuable market-based assets will weaken the positive effect of CEO's stock option pay on the number of product-harm crises. Thus, we propose H_5:

H_5: When there is a Marketing CEO in the firm, the positive effect of CEO stock option pay on the number of product-harm crises will be weaker.

Method

Empirical Context: The U.S. Medical Device Industry

To ensure that it is relevant to study the role of firms' senior leadership in product-harm crises, we seek an industry where product recalls are largely voluntary, as opposed to being mandatory based on a regulator's instructions. One such industry is the U.S. medical device industry, where both new product introductions and product recalls are largely voluntary, as we next discuss.

At the outset, with respect to new product introductions, the U.S. FDA does not mandate clinical testing of most medical devices (upwards of 70%) but clears them for sale through a premarket notification process. This suggests that, crucial to this research, U.S. medical device firms have considerable latitude in new product quality and safety decisions. With respect to product recalls, most are voluntarily undertaken by medical device firms. Only in a few cases, does the FDA mandate that the firm recalls the defective product.

In sum, the U.S. FDA has no control over product introductions and product recalls in the U.S. medical device industry. Hence, product-harm crises, proxied by product recalls, represent strategic choices in which firms' leadership will likely play a key role. All product recalls in the U.S. medical device industry are recorded by the U.S. FDA, ensuring reliable data for hypotheses testing. In Appendix A, we describe, in detail, the new product introduction and recall processes in the U.S. medical device industry.

Given the crucial nature of medical devices in patients' health, a product recall constitutes a product-harm crisis as it has negative effects on patients' health, healthcare costs, and reputations of hospitals and doctors. Moreover, from the perspective of laypeople, regulators, industry experts, and investors, product recalls, which hurt health outcomes, have been imbued with a negative (rather than a neutral or positive) connotation, so that they are product-harm crises, substantively and from a public relations perspective.

There are three other industries where product recalls are voluntary and data are available with a third-party regulator, suggesting that they may also be potential candidates for empirical testing: food (FDA), drugs (FDA), and automotive (National Highway Transport Safety Administration). However, the FDA offers comprehensive data on product recalls of medical device firms but not of food (n = 263) and drug (n = 664) firms. The U.S. medical device industry also has more publicly-listed firms (n = 487; final sample = 75) in Standard and Poor's Compustat between 2003 and 2015 than the U.S. automotive industry (n = 43), ensuring adequate variance in the explanatory variables. The U.S. medical device industry's revenue in 2015 was U.S. $43 billion with an annual growth rate of 1.5% (U.S. Department of Commerce 2016), indicating that it is an economically substantive context.

Data

To test the hypotheses, we collected data on product recalls, CEOs' marketing backgrounds, and characteristics of firms' TMTs from multiple sources including the FDA Medical Device Recalls database, Standard and Poor's Compustat, ExecuComp, and various online sources (e.g., Bloomberg, LinkedIn).

We collected from Compustat data on firms in the Standard Industry Classification (SIC) codes of 3841 (Surgical and Medical Instruments and Apparatus), 3842 (Orthopedic, Prosthetic and Surgical Appliances and Supplies), 3843 (Dental Equipment and Supplies), 3844 (X-ray Apparatus and Tubes and related Irradiation Apparatus), 3845 (Electromedical and Electrotherapeutic Apparatus), and 3851 (Ophthalmic Goods) between 2002 and 2014. We then collected data on these firms' product recalls between 2003 and 2015 from the FDA Medical Device Recalls database.

To compute measures of departmental power, we collected data on job titles and compensation for firms' TMT members from ExecuComp (Feng et al. 2015). Merging all this data resulted in a panel of 557 firm-years for 75 medical device firms between 2003 and 2015.

Measures

Dependent variable. The dependent variable, the number of product-harm crises for a firm each year, is its annual count of product recalls. The firms in our sample had a total of 2,167 product-harm crises. The firms with the most number of product-harm crises were Stryker Corporation (358), followed by Medtronic Inc. (238), and Boston Scientific Inc. (205). Some firms in our sample had no product recalls between 2003 and 2015 (e.g., MSA Safety and Align Technology). The number of product-harm crises of a firm in a year, measured as the number of product recalls, is an over-dispersed count variable (mean = 3.89, standard deviation = 7.10) ranging between 0 and 50, with a high incidence of zeros (40%).

Independent variables. We obtained names of firms' CEOs from ExecuComp to construct the Marketing CEO variable. We obtained data on CEOs' functional backgrounds, before they were appointed CEOs, from LinkedIn, Bloomberg, Equilar, and corporate websites. We used marketing- or sales-related words (e.g., *marketing, sales, brand,* and *advertising*) in CEOs' previous job titles as evidence of marketing functional experience. We classified a CEO as a *Marketing CEO* using a dummy variable of 1 (0 otherwise) if the CEO had marketing experience; 36 % of CEO-years in the sample were classified as Marketing CEOs.[5]

[5] We examined the effect of a CEO change in a firm on the number of product-harm crises; a t-test revealed that the year-to-year change in the number of product-harm crises is not different when the CEO changes vs. not (m_1 = 1.85 vs. m_2 =1.77, t = -0.19, $p > 0.10$).

Following Wowak et al. (2015), we measured *CEO's stock option pay* as the value of unexercised exercisable in-the-money options assigned to the CEO in a given year.

We measured *marketing department power* in a firm using the measure developed by Feng et al. (2015), which focuses on the power of the department on the firm's TMT. We adapted this measure for *finance department power, operations department power,* and *R&D department power*. For this purpose, we used the information in the job titles of all executives (i.e., the firm's TMT) listed in ExecuComp. We classified an executive as a marketing executive if his/her job title contained marketing- or sales-related words (e.g., *marketing, sales, brand, customer, communications,* and *advertising*). Similarly, an executive was classified as a finance executive, operations executive, or R&D executive using finance-related words (e.g., *financial, finance, controller, administrative, legal, investor,* and *accounting*), operations-related words (e.g., *operations, operating,* and *plant*) or R&D-related words (e.g., *R&D, research, technology,* and *technical*). We classified executives not assigned to marketing, finance, operations, or R&D departments as general management (GM) executives and computed their power.

After classifying each senior executive in a firm's TMT, following Feng et al. (2015), we computed five indicators of marketing department power (for each year). First, we computed (1) the proportion of marketing executives in the TMT scaled by its size and (2) the proportion of marketing executives' pay over the TMT's total pay. Then, we assigned a hierarchical ranking score to each marketing-related job title as follows: president = 6, executive vice president = 5, senior vice president = 4, vice president = 3, other = 2, and no marketing executives = 1. We computed two additional variables using this ranking score: (3) the score of the highest-ranked marketing executive on the TMT and (4) the cumulative score of all marketing executives on the TMT. Finally, we measured (5) the number of responsibilities of marketing executives on the TMT listed on their job titles. Using principal component factor analysis, we combined the five indicators of marketing department power into a single factor.

We proceeded analogously for finance department power, operations department power, R&D department power, and GM department power. In Appendix E, we report details of marketing (Tables W1 and W11), finance (Tables W2 and W21), operations (Tables W3 and W31), R&D (Tables W4 and W41), and GM department power (Tables W5 and W51). Each factor explains a substantial variance in the five indicators; 81% in marketing department power, 65% in finance department power, 82% in operations department power, 80% in R&D department power, and 67% in GM department power.

Control variables. We also included a number of control variables in the regression model used to test the hypotheses. We included the firm's R&D intensity (Kashmiri and Brower 2016; Thirumalai and Sinha 2011) and labor intensity (Thirumalai and Sinha 2011). We included the firm's age, measured as the difference between the current year and the year in which the firm first appeared in Compustat (Wowak et al. 2015), slack resources, measured as the ratio of total assets over total liabilities (Chatterjee and Hambrick 2011), firm size, measured by total assets, and firm performance, measured by return on assets (ROA) (Wowak et al. 2015) as well as by the year-to-year percentage change in sales. Further, we controlled for the firm's financial leverage (Kashmiri and Brower 2016) and financial distress, measured by Altman's Z (Wowak et al. 2015). We obtained all these measures from Compustat. As more innovative firms may experience more frequent recalls, we included the total number of patents filed by the firm in the U.S., which we obtained from Google Patents database. Finally, we controlled for the size of the firm's TMT (Li et al. 2013) and for firm's reputation, measured as the residual from the regression of firm's intangible value on lagged firm size, firm performance, total assets, and age (firm- and year-fixed effects included)[6].

With respect to CEO characteristics, we included the CEO's age (Gerstner et al. 2013; Chatterjee and Hambrick 2011), tenure, total compensation (TC), and the year-to-year percentage change in total compensation (TCC), as these affect product-harm crises (Wowak et al. 2015). We included CEO duality (dummy variable =1, else = 0) if the CEO was also the Chairman of the board (Wowak et al. 2015), CEO-founder (dummy variable = 1, else = 0) if the CEO was also the firm's founder (Wowak et al. 2015), and CEO marketing education (dummy variable = 1, else = 0) if the CEO had formal marketing education.

We provide the descriptions and sources for all variables in Table 2 and the descriptive statistics and correlations of the key variables in Table 3. We present detailed logic for the inclusion of the various control variables in Table W1 in Appendix F. All variance inflation factors are well below 10 indicating no threat to the validity of the results from multicollinearity.

---- Insert Table 2 and Table 3 about here ----

We next consider the economic relevance of product-harm crises in the U.S. medical device industry by examining their effects on firm performance. We specify three fixed effects models with the following dependent variables: 1) cash flow, measured as the ratio of the sum of income before extraordinary items and depreciation and amortization over total assets, 2) stock price volatility, measured as the standard deviation of stock prices in a year, and 3) intangible value, measured by Tobin's q (Chung and Pruitt 1994). We report the results in Columns 1-3 in Table 4. The number of product-harm crises decreases cash flow (b = -0.002, $p < 0.01$) and intangible value (b = -0.03, $p < 0.01$) but does not affect stock price

[6] Details of this regression are available upon request from the authors.

volatility (b = 0.06, $p > 0.10$). Overall, product-harm crises in the U.S. medical device industry significantly hurt firm performance and are economically relevant.

---- Insert Table 4 here ----

Model Estimation

As the dependent variable is a count variable, we use a zero-inflated negative binomial regression model to account for over-dispersion and excessive zeros (Cameron and Trivedi 2013). The model also includes fixed effects for firms and years to account for unobserved firm heterogeneity and time effects.

Marketing CEO and the various departmental power variables may be endogenous as firm-level omitted variables may affect both these characteristics of firms' TMTs and the number of product-harm crises. Hence, we seek instrumental variables related to these endogenous variables but not to product-harm crises. We use as instrument for Marketing CEO in firm *i* in a given year the average number of Marketing CEOs in other U.S. medical device firms in that year (i.e., excluding firm *i*). For marketing department power in firm *i* in a given year, we use the average marketing department power in other firms in that year. We proceed analogously for finance, operations, R&D, and GM department power. As department power measures are factor scores, they include positive and negative values; hence, we rescale them between 0 and 100 before computing the instruments.

To verify that these instruments are indeed good instruments, we need to justify their relevance, i.e., that they are correlated with the endogenous independent variables, and that they meet the exclusion restriction, i.e., that they are not correlated with the error term in the model (Angrist and Pischke 2009). The instruments should be correlated with the endogenous independent variables as the focal firm faces similar market conditions as the peer firms, because they all operate in the medical device industry. Further, the expectations of the focal firm and of the peer firms are similar because our sample is restricted to only one industry. Thus, similar market conditions and similar expectations make the instruments relevant. Our instrumental variables also meet the exclusion restriction as it is not likely that peer firms' decisions on their TMTs would relate to the focal firm's omitted variables affecting the occurrence of product-harm crises (see Germann, Ebbes, and Grewal 2015 for a similar logic). Following Khodakarami, Petersen, and Venkatesan (2015), we test our exclusion restriction regressing the number of product-harm crises on the instrumental variables, their interactions, and the control variables. Results show that the instrumental variables do not affect the number of product-harm crises, therefore supporting the respect of the exclusion restriction. We report these results in Table B1 in Appendix B. We use the control function approach (Petrin and Train 2010) to instrument the endogenous variables. For example, the model for Marketing CEO in the firm is as follows:

$$\begin{aligned}
&\textit{Marketing CEO}_{it-1} = \varphi_0 + \varphi_1 \textit{Marketing CEO_ Peer firms}_{it-1} + \varphi_2 \textit{CEO stock option pay}_{it-1} + \\
&\varphi_3 \textit{Marketing department power_ Peer firms}_{it-1} + \varphi_4 \textit{Finance department power_ Peer firms}_{it-1} \\
&+ \varphi_5 \textit{Operations department power_ Peer firms}_{it-1} + \varphi_6 \textit{R\&D department power_ Peer firms}_{it-1} \\
&+ \varphi_7 \textit{GM department power_ Peer firms}_{it-1} + \varphi_8 \textit{Marketing CEO_ Peer firms}_{it-1} \times \textit{Marketing} \\
&\textit{department power_ Peer firms}_{it-1} + \varphi_9 \textit{Marketing CEO_ Peer firms}_{it-1} \times \textit{Finance department} \\
&\textit{power_ Peer firms}_{it-1} + \varphi_{10} \textit{Marketing CEO_ Peer firms}_{it-1} \times \textit{Operations department power_} \\
&\textit{Peer firms}_{it-1} + \varphi_{11} \textit{Marketing CEO _ Peer firms}_{it-1} \times \textit{R\&D department power_ Peer firms}_{it-1} + \\
&\varphi_{12} \textit{Marketing CEO_ Peer firms}_{it-1} \times \textit{GM department power_ Peer firms}_{it-1} + \varphi_{13} \textit{Marketing} \\
&\textit{CEO _ Peer firms}_{it-1} \times \textit{CEO stock option pay}_{it-1} + \varphi_{14} \textit{R\&D intensity}_{it-1} + \varphi_{15} \textit{Labor intensity}_{it-1} \\
&+ \varphi_{16} \textit{Firm age}_{it-1} + \varphi_{17} \textit{Slack resources}_{it-1} + \varphi_{18} \textit{Firm size}_{it-1} + \varphi_{19} \textit{Firm performance}_{it-1} + \\
&\varphi_{20} \textit{Sales Change}_{it-1} + \varphi_{21} \textit{Financial leverage}_{it-1} + \varphi_{22} \textit{Financial distress}_{it-1} + \varphi_{23} \textit{Patents}_{it-1} + \\
&\varphi_{24} \textit{Reputation}_{it-1} + \varphi_{25} \textit{Size of TMT}_{it-1} + \varphi_{26} \textit{CEO age}_{it-1} + \varphi_{27} \textit{CEO duality}_{it-1} + \varphi_{28} \textit{CEO-} \\
&\textit{founder}_{it-1} + \varphi_{29} \textit{CEO tenure}_{it-1} + \varphi_{30} \textit{CEO TC}_{it-1} + \varphi_{31} \textit{CEO TCC}_{it-1} + \varphi_{32} \textit{CEO marketing} \\
&\textit{education}_{it-1} + \textit{Year FEs} + \textit{Firm FEs} + \varepsilon_{Ait}.
\end{aligned}$$

(Equation 1)

where φs are the parameters to be estimated, subscripts i represent firms, subscripts t represent years, and ε_{Ait}s represent error terms. We report the results for Equation 1 in Column 1 of Table B2 in Appendix B. We use a similar approach for marketing department power (Column 2, Table B2), finance department power (Column 3, Table B2), operations department power (Column 1, Table B3), R&D department power (Column 2, Table B3), and GM department power (Column 3, Table B3). The results show that Marketing CEOs in peer firms predict a Marketing CEO in the focal firm ($p < 0.01$) and that marketing, finance, operations, R&D, and GM department power in peer firms predict marketing, finance, operations, R&D, and GM department power in the focal firm ($p < 0.01$) respectively.[7]

For hypotheses testing, we estimate the model below, using the errors from the instrumental variable equations as follows:

$Number\ of\ product\text{-}harm\ crises_{it} = \mu_0 + \mu_1 Marketing\ CEO_{it-1} + \mu_2 CEO\ stock\ option\ pay_{it-1} + \mu_3 Marketing\ department\ power_{it-1} + \mu_4 Finance\ department\ power_{it-1} + \mu_5 Operations\ department\ power_{it-1} + \mu_6 R\&D\ department\ power_{it-1} + \mu_7 GM\ department\ power_{it-1} + \mu_8 Marketing\ CEO_{it-1} \times Marketing\ department\ power_{it-1} + \mu_9 Marketing\ CEO_{it-1} \times Finance\ department\ power_{it-1} + \mu_{10} Marketing\ CEO_{it-1} \times Operations\ department\ power_{it-1} + \mu_{11} Marketing\ CEO_{it-1} \times R\&D\ department\ power_{it-1} + \mu_{12} Marketing\ CEO_{it-1} \times GM\ department\ power_{it-1} + \mu_{13} Marketing\ CEO_{it-1} \times CEO\ stock\ option\ pay_{it-1} + \mu_{14} R\&D\ intensity_{it-1} + \mu_{15} Labor\ intensity_{it-1} + \mu_{16} Firm\ age_{it-1} + \mu_{17}\ Slack\ resources_{it-1} + \mu_{18}\ Firm\ size_{it-1} + \mu_{19} Firm\ performance_{it-1} + \mu_{20} Sales\ Change_{it-1} + \mu_{21} Financial\ leverage_{it-1} + \mu_{22} Financial\ distress_{it-1} + \mu_{23} Patents_{it-1} + \mu_{24} Reputation_{it-1} + \mu_{25} Size\ of\ TMT_{it-1} + \mu_{26} CEO\ age_{\ it-1} + \mu_{27} CEO\ duality_{it-1} + \mu_{28} CEO\text{-}founder_{it-1} + \mu_{29} CEO\ tenure_{it-1} + \mu_{30} CEO\ TC_{it-1} + \mu_{31} CEO\ TCC_{it-1} + \mu_{32} CEO$

[7] The instruments are negatively correlated with the endogenous regressors as the following example shows. Let us assume that three firms operate in the industry at time t. Firm A has marketing department power 10, firm B has marketing department power 1, and firm C has marketing department power 5. The instrument for firm A's marketing department power is 3, i.e., the sum of peer firms' marketing department power divided by 2. Similarly, the instruments for firm B and firm C will be 7.5 and 5.5 respectively. Hence, the relatively high value of marketing department power in firm A does not enter the computation for firm A's instrument while it enters the computation for both firm B's and firm C's instruments. Hence, firms with lower values of the endogenous variables will exhibit higher values of the instrumental variables and vice versa.

$marketing\ education_{it-1} + \mu_{33}\varepsilon_{Ait} + \mu_{34}\varepsilon_{Bit} + \mu_{35}\varepsilon_{Cit} + \mu_{36}\varepsilon_{Dit} + \mu_{37}\varepsilon_{Eit} + \mu_{38}\varepsilon_{Fit} + Year\ FEs + Firm\ FEs + \varepsilon_{1it}$ (Equation 2)

where μs are the parameters to be estimated, subscripts *i* represent firms, subscripts *t* represent years, ε_{Ait}s-ε_{Fit}s represent the errors from equations estimated in Columns 1-3 of Table B2 and Columns 1-3 of Table B3 respectively and ε_{1it}s represent error terms. To ensure correct model specification, we include the main effects of CEO's stock option pay, marketing department power, finance department power, operations department power, and R&D department power in Equation 2 above. We lag all explanatory variables by one year to further mitigate endogeneity concerns. For model completeness, we include all related effects of GM department power in the model although we do not formally hypothesize them; we obtain similar results without them.

Results

We first estimate a model (Log pseudo-likelihood = -853.18) with the main effect of a Marketing CEO in a firm and all the control variables (results not reported here in the interest of brevity but available upon request from the authors). In this model, a Marketing CEO in a firm decreases (b = -0.33, $p < 0.05$) and CEO's stock option pay increases (b = .007, $p < 0.01$) the number of product-harm crises. We then estimate the hypothesized model with the inclusion of all explanatory variables and related interactions (H_1-H_5) in Column 1 in Table 5 (Log pseudo-likelihood = -824.73).

The results marginally support H_1, that having a Marketing CEO in a firm when there is high marketing department power would decrease the number of product-harm crises (b = -0.25, $p < 0.10$). The results strongly support H_2, that having a Marketing CEO in a firm when there is high finance department power would decrease the number of product-harm crises (b = -0.31, $p < 0.01$). The results do not support H_3, that having a Marketing CEO in a firm when there is high operations department power would decrease the number of product-harm crises (b = 0.04, $p > 0.10$). The results support H_4, that having a Marketing CEO in a firm when there is high R&D department power would decrease the number of product-harm crises (b = -0.25, $p < 0.05$). Finally, the results support H_5, that a Marketing CEO would weaken the positive effect of CEO's stock option pay on the number of product-harm crises (b = -0.01, $p < 0.05$). We note here that GM department power is computed starting from executives with no marketing, finance, operations, nor R&D backgrounds so that this measure is noisy; hence, we do not interpret the related coefficients.

With all the interaction effects included, Marketing CEO (b = 0.01, $p > 0.10$) has no direct effect on the number of product-harm crises. With respect to the control variables, marketing department power has a negative main effect on the number of product-harm crises (b = -0.18, $p < 0.05$). Consistent with the evidence in the literature (Wowak et al. 2015), CEO's stock option pay has a positive main effect on the number of product-harm crises (b = 0.007, $p < 0.05$) as do firm age (b = 0.06, $p < 0.05$) and TMT size (b = 0.20, $p < 0.01$). The firm's performance, measured by its ROA, has a negative main effect on the number of product-harm crises (b = -1.81, $p < 0.05$) as does the year-to-year percentage change in CEO compensation (b = -1.51, $p < 0.01$). All other control variables have no effect on the number of product-harm crises.

We next examine whether Marketing CEOs reduce the number of product-harm crises by reducing the firm's risk-taking propensity (the mechanism that we propose). Following Kashmiri and Mahajan (2017), we measured the firm's risk-taking as the logged sum of its capital expenditures, R&D expenditures, and acquisitions. A paired sample t-test revealed that firms with a Marketing CEO (vs. not) engage less in risky activities ($m_1 = 4.37$ vs. $m_2 = 4.71$, t = 2.50, $p < 0.01$), while it is the opposite for firms with either a Finance CEO (vs. not) (m_1 =

4.89 vs. m_2 = 4.47, t = -2.80, $p < 0.01$) or an Operations CEO (vs. not) (m_1 = 5.05 vs. m_2 = 4.26, t = -6.09, $p < 0.01$). There is no statistically significant difference between firms with a R&D CEO (vs. not) (m_1 = 4.61 vs. m_2 = 4.59, t = -0.15, $p > 0.10$).

---- Insert Table 5 about here ----

As the zero-inflated negative binomial model is a non-linear model, the effect of an explanatory variable depends on the values of all other explanatory variables. Hence, it is useful to interpret the coefficients at different levels of the explanatory variables (Ai and Norton 2003). An appropriate solution, in our model of the number of product-harm crises, is to interpret the results on a multiplicative scale, by considering incidence rate ratios (i.e., exponentiated coefficients) that can be interpreted as marginal effects (Buis 2010).

Hence, we estimate the model in Column 1 of Table 5 in the incidence rate ratio metric (See Column 2 in Table C1 in Appendix C), i.e., the ratio by which the dependent variable changes for a unit change in the explanatory variable. Consistent with the results in Column 1 of Table 5, the incidence rate ratio for marketing department power (b = 0.83, $p < 0.05$) and for the interaction effects of marketing CEO with CEO's stock option pay (b = 0.99, $p < 0.05$), finance department power (b = 0.74, $p < 0.01$), and R&D department power (b = 0.78, $p < 0.05$) are significantly lower than 1. In terms of marginal effects, when there is a marketing CEO in the firm, one standard deviation increase in finance department power, for example, decreases the number of product-harm crises by (1-0.74)*100%, i.e., by 26%.

Robustness Checks

We next report analyses that examine the robustness of the results to alternative model specifications, samples, and measures. We examine the implications of these findings in detail in the discussion section.

Alternative count model specification. We first examine the robustness of the results to an alternative count model specification. We replaced the zero-inflated negative binomial model with a Poisson model. The results, reported in Column 2 in Table 5, are generally consistent with the results in Column 1 in Table 5, although the negative interaction effect of Marketing CEO and CEO's stock option pay on the number of product-harm crises is only marginally significant in the Poisson model (b = -0.01, $p < 0.10$).

Sampling variations. To ensure that the results are not driven by influential outliers in the dependent variable, we winsorize the data at 5%. The results, reported in Column 3 in Table 5, are again consistent with those in Column 1 of Table 5.

CEO's stock option pay. Following Wowak et al. (2015), we do not expect CEO's stock option pay to be endogenous. Nonetheless, to ensure that the endogeneity of the CEO's stock option variable does not threaten the validity of the results, we use a control function approach for CEO's stock option pay, using as instrument the average stock option pay of other CEOs in the industry in a given year. The results, reported in Column 1 in Table 6, are robust to the endogeneity correction for CEO's stock option pay.

Dependent variable. When a manufacturer recalls a medical device, the FDA evaluates the degree of health risk represented by the recalled product and classifies the recall as a class I, class II, or class III recall. Class I recalls involve products with a reasonable probability of serious adverse health consequences, class II recalls involve products with temporary or medically reversible adverse health consequences, and class III recalls involve products with minimal adverse health effects. We consider all three types of product recalls in our dependent variable. To examine the robustness of the results to the definition of product-harm crises, we exclude class III product recalls (i.e., recalls with minimal adverse health consequences) in the measure of the dependent variable. We report the results in Column 2 in

Table 6, which are again consistent with those in Column 1 of Table 5.

Marketing CEO vs. *CMO*. We next examine whether a CMO in the firm, like a Marketing CEO, can play a facilitative role in reducing the number of product-harm crises. Using the approach of Nath and Mahajan (2008, 2011) and Germann et al. (2015), we classify a CMO as being present in a firm (1 if present, 0 otherwise) if at least one executive on the TMT, in a given year, has marketing- or sales-related words in his/her job title. We re-estimated the model in Column 1 of Table 5 replacing the Marketing CEO with the CMO. We report the results in Column 3 in Table 6. The results indicate a positive interaction effect between marketing department power and CMO (b = 2.73, $p < 0.05$) on the number of product-harm crises, an empirical finding which is reasonable, as we subsequently argue in the discussion section. In addition, there is a positive interaction effect between CEO's stock option pay and CMO (b = 0.02, $p < 0.05$) on the number of product-harm crises. Finally, the CMO's interactions with powerful finance and R&D departments have no effect on the number of product-harm crises.

Independent variable. To examine the robustness of the results to the definition of Marketing CEO, we conduct three additional analyses. First, we do not classify as Marketing CEOs those with only sales experience (we are unable to estimate a model classifying as Marketing CEOs those with only sales experience, as this sample is too small). We report the results in Column 1 in Table 7. The results are generally consistent with the results in Column 1 in Table 5, although the negative interaction effect between (NoSales) Marketing CEO and marketing department power on the number of product-harm crises is now statistically significant (b = -0.35, $p < 0.05$) and the negative interaction effect between (NoSales) Marketing CEO and R&D department power on the number of product-harm crises is no longer significant (b = -0.15, $p > 0.10$).

Second, we classify as Marketing CEOs only those who held senior marketing positions before being appointed CEOs. Examples of senior positions are *director of marketing*, *president of marketing*, and *vice president of marketing*. We report the results in Column 2 in Table 7. Results are again generally consistent with those in Column 1 in Table 5, although the negative interaction effect of (Senior) Marketing CEO and R&D department power on the number of product-harm crises is now not significant (b = -0.08, $p > 0.10$) and the negative interaction effect of (Senior) Marketing CEO and CEO's stock option pay is now only marginally significant (b = -0.01, $p < 0.10$). We also note that the interaction effect of (Senior) Marketing CEO and marketing department power is now negative and significant (b = -0.35, $p < 0.05$)

Finally, we focus on Pure (vs. Hybrid) Marketing CEOs, i.e., those who have never held finance-, operations-, or R&D-related positions before being appointed CEOs. We report the results in Column 3 in Table 7. Both the (Pure) Marketing CEO (b = -1.25, $p < 0.05$) and marketing department power (b = -0.16, $p < 0.05$) have a negative effect on the number of product-harm crises, suggesting that (Pure) Marketing CEOs can reduce the number of product-harm crises by personal advocacy (i.e., direct role). Further, the negative interaction effects of (Pure) Marketing CEO and marketing department power (b = -0.83, $p < 0.05$) and of (Pure) Marketing CEO and finance department power (b = -1.01, $p < 0.01$) on the number of product-harm crises are now statistically significant.

Marketing vs. *other functional backgrounds of CEOs*. We focus on Marketing CEOs as marketing is an outside-in department with responsibility for brands and customers and is therefore different from inside-out departments such as finance, operations, and R&D. To explore the role of other functional backgrounds of CEOs, we conducted falsification checks by replacing the Marketing CEO with Finance CEO, Operations CEO, and R&D CEO respectively in the model of number of product-harm crises (we do not consider the GM CEO which, as we noted above, is a noisy measure). We report the results in Column 1-3 respectively of Table D1 in Appendix D. When there is a R&D CEO, there is a positive interaction effect of R&D CEO and marketing department power on the number of product-harm crises (b = 0.40, $p < 0.05$). The results indicate a positive main effect of an Operations CEO (b = 0.49, $p < 0.01$), but no effect of the Finance CEO, on the number of product-harm crises.

Discussion

Product-harm crises, which negatively affect consumers' well-being and firm performance, are becoming more common. While there is a large body of work on the negative effects of product-harm crises on various performance outcomes, there is less work on their antecedents, in general, and on the marketing leadership of firms, in particular. As Cleeren et al. (2017) note "Executives [including, we assume, the Marketing CEO] can attenuate, through appropriate actions before, during, and after the crisis, its negative consequences".

The issue that we focus on is whether marketing leadership in a firm, embodied in a Marketing CEO, can affect its number of product-harm crises. We empirically test the hypotheses in the U.S. medical device industry, where product-harm crises are the result of firms' voluntary actions and have significant negative outcomes for patients, doctors, hospitals, investors, and medical device firms. Our findings, which are robust, indicate that powerful finance and R&D departments in conjunction with a Marketing CEO reduce the number of product-harm crises. Further, a Marketing CEO weakens the positive effect of CEO's stock option pay on the number of product-harm crises. We conclude with a discussion of the paper's theoretical contributions, managerial implications, and limitations and opportunities for future research.

Theoretical Contributions

First, we extend the limited literature on the leadership antecedents of product-harm crises, which has established a role for CEOs' stock option pay (Wowak et al. 2015), CMO presence (Kashmiri and Brower 2016), marketing department power (Kashmiri, Nicol, and Arora 2017), and CEO narcissism (Kashmiri, Nicol, and Arora 2017), and examine the facilitative role of Marketing CEOs, in conjunction with the power of different departments (Finkelstein 1992), on the number of product-harm crises.

We had argued that a Marketing CEO is a strong advocate for customers and brands, lowering risk-taking, and emphasizing product quality and safety. However, we had also argued that, because of the different demands on the CEO, which include delivering on revenue and profit for investors, we did not anticipate a direct effect of a Marketing CEO on the number of product-harm crises. Instead, the Marketing CEO is an advocate for product quality and safety with powerful departmental colleagues, involved in new product introductions, therefore reducing the number of product-harm crises.

Support for the negative interaction effects (Marketing CEO and finance department power, R&D department power. and increasing CEO's stock option pay) on the number of product-harm crises suggests that a Marketing CEO does, indeed, play a facilitative role in reducing the number of product-harm crises. The lack of empirical support for the interaction effect between a Marketing CEO and a powerful operations department on the number of product-harm crises is surprising. We conjecture that this may be because, in the temporal sequence of the new product introduction process, the operations department is at the bottom of the funnel, after new product development (Olson et al. 2001), which is at the top of the funnel. Perhaps, a Marketing CEO may incorrectly assume that issues related to product quality and safety related to the operations departments in the product introduction process have already been effectively addressed in the development process. Further research that explores this issue, including other methods (e.g., surveys of senior executives, including CEOs), would be useful.

The negative interaction effect between a Marketing CEO and CEO's stock option pay (which has a positive main effect) on the number of product-harm crises supports the theoretical mechanism we argue for, i.e., that Marketing CEOs, because of their deep understanding of the importance of customers as valuable market-based assets, are risk-averse in directing product development, ignore their personal pecuniary gains, and decrease the number of product-harm crises. Additional analysis using a composite measure of firms' risk-taking provides support, albeit indirect, for reduced risk-taking by Marketing CEOs, supporting this logic. Further research on whether the nature of products developed (radical vs. incremental) and the speed of product introductions in firms with (or without) Marketing CEOs affect the number of product-harm crises will be a useful extension to this research.

Additional falsification checks (Table C2 in Appendix C) indicate that finance, operations, or R&D CEOs do not play the same facilitative role as Marketing CEOs in reducing the number of product-harm crises. Overall, the lack of evidence for the effects of CEOs of other functional backgrounds on the number of product-harm crises suggests that it is not the reputational concerns of the Marketing CEO (which CEOs of any functional backgrounds will also have) but reduced risk-taking by the Marketing CEO that decreases the number of product-harm crises. We suggest that Marketing CEOs, but not other functional CEOs, play a facilitative role in decreasing the number of product-harm crises, because marketing plays a key customer-connecting role (Moorman and Rust 1999). Further research that explores the role of Marketing CEOs on other firm outcomes, including mergers and initial public offerings, would be useful.

The empirical evidence provides only weak support ($p < .10$) for the interaction effect between a Marketing CEO and increasing marketing department power on the number of product-harm crises. However, additional analyses indicate that this interaction effect is strengthened under three types of Marketing CEOs—(NoSales) Marketing CEOs, i.e., those without exclusive sales experience (Column 1 in Table 7), (Senior) Marketing CEOs, i.e., those with senior marketing experience (Column 2 in Table 7), and (Pure) Marketing CEOs, i.e., those with only marketing (no other functional) experience (Column 3 in Table 7). However, interaction effects of (NoSales) Marketing CEOs, (Senior) Marketing CEOs, and (Pure) Marketing CEOs with powerful R&D departments are no longer significant. These findings suggest that all Marketing CEOs are not equal when it comes to product-harm crises. Some ((NoSales) Marketing CEOs, (Senior) Marketing CEOs, and (Pure) Marketing CEOs) appear to be more effective in working with powerful marketing departments and less effective in working with powerful R&D departments to reduce the number of product-harm crises. This suggests that Marketing CEOs with other functional experiences (vs. only marketing experience) are more effective in working with R&D departments to decrease the number of product-harm crises.

The falsification checks also generate insights on the role of other functional backgrounds of CEOs—finance, operations, and R&D—in product-harm crises. Firms with Operations CEOs have more product-harm crises. R&D CEOs, along with powerful marketing departments in firms, increase the number of product-harm crises, a finding which contrasts with the beneficial effect of the Marketing CEO along with powerful R&D departments. Marketers are primarily concerned with identifying and meeting customer needs and fending off competitive threats, while R&D personnel focus on issues of technical innovativeness and feasibility (Weinrauch and Anderson 1982). This suggests a potentially contentious relationship between senior R&D executives and marketing executives (Ruekert and Walker 1987). Further research exploring this issue in the product-harm crises context, including remedies for it, would be insightful.

Second, our findings contribute to the literature on the role of various departments in shaping firms' strategies (Feng et al. 2015; Finkelstein 1992) by highlighting the role of the Marketing CEO, in conjunction with various departmental powers, on firm's strategy and outcomes. By computing the power of finance, R&D, and operations departments, we heed Feng et al. (2015, p. 14)'s call that "future researchers could use our measurement approach to calibrate the power of other functional departments and explore the existence and performance effect of the interplay between the power of marketing departments and that of other functional departments."

Third, our findings contribute to the marketing leadership literature which has, hitherto, examined the role of the CMO in determining firm value (Nath and Mahajan 2008) and in product-harm crises (Kashmiri and Brower 2015). The results (Column 3 of Table 6) show a positive interaction effect between marketing department power and CMO (b = 2.73, $p < 0.05$) on the number of product-harm crises. As expected, marketing department power and the presence of a CMO in the firm are highly correlated. Hence, one way to interpret the interaction effect term between marketing department power and CMO is as the squared term of marketing department power. Marketing department power has a negative main effect (b = - 3.04, $p < 0.05$) on the number of product-harm crises in this model which, combined with the positive square term of marketing department power (b = 2.73, $p < 0.05$) suggests diminishing returns to the negative effect of marketing department power on the number of product-harm crises, which we consider to be a reasonable empirical finding.

However, we find no empirical support for the interaction effect (Column 3 of Table

6) of the CMO with either powerful finance department or R&D department (unlike for the Marketing CEO) suggesting that there are limits to the influence of the CMO (vs. a Marketing CEO) in reducing the number of product-harm crises. Overall, these findings highlight the different roles of the Marketing CEO and CMO in reducing the number of product-harm crises. Further research exploring this issue can generate useful insights on other differences between Marketing CEOs and CMOs.

Fourth, while empirical findings on upper echelons theory suggest that CEOs affect firms' strategies and outcomes (e.g., Bertrand and Schoar 2003; Miller and Shamsie 2001), past research has not examined the effects of functional backgrounds of CEOs on product-harm crises. This research's findings that Marketing CEOs, in conjunction with departmental power and CEO's stock option pay, decrease the number product-harm crises, extend the upper echelons literature to a managerially relevant outcome, the number of product-harm crises, which has negative effects on firm performance.

Finally, this paper's findings extend the nascent literature on top-down influences from firms' leadership on new products (e.g., Bantel and Jackson 1989; Rao, Chandy, and Prabhu 2008). In doing so, we offer insights on the hitherto unexamined top-down role of the firm's Marketing CEO, in conjunction with powerful departments and CEO's stock option pay, in product-harm crises, a key negative outcome of new product development processes, which have been typically studied, in the literature, at the project-level or middle-management level.

Managerial Implications

Given the negative effects of product-harm crises on firm performance (see results in Table 4), this study's findings generate useful implications for executives trying to reduce the number of product-harm crises. First, the findings indicate that a Marketing CEO, in conjunction with powerful finance and R&D department power and CEO's stock option pay, decreases the number of product-harm crises, shielding the firm from downside risk and value destruction caused by product-harm crises. The research's findings indicate that Marketing CEOs are effective at preventing product-harm crises in firms with powerful finance departments and R&D departments.

Specifically, the incidence rate ratio analysis indicates that, when there is a marketing CEO in a firm, a standard deviation increase in finance department power decreases the number of product harm crises by (1-0.74)*100% = 26% and one standard deviation increase in R&D department power decreases the number of product-harm crises by 22%, which we consider to be substantial reductions. We view these findings as being useful to firms with high R&D (e.g., high technology firms) and finance department power (e.g., regulated industries). Such firms can appoint Marketing CEOs to reduce the number of product-harm crises.

Second, our findings present useful guidance to boards of directors on CEO appointments with the goal of reducing product-harm crises. Although TMT appointments are clearly driven by many other corporate governance considerations and not just by the need to lower product-harm crises, boards of directors must factor into their CEO appointment decisions the benefits of appointing a Marketing CEO in lowering the number of product-harm crises.

Third, the negative effect (not formally hypothesized) of marketing department power in the firm on the number of product-harm crises is noteworthy. This negative effect of marketing department power indicates that, while a Marketing CEO is not able to, independently, decrease the number of product-harm crises, powerful marketing departments, independently, do.

Fourth, the findings indicate that an effective governance solution for reducing CEOs' positive influence on the number of product-harm crises when CEO's stock option pay is high would be to appoint a Marketing CEO, which counteracts the firm's risk-taking behaviors induced by high stock option pay. Overall, these findings send a message to boards of directors that Marketing CEOs play a strong customer-connecting role, strengthening the hands of senior marketing executives when being considered for appointment to the CEO position.

Fifth, product-harm crises, especially in the medical device industry, are the subject of class action lawsuits, which represent serious threats to firm performance and survival. Hence, the findings of this research will be useful to executives of medical device firms, hospitals, investors, doctors, and insurers in assessing the risk-taking propensity of medical device firms, based on the leadership and CEO's stock option pay characteristics.

Finally, officials at the Inspector General's office for Health and Human Services reported (2017) that Medicare had lost U.S. $1.5 billion because of the recall of seven defective heart devices between 2005 and 2014. David Lamir, an official in the inspector general's Boston office, said that the $1.5 billion figure represented a "drop in the bucket" of the true costs to Medicare from defective medical devices. As Fuhr et al. from McKinsey and Company (2009, p. 1) noted "The medical device industry is approaching a tipping point where the increasing likelihood of a quality event, the rising costs of such events, and the public nature of quality performance will force companies to focus on quality and reliability throughout product design, manufacturing, and marketing." Yet, the best approach to identify medical device defects and decrease associated Medicare spending remains a contentious issue (Schulte and Jewett 2017). If the guidelines identified from our research's findings are implemented, we anticipate a reduction in the number of product-harm crises, improving outcomes for various stakeholders, including patients, doctors, hospitals, medical device firms, and investors.

Limitations and Opportunities for Further Research

In this first study on the role of CEOs' functional backgrounds in product-harm crises, we focused on the hitherto unexplored effects of a Marketing CEO, in conjunction with marketing, finance, operations, and R&D department power and CEO's stock option pay, on the number of product-harm crises. However, we are unable to classify the products in our sample as being either radical or incremental innovations. Future research that explores relationships between Marketing CEOs and other aspects of marketing and business strategies (e.g., new product development approaches, including radical vs. incremental innovations, technology development modes—in-house vs. alliances) and firm outcomes will be useful.

Second, following empirical precedent in the marketing literature on product-harm crises, we used secondary data to construct the variables. While secondary data have some advantages (e.g., no subjectivity bias), they preclude consideration of organizational factors (e.g., locus in firm) that may affect product-harm crises. Also, motivated by data availability, we used publicly-listed U.S. medical device firms as the empirical context for hypotheses testing. However, some medical device firms are private firms. A potential research opportunity is to study product-harm crises in private firms, both in the U.S. and in other countries, using primary data collection methods, including surveys and in-depth interviews of senior management. Further, given our interest in the role of the Marketing CEO in product-harm crises, we use annual data, the unit of analysis for firm-level corporate governance (i.e., TMT data). Research using more granular data in continuous time (days, weeks) is an opportunity for further research.

Third, product-harm crises are complex phenomena with many firm-level and environmental antecedents. We include a comprehensive set of control variables, but future research examining the role of the firm's ownership (institutional vs. retail investors), strategic investments (in-house vs. outsourced manufacturing, patenting policy), and focus/orientation (e.g. differentiation vs. cost-leadership) will be a useful extension to this work.

Finally, the choice of the U.S. medical device industry as the empirical context allows for hypotheses testing without potential noise from cross-industry variations. However, as a result, the generalizability of this research's findings emerges as a potential issue. Future work using cross-industry samples that incorporate industry characteristics (e.g., uncertainty) on the organizational antecedents of product-harm crises will be a useful extension to this work.

In sum, this research takes a step toward exploring the role of functional backgrounds of CEOs, in general, and Marketing CEOs, in particular, in product-harm crises. In doing so, the research's findings draw attention to the Marketing CEO who, as a custodian of the firm's brands and a strong advocate for customers, plays a facilitative role, along with powerful finance and R&D departments and CEO's stock option pay, in decreasing the number of product-harm crises.

References

Agle, Bradley R., Ronald K. Mitchell, and Jeffrey A. Sonnenfeld (2009), “Who Matters to CEOs? An Investigation of Stakeholder Attributes and Salience, Corporate Performance, and CEO Values,” *Academy of Management Journal*, 42 (5), 507-525.

Ai, Chunrong, and Edward C. Norton (2003), “Interaction Terms in Logit and Probit Models,” *Economics Letters*, 80 (1), 123-129.

Altman, Edward I. (1968), “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy,” *Journal of Finance*, 23 (4), 589-609.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton, New Jersey: Princeton University Press.

Arellano, Manuel and Stephen Bond (1991), “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies,* 58 (2), 277-297.

Badawy, Michael K. (1971), “Industrial Scientists and Engineers: Motivational Style Differences,” *California Management Review*, 14 (1), 11-16.

Bantel, Karen A. and Susan E. Jackson (1989), “Top Management and Innovations in Banking: Does the Composition of the Top Team Make a Difference?” *Strategic Management Journal*, 10 (S1), 107-124.

Bargeron, Leonce L., Kenneth M. Lehn, and Chad J. Zutter (2010), “Sarbanes-Oxley and Corporate Risk-Taking,” *Journal of Accounting and Economics*, 49 (1-2), 34-52.

Bass, Bernard M. (1990), “From Transactional to Transformational Leadership: Learning to Share the Vision,” *Organizational Dynamics*, 18 (3), 19-31.

Bertrand, Marianne and Antoinette Schoar (2003), “Managing with Style: The Effect of Executives on Firm Policies,” *Quarterly Journal of Economics*, 68 (4), 1169-1208.

Boyd, D. Eric, Rajesh K. Chandy, and Marcus Cunha Jr. (2010), “When Do Chief Marketing Officers Affect Firm Value? A Customer Power Explanation,” *Journal of Marketing Research*, 47 (6), 1162-1176.

Buis, Maarten L. (2010), “Stata tip 87: Interpretation of Interactions in Non-linear Models,” *The Stata Journal*, 10 (2), 305-308.

Cameron, Colin A. and Pravin K. Trivedi (2013), *Regression Analysis of Count Data*. Cambridge, UK: Cambridge University Press.

Chatterjee, Arijit and Donald C. Hambrick (2011), “Executive Personality, Capability Cues, and Risk Taking: How Narcissistic CEOs React to their Successes and Stumbles,” *Administrative Science Quarterly*, 56 (2), 202-237.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), “Does a Firm's Product-Recall Strategy Affect its Financial Value? An Examination of Strategic Alternatives during Product-Harm Crises,” *Journal of Marketing*, 73 (6), 214-226.

Chung, Kee H. and Stephen W. Pruitt (1994), “A Simple Approximation of Tobin’s q,” *Financial Management*, 23 (3), 70-74.

Cleeren, Kathleen, Marnik G. Dekimpe, and Harald J. Van Heerde (2017), "Marketing Research on Product-Harm Crises: A Review, Managerial Implications, and an Agenda for Future Research," *Journal of the Academy of Marketing Science*, 45 (5), 593-615.

----, Harald J. Van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises," *Journal of Marketing*, 77 (2), 58-77.

----, Marnik G. Dekimpe, and Kristiaan Helsen (2008), "Weathering Product-Harm Crises," *Journal of the Academy of Marketing Science*, 36 (2), 262-270.

Cyert Richard M. and James G. March (1963), *A Behavioral Theory of the Firm*. Englewood Cliffs, NJ: Prentice-Hall Publishing.

Daughety, Andrew F. and Jennifer F. Reinganum (1995), "Product Safety: Liability, R&D and Signaling," *American Economic Review*, 85 (5), 1187-1206.

Day, George S. (1997), "Aligning the Organization to the Market," in *Reflections on the Future of Marketing*, D.R. Lehman and K.E. Jocz, eds. Cambridge, MA: Marketing Science Institute, 67-93.

Dearborn, Dewitt C. and Herbert A. Simon (1958), "Selective Perception: A Note on the Departmental Affiliations of Executives," *Sociometry*, 21 (2), 144-150.

Diaz, Maria Dolores Saura and Luis R. Gomez-Mejia (1997), "The Effectiveness of Organizationwide Compensation Strategies in Technology Intensive Firms," *Journal of High Technology Management Research*, 8 (2), 301-315.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), "Does it Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry," *Journal of Marketing*, 81 (2), 111-129.

Feng, Hui, Neil A. Morgan, and Lopo, L. Rego (2015), "Marketing Department Power and Firm Performance," *Journal of Marketing*, 79 (5), 1-20.

Finkelstein, Sydney, Donald C. Hambrick, and Albert A. Cannella Jr. (2009), *Strategic Leadership: Top Executives and Their Effects on Organizations*. St. Paul, MN: West Publishing.

----, (1992), "Power in Top Management Teams: Dimensions, Measurement, and Validation," *Academy of Management Journal*, 35 (3), 505-538.

Fligstein, Neil (1987), "The Intraorganizational Power Struggle: Rise of Finance Personnel to Top Leadership in Large Corporations, 1919-1979," *American Sociological Review*, 52 (1), 44-58.

Fuhr, Ted, Katy George, and Janice Pai (2009), "The Business Case of Medical Device Quality," *McKinsey Center for Government*. Available at: https://www.mckinsey.com/~/media/McKinsey/dotcom/client_service/Public%2520Sector/Regulatory%2520excellence/The_business_case_for_medical_device_quality.html

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!" *Journal of Marketing*, 79 (3), 1-22.

----, Rajdeep Grewal, William T. Ross Jr., and Rajendra K. Srivastava (2014), “Product Recalls and the Moderating Role of Brand Commitment,” *Marketing Letters*, 25 (2), 179-191.

Gerpott, Torsten J., Michel Domsch, and Robert T. Keller (1988), “Career Orientations in Different Countries and Companies: An Empirical Investigation of West German, British and US Industrial R&D Professionals,” *Journal of Management Studies*, 25 (5), 439-462.

Gerstner, Wolf-Christian, Andreas König, Albrecht Enders, and Donald C. Hambrick (2013), “CEO Narcissism, Audience Engagement, and Organizational Adoption of Technological Discontinuities,” *Administrative Science Quarterly*, 58 (2), 257-291.

Gigone, Daniel and Reid Hastie (1993), “The Common Knowledge Effect: Information Sharing and Group Judgment,” *Journal of Personality and Social Psychology*, 65 (5), 959-974.

Gupta, Ashok K., S.P. Raj, and David Wilemon (1986), “A Model for Studying R&D-Marketing Interface in the Product Innovation Process,” *Journal of Marketing*, 50 (2), 7-17.

Hambrick, Donald C. (2007), “Upper Echelons Theory: An Update,” *Academy of Management Review*, 32 (2), 334-343.

----, and Phyllis A. Mason (1984), “Upper Echelons: The Organization as a Reflection of Its Top Executives,” *Academy of Management Review*, 9 (2), 193-206.

Haunschild, Pamela R. and Mooweon Rhee (2004), “The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls,” *Management Science*, 50 (11), 1545-1560.

Hickson, David J., C. R. Hinings, C. A. Lee, Rodney E. Schneck, and Johannes M. Pennings (1971), “A Strategic Contingencies’ Theory of Intraorganizational Power,” *Administrative Science Quarterly*, 16 (2), 216-229.

Homburg, Christian, John P. Workman Jr., and Harley Krohmer (1999), “Marketing’s Influence within the Firm,” *Journal of Marketing*, 63 (2), 1-17.

Hora, Manpreet, Hari Bapuji, and Aleda V. Roth (2011), “Safety Hazard and Time to Recall: The Role of Recall Strategy, Product Defect Type, and Supply Chain Player in the U.S. Toy Industry,” *Journal of Operations Management*, 29 (7-8), 766-777.

Jensen, Michael C. and Kevin J. Murphy (1990), “Performance Pay and Top-Management Incentives,” *Journal of Political Economy*, 98 (2), 225-264.

----, and William H. Meckling (1976), “Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure,” *Journal of Financial Economics*, 3 (4), 305-360.

Kalaignanam, Kartik, Tarun Kushwaha, and Meike Eilert (2013), “The Impact of Product Recalls on Future Product Reliability and Future Accidents: Evidence from the Automobile Industry,” *Journal of Marketing*, 77 (1), 41-57.

----, Tarun Kushwaha, and Tracey A. Swartz (*2017*), “The Differential Impact of New Product Development “Make/Buy” Choices on Immediate and Future Product Quality: Insights from the Automobile Industry,” *Journal of Marketing*, 81 (6), 1-23.

Kashmiri, Saim and Vijay Mahajan (2017), "Values That Shape Marketing Decisions: Influence of Chief Executive Officers' Political Ideologies on Innovation Propensity, Shareholder Value, and Risk," *Journal of Marketing Research,* 54 (2), 260-278.

----, Saim, Cameron D. Nicol, and Sandeep Arora (2017), "Me, Myself, and I: Influence of CEO Narcissism on Firms' Innovation Strategy and the Likelihood of Product-Harm Crises," *Journal of the Academy of Marketing Science,* 45 (5), 633-656.

----, and Jacob Brower (2016), "Oops! I did it again: Effect of Corporate Governance and Top Management Team Characteristics on the Likelihood of Product-Harm Crises," *Journal of Business Research*, 69 (2), 621-630.

Khodakarami, Farnoosh, J. Andrew Petersen, and Rajkumar Venkatesan (2015), "Developing Donor Relationships: The Role of the Breadth of Giving," *Journal of Marketing*, 79 (4), 77-93.

Krajewski, Lee J., Larry P. Ritzman, and Manoj K. Malhotra (2013), *Operations Management: Processes and Supply Chains.* London, UK: Pearson Publishing.

Li, Qiang, Patrick G. Maggitti, Ken G. Smith, Paul E. Tesluk, and Riitta Katila (2013), "Top Management Attention to Innovation: The Role of Search Selection and Intensity in New Product Introductions," *Academy of Management Journal*, 56 (3), 893-916.

Liu, Angela X., Yong Liu, and Ting Luo (2016), "What Drives a Firm's Choice of Product Recall Remedy? The Impact of Remedy Cost, Product Hazard, and the CEO," *Journal of Marketing*, 80 (3), 79-95.

Liu, Yan and Venkatesh Shankar (2015), "The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry," *Management Science,* 61 (10), 2514-2535.

Lobo, Gerald J. and Jian Zhou (2006), "Did Conservatism in Financial Reporting Increase after the Sarbanes-Oxley Act? Initial Evidence," *Accounting Horizons*, 20 (1), 57-73.

Miller, Danny and Jamal Shamsie (2001), "Learning across the Life Cycle: Experimentation and Performance among the Hollywood Studio Heads," *Strategic Management Journal*, 22 (8), 725-745.

Moorman, Christine and Roland T. Rust (1999), "The Role of Marketing," *Journal of Marketing*, 63 (Special Issue), 180-197.

Nath, Pravin and Vijay Mahajan (2011), "Marketing in the C-Suite: A Study of Chief Marketing Officer Power in Firms' Top Management Teams," *Journal of Marketing*, 75 (1), 60-77.

---- and ---- (2008), "Chief Marketing Officers: A Study of Their Presence in Firms' Top Management Teams," *Journal of Marketing*, 72 (1), 65-81.

Olson, Eric M., Orville C. Walker, Robert W. Ruekert, and Joseph M. Bonnerd (2001), "Patterns of Cooperation during new Product Development among Marketing, Operations and R&D: Implications for Project Performance," *Journal of Product Innovation Management*, 18 (4), 258-271.

Paşa, Mehmet and Steven M. Shugan (1996), "The Value of Marketing Expertise," *Management Science*, 42 (3), 370-388.

Petrin, Amil and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47 (1), 3-13.

Rao, Raghunath Singh, Rajesh K. Chandy, and Jaideep C. Prabhu (2008), "The Fruits of Legitimacy: Why Some New Ventures Gain More from Innovation Than Others," *Journal of Marketing*, 72 (4), 58-75.

Rhee, Mooweon and Pamela Haunschild (2006), "The Liability of Good Reputation: A Study of Product Recalls in the U.S. Automobile Industry," *Organization Science*, 17 (1), 101-117.

Ruekert, R.W. and O. C. Walker (1987), "Interactions Between Marketing and R&D Departments in Implementing Different Business Strategies," *Strategic Management Journal*, 8 (3), 233-248.

Sanders, Gerard and Donald C. Hambrick (2007), "Swinging for the Fences: The Effects of CEO Stock Options on Company Risk Taking and Performance," *Academy of Management Journal*, 50 (5), 1055-1078.

Schulte, Fred and Christina Jewett (2017), "Replacing Faulty Heart Devices Costs Medicare $1.5 Billion in 10 Years," *The New York Times* at https://www.nytimes.com/2017/10/02/health/heart-devices-medicare.html.

Thirumalai, Sriram and Kingshuk K. Sinha (2011), "Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences," *Management Science*, 57 (2), 376-392.

Tobias, Aurelio and Michael J. Campbell (1998), "Time Series Regression for Counts allowing for Autocorrelation," *Stata Technical Bulletin*, Nov., 33-37.

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230-245.

Verhoef, Peter C. and Peter S.H. Leeflang (2009), "Understanding the Marketing Department's Influence within the Firm," *Journal of Marketing*, 73 (2), 14-37.

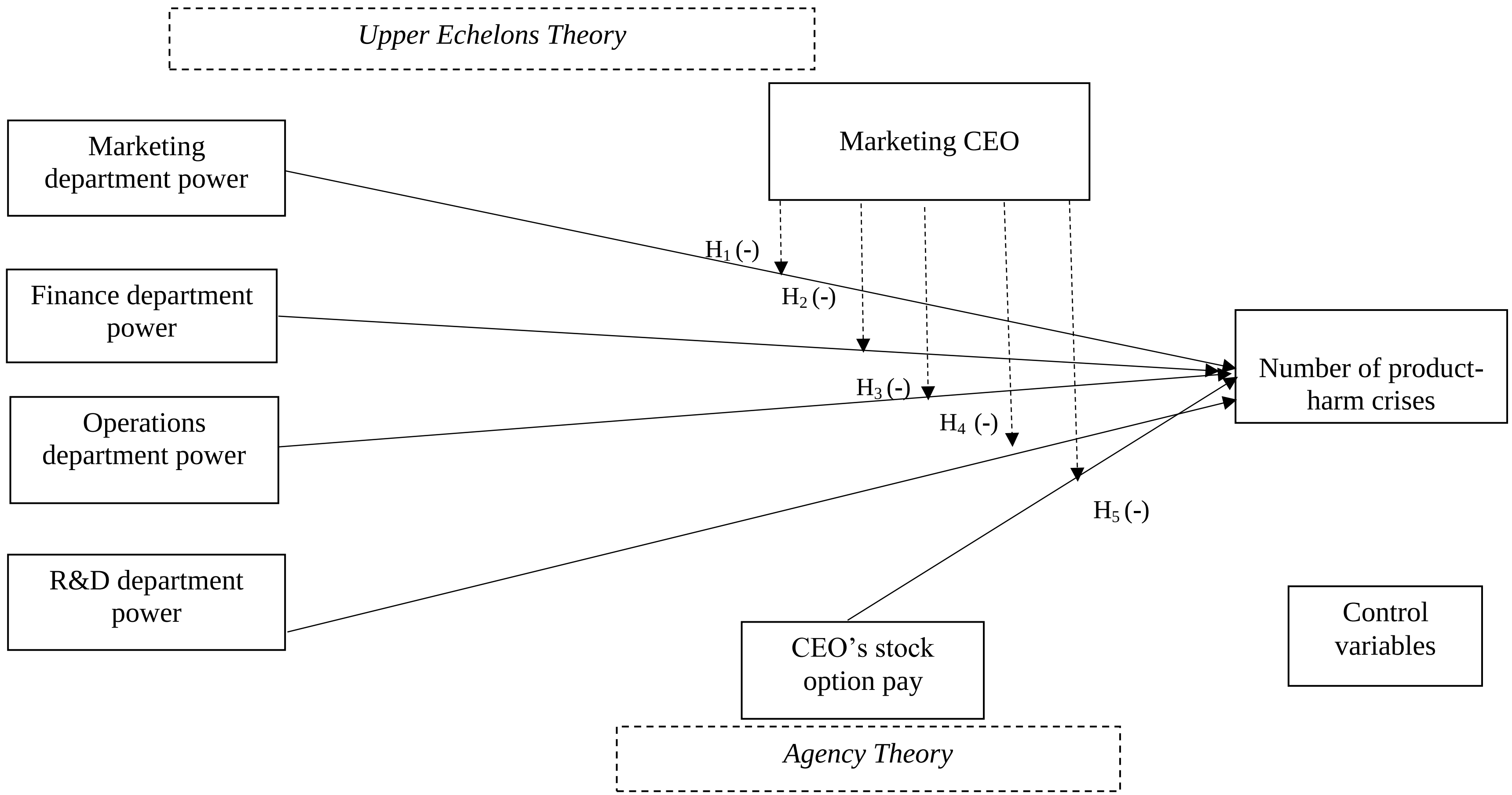
Weinrauch, J. Donald and Richard Anderson (1982), "Conflicts between Engineering and Marketing Units," *Industrial Marketing Management*, 11 (October), 291-301.

Wiseman, Robert M. and Luis R. Gomez-Mejia (1998), "A Behavioral Agency Model of Managerial Risk Taking," *Academy of Management Review*, 23 (1), 133-153.

Wowak, Adam J., Michael J. Mannor, and Kaitlin D. Wowak (2015), "Throwing Caution to the Wind: The Effect of CEO Stock Option Pay on the Incidence of Product Safety Problem," *Strategic Management Journal*, 36 (7), 1082-1092.

Zuckerman, Diana M., Paul Brown, and Steven E. Nissen (2011), "Medical Device Recalls and the FDA Approval Process," *Archives of Internal Medicine*, 171 (11), 1006-1011.

Figure 1: Marketing CEO's Advocacy, Department Power, and Product-Harm Crises



Notes: The dashed lines of interaction effects represent the hypothesized effects. For model completeness, we include the main effect of Marketing CEO in the model that we estimate, although it is not displayed in the figure above.

Table 1: Literature Review: Antecedents of Product-Harm Crises

Reference*	Dependent Variable	Firm	CEO	Marketing CEO	Role of Marketing in TMT	Role of other Functions in TMT	Unit of analysis	Industry
Haunschild and Rhee (2004)	Number of Product Recalls	Yes	No	No	No	No	Firm-year	Automobile
Chen et al. (2009)	Proactive vs. Reactive Recalls	Yes	No	No	No	No	Firm-recall (event study)	Consumer products
Hora et al. (2011)	Time to recall a product	Yes	No	No	No	No	Toy-recall	Toys
Thirumalai and Sinha (2011)	Number of Product Recalls	Yes	No	No	No	No	Firm-recall (event study)	Medical Devices
Kalaignanam et al. (2013)	Product reliability	Yes	No	No	No	No	Make-year	Automobile
Wowak et al. (2015)	Number of product recalls	Yes	Yes	No	No	No	Firm-year	Consumer products and health care
Kashmiri and Brower (2016)	Likelihood of product-harm crises (0/1)	Yes	No	No	No	No	Firm-year	Multiple industries
Liu et al. (2016)	Recall Remedy Decisions	Yes	Yes	No	No	No	Firm-year	Consumer products
Eilert et al. (2017)	Time to recall a product	Yes	No	No	No	No	Make-recalls (event study)	Automobile
Kashmiri et al. (2017)	Likelihood of product-harm crises (0/1)	Yes	Yes	No	Yes	No	Firm-year	Multiple industries
Our study	*Count of product-harm crises*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Firm-year*	*Medical Devices*

Table 2: Variables, Measures, and Sources

Variable	Measure	Data Source
Number of product-harm crises	Annual number of product recalls	The FDA Recalls database
Marketing CEO	1 if the CEO has previous functional experience in Marketing or Sales, 0 otherwise	ExecuComp and web-scraping
Marketing department power		
Finance department power		
Operations department power	Feng, Morgan, and Rego (2015)	ExecuComp
R&D department power		
GM department power		
CEO's stock option pay	CEO exercisable stock options	
R&D intensity	R&D expenditures over sales	
Labor intensity	Number of employees over sales	
Firm age	Difference in years between the current year and the first year in which the firm was covered in Compustat	
Slack resources	Assets over liabilities	Compustat
Firm size	Total Assets	
Firm performance	Net income over assets	
Sales change	Year-to-year percentage change in sales	
Financial leverage	Long-term debt over common equity	
Financial distress	Altman's Z (Altman 1968)	
Patents	Number of patents filed for by the firm in the U.S.	Google Patents
Reputation	Residual from the regression of firm's intangible value on lagged sales, ROA, assets, and age (firm- and year-fixed effects included)	Elaboration from Compustat
Size of TMT	Total number of executives on the TMT	
CEO age	CEO age	ExecuComp
CEO duality	1 if the CEO is also Chairman of the board, 0 otherwise	
CEO-founder	1 if the CEO is also the founder of the firm, 0 otherwise	ExecuComp and web- scraping
CEO tenure	Difference in years between the current year and the year in which the CEO was appointed	ExecuComp
CEO marketing education	1 if the CEO has formal marketing education, 0 otherwise	ExecuComp and web-scraping
CEO total compensation (TC)	CEO's total compensation	ExecuComp
CEO TC change (TCC)	Year-to-year percentage change in CEO's total compensation	ExecuComp

Table 3: Descriptives and Correlation Matrix of Variables

	Mean	Std. Dev	1.	2.	3.	4.	5.	6.	7.	8.
1. Number of product-harm crises	3.89	7.10	1.00							
2. Marketing CEO	.36	.48	.005	1.00						
3. Marketing department power	-.02	1.00	-.20*	.20*	1.00					
4. Finance department power	.04	.96	-.06	-.10*	-.12*	1.00				
5. Operations department power	.02	1.00	-.10*	.05	.15*	-.01	1.00			
6. R&D department power	.02	1.01	-.07	.05	.28*	-.0004	.11*	1.00		
7. GM department power	.02	1.01	.31*	-.03	-.47*	-.26*	-.46*	-.28*	1.00	
8. CEO's stock option pay	10,329.23	17,230.45	.13*	-.06	-.07	-.17*	-.05	-.09*	.07	1.00

Notes: *p < .05. All Variance Inflation Factors are well below 10.

Table 4: Impact of Product-Harm Crises on Firm Performance

		Dependent variable	
	Cash flow	Stock price volatility	Tobin's q
Number of product-harm crises	-.002 (.001)***	.06 (.06)	-.03 (.01)***
Year-Fixed Effects	YES	YES	YES
Firm-Fixed Effects	YES	YES	YES
Observations	608	597	595
R-sq	0.52	0.63	0.66

Notes: **p < .10. **p < .05. ***p < .01*. All regressions include a constant. Robust standard errors. Unstandardized parameter estimates and standard errors in parenthesis.

Table 5: Results: Marketing CEO and the Number of Product-Harm Crises

Variable	Zero-inflated negative binomial model Column 1	Poisson model Column 2	Dependent variable winsorized at 5% Column 3[@]
Marketing CEO × Marketing department power (H_1)	-.25 (.14)*	-.23 (.14)	-.26 (.14)*
Marketing CEO × Finance department power (H_2)	-.31 (.12)***	-.24 (.11)**	-.29 (.11)***
Marketing CEO × Operations department power (H_3)	.04 (.12)	.08 (12)	.02 (.11)
Marketing CEO × R&D department power (H_4)	-.25 (.11)**	-.29 (.11)**	-.25 (.11)**
Marketing CEO × CEO's stock option pay† (H_5)	-.01 (.005)**	-.01 (.005)*	-.01 (.005)**
Marketing CEO	.01 (.22)	-.004 (.21)	-.04 (.21)
CEO's stock option pay†	.007 (.003)**	.007 (.003)**	.007 (.003)***
Marketing department power	-.18 (.08)**	-.19 (.08)**	-.17 (.08)**
Finance department power	-.14 (.09)	-.19 (.09)**	-.15 (.08)*
Operations department power	-.13 (.08)*	-.17 (.08)**	-.14 (.07)*
R&D department power	-.002 (.07)	-.01 (.07)	.01 (.06)
GM department power	-.10 (.12)	-.15 (.12)	-.10 (.12)
Marketing CEO × GM department power	-.20 (.18)	-.10 (.16)	-.22 (.17)
R&D intensity	1.66 (1.08)	2.21 (1.06)**	1.16 (1.02)
Labor intensity	-135.01 (98.32)	-199.35 (98.92)**	-135.46 (96.16)
Firm age	.06 (.03)**	.05 (.03)**	.05 (.03)**
Slack resources	.002 (.05)	.00005 (.05)	.004 (.05)
Firm size†	-.002 (.01)	-.007 (.01)	-.003 (.01)
Firm performance	-1.81 (.70)**	-1.66 (.72)**	-1.75 (.68)**
Sales change	-.49 (.35)	-.61 (.36)*	-.51 (.35)
Financial leverage	.04 (.17)	-.01 (.17)	.06 (.16)
Financial distress	.004 (.02)	.001 (.03)	.002 (.02)
Patents	.0001 (.0003)	.0001 (.0002)	.0001 (.0002)
Reputation†	.02 (.03)	.006 (.02)	.03 (.02)
Size of TMT	.20 (.07)***	.21 (.07)***	.20 (.07)***
CEO age	.01 (.01)	.01 (.01)	.01 (.01)
CEO duality	-.11 (.14)	-.06 (.13)	-.10 (.12)
CEO-founder	.08 (.38)	-.03 (.36)	-.07 (.35)
CEO tenure	-.02 (.01)*	-.02 (.01)	-.02 (.01)
CEO TC†	.01 (.02)	-.004 (.02)	.02 (.02)
CEO TCC†	-1.51 (.49)***	-1.09 (.51)**	-1.61 (.49)***
CEO marketing education	-.33 (.34)	-.53 (.30)*	-.27 (.32)
Error_Marketing CEO	1.09 (.98)	.49 (1.04)	.97 (.94)
Error_Marketing department power	1.92 (.50)***	1.63 (.47)***	1.82 (.48)***
Error_Finance department power	-.08 (.46)	.33 (.46)	-.07 (.44)
Error_Operations department power	.13 (.43)	.25 (.43)	.22 (.42)
Error_R&D department power	.06 (.34)	.29 (.36)	.08 (.34)
Error GM department power	1.65 (.58)***	1.66 (.61)***	1.41 (.55)**
Year- and Firm-FEs	YES	YES	YES
Inflate - Intercept	-37.82 (.14)***		-47.00 (.17)***
Observations	*557*	*557()*	*557()*
Log pseudolikelihood	*-824.73*	*-851.20*	*-807.17*

Notes: [@] zero-inflated negative binomial model. *$p < .10$. **$p < .05$. ***$p < .01$. All regressions include a constant. Robust standard errors. Unstandardized parameter estimates and standard errors in parenthesis. † Coefficient × 10^3

Table 6: Robustness Checks: Marketing CEO and the Number of Product-Harm Crises

Variable	Endogenous CEO's stock option pay Column 1[@]	Class III recalls excluded Column 2[@]	CMO replaces Marketing CEO Column 3[@]
Marketing CEO × Marketing department power (H_1)	-.25 (.14)*	-.24 (.15)	2.73 (1.31)**
Marketing CEO × Finance department power (H_2)	-.29 (.12)**	-.30 (.12)**	-.13 (.14)
Marketing CEO × Operations department power (H_3)	.01 (.11)	-.01 (12)	-.08 (.17)
Marketing CEO × R&D department power (H_4)	-.26 (.11)**	-.29 (.11)***	-.03 (.10)
Marketing CEO × CEO's stock option pay† (H_5)	-.01 (.005)***	-.01 (.005)**	.02 (.008)**
Marketing CEO	.08 (.20)	.09 (.22)	1.85 (1.02)*
CEO's stock option pay†	.009 (.003)***	.008 (.003)**	.003 (.003)
Marketing department power	-.17 (.08)**	-.20 (.09)**	-3.04 (1.34)**
Finance department power	-.14 (.09)	-.16 (.09)*	-.23 (.10)**
Operations department power	-.11 (.08)	-.13 (.08)*	-.15 (.07)**
R&D department power	-.02 (.07)	-.01 (.07)	-.11 (.07)
GM department power	-.07 (.12)	-.10 (.12)	-.22 (.14)
Marketing CEO × GM department power	-.27 (.18)	-.24 (.18)	.01 (.23)
R&D intensity	1.47 (1.07)	1.62 (1.04)	1.82 (1.09)*
Labor intensity	-139.48 (100.47)	-114.91 (102.64)	-139.80 (92.64)
Firm age	.05 (.03)*	.07 (.03)**	.06 (.03)**
Slack resources	.003 (.05)	-.01 (.05)	.01 (.04)
Firm size†	-.00003 (.01)	-.003 (.01)	-.002 (.01)
Firm performance	-2.01 (.69)***	-1.93 (.73)***	-1.48 (.66)**
Sales change	-.45 (.35)	-.54 (.37)	-.41 (.36)
Financial leverage	.02 (.17)	.02 (.17)	.05 (.16)
Financial distress	.01 (.02)	.01 (.02)	-.01 (.02)
Patents	.0002 (.0003)	.003 (.0003)	.001 (.0004)
Reputation†	.02 (.02)	.01 (.03)	.03 (.03)
Size of TMT	.19 (.07)***	.21 (.07)***	.39 (.11)***
CEO age	.01 (.01)	.01 (.01)	.01 (.01)
CEO duality	-.08 (.15)	-.08 (.14)	-.17 (.13)
CEO-founder	.25 (.37)	.13 (.41)	-.18 (.34)
CEO tenure	-.03 (.01)**	-.02 (.01)*	-.01 (.01)
CEO TC†	.01 (.02)	.008 (.02)	-.002 (.02)
CEO TCC†	-1.46 (.50)***	-1.34 (.48)***	-1.04 (.50)**
CEO marketing education	-.34 (.33)	-.43 (.35)	-.46 (.29)
Year- and Firm-FEs	YES	YES	YES
Inflate - Intercept	-38.33 (.14)***	-39.48 (.11)***	-39.42 (.13)***
Observations	*557*	*557*	*557*
Log pseudolikelihood	*-822.66*	*-787.20*	*-827.32*
Adj R-Sq			

Notes: [@] zero-inflated negative binomial model. **p < .10. **p < .05. ***p < .01*. All regressions include a constant. Robust standard errors. Unstandardized parameter estimates and standard errors in parenthesis. † Coefficient × 10^3. Errors from Equations A1-A6 are included but not reported here in the interest of brevity.

Table 7: Robustness Checks: Marketing CEO and the Number of Product-Harm Crises

Variable	(No Sales) Marketing CEO Column 1@	(Senior) Marketing CEO Column 2@	(Pure) Marketing CEO Column 3@
Marketing CEO × Marketing department power (H_1)	-.35 (.17)**	-.35 (.17)**	-.83 (.33)**
Marketing CEO × Finance department power (H_2)	-.25 (.13)**	-.31 (.14)**	-1.01 (.28)***
Marketing CEO × Operations department power (H_3)	-.05 (.12)	.17 (.14)	-.14 (.40)
Marketing CEO × R&D department power (H_4)	-.15 (.12)	-.08 (.15)	.25 (.19)
Marketing CEO × CEO's stock option pay† (H_5)	-.01 (.006)**	-.01 (.006)*	.008 (.01)
Marketing CEO	-.02 (.24)	-.10 (.27)	-1.25 (.55)**
CEO's stock option pay†	.008 (.003)***	.008 (.003)***	.004 (.003)
Marketing department power	-.15 (.08)*	-.21 (.08)***	-.16 (.07)**
Finance department power	-.14 (.09)	-.21 (.09)**	-.09 (.08)
Operations department power	-.11 (.07)	-.19 (.07)***	-.05 (.06)
R&D department power	-.03 (.07)	-.05 (.07)	-.04 (.06)
GM department power	-.09 (.12)	-.21 (.11)*	-.03 (.11)
Marketing CEO × GM department power	-.21 (.19)	-.04 (.23)	-.30 (.57)
R&D intensity	1.62 (1.12)	2.23 (1.14)*	2.28 (1.21)*
Labor intensity	-133.87 (96.20)	-129.66 (97.18)	-40.44 (91.46)
Firm age	.06 (.03)**	.05 (.03)*	.10 (.03)***
Slack resources	.01 (.05)	-.01 (.05)	.04 (.05)
Firm size†	-.004 (.01)	.001 (.01)	-.02 (.01)
Firm performance	-1.65 (.75)**	-1.46 (.72)**	-.75 (.78)
Sales change	-.49 (.36)	-.48 (.36)	-.40 (.35)
Financial leverage	.10 (.17)	.10 (.17)	.08 (.16)
Financial distress	.003 (.02)	.01 (.02)	.001 (.02)
Patents	.0002 (.0003)	.0004 (.0003)	.001 (.0003)
Reputation†	.02 (.03)	.004 (.03)	-.001 (.03)
Size of TMT	.19 (.07)***	.21 (.07)***	.09 (.07)
CEO age	.01 (.01)	.01 (.01)	.002 (.01)
CEO duality	-.10 (.14)	-.21 (.14)	-.15 (.13)
CEO-founder	.14 (.38)	-.15 (.38)	.13 (.33)
CEO tenure	-.02 (.01)**	-.01 (.01)	-.01 (.01)
CEO TC†	.008 (.02)	.002 (.02)	.003 (.002)
CEO TCC†	-1.43 (.49)***	-1.28 (.48)***	-1.10 (.46)**
CEO marketing education	-.30 (.35)	-.31 (.37)	.03 (.27)
Year- and Firm-FEs	YES	YES	YES
Inflate - Intercept	-37.83 (.13)***	-38.31 (.14)***	-38.97 (.14)***
Observations	*557*	*557*	*557*
Log pseudolikelihood	*-828.21*	*-826.99*	*-821.86*

Notes: @ zero-inflated negative binomial model. *$p < .10$. **$p < .05$. ***$p < .01$. All regressions include a constant. Robust standard errors. Unstandardized parameter estimates and standard errors in parenthesis. † Coefficient × 10^3. Errors from Equations A1-A6 are included but not reported here in the interest of brevity.

Appendix A

New Product Approval and Product-Harm Crises in the U.S. Medical Device Industry

Medical devices, which vary in complexity and technology (e.g., thermometers, blood pressure monitors, dialysis, and various body implants), are used by both consumers (retail) in their homes and by providers (physicians/hospitals) (B2B) for use in the delivery of health care services.

Given the crucial role of medical devices in health care and therefore in patients' health outcomes, the Food and Drug Administration (http://www.fda.gov) oversees the U.S. medical device industry. Below, we describe the new product introductions and product recalls processes in the U.S. medical device industry.

New Product Introductions

There are currently approximately 175,000 different medical devices on the U.S. market that are overseen by the U.S. FDA's Center for Devices and Radiological Health (CDRH). Every year, the CDRH receives about 22,000 submissions for clearance or approval of new medical devices.

The FDA has established classifications for approximately 1,700 different generic types of devices, each of which is assigned to one of three regulatory classes based on the level of control deemed necessary by the FDA to assure the safety and effectiveness of the device: 1) class I: General controls, 2) class II: General and special controls, and 3) class III: General controls and premarket approval. Class I includes devices with the lowest risk and class III includes those with the greatest risk. The class to which a medical device is assigned determines, among other things, the type of premarketing application required for FDA clearance to market.

FDA has two different tracks for granting permissions to firms for marketing new products. In the first track, under Section 510(k) of the Food, Drug and Cosmetic Act, it requires device manufacturers, who must register, to notify FDA of their intent to market a medical device at least 90 days in advance, as premarket notification (PMN) under which new devices are cleared for market if they are "substantially equivalent" (SE) to existing products. Many medical devices routinely receive FDA clearance based on older devices, which were not subject to rigorous pre-market testing. Examples of products cleared through 510(k)s include x-ray machines, dialysis machines, fetal monitors, lithotripsy machines, and muscle stimulators.

In the second track, a premarket approval application (PMA) is required[8] . To determine that a device is safe and effective, PMA requires scientific evidence that the possible benefits to health from the intended use of a device outweigh possible risks and that the device will significantly improve health outcomes. Examples of PMAs include digital mammography, minimally invasive and non-invasive glucose testing devices, implanted defibrillators, and implantable middle ear devices.

Most new medical devices are cleared through the 510(k)s program, which has both advocates and critics. Medical device firms and some doctors oppose tighter reporting, arguing that it would be costly and difficult to integrate with existing payment claim forms and not be useful. Mark Leahey, who heads the Medical Device Manufacturers Association,

[8] Unless the device is a pre-amendments device (on the market prior to the passage of the medical device amendments in 1976, or substantially equivalent to such a device) and PMA's have not been called for.

an industry trade group, noted that "It is abundantly clear that data collected in electronic health records is a far superior and more cost-effective method (compared to increased FDA regulation) for monitoring the performance of medical devices."[9]

Critics contend that the 510(k) process results in the marketing of unsafe products, potentially harming consumers' health. Using FDA's high-risk List of Device Recalls from 2005 through 2009, Zuckerman, Brown, and Nissen (2011) concluded that "Most medical devices recalled for life-threatening or very serious hazards were originally cleared for market using the less stringent 510(k) process or were considered so low risk that they were exempt from review (78%). These findings suggest that reform of the regulatory process is needed to ensure the safety of medical devices."

Product Harm-Crises

The FDA defines a product recall as "…a firm's removal or correction of a marketed product that the FDA considers to be in violation of the laws it administers and against which the agency would initiate legal action"[10]. A product recall in the medical device industry is aimed at removing products that violate FDA laws from the market. A product-harm crisis in the U.S. medical device industry is triggered when there is a product recall in the medical device supply chain, typically undertaken by a firm's decision to remove and/or correct products that are in violation of FDA laws. Product recalls, which may be triggered by quality failures such as manufacturing defects, functional defects, packaging errors, and software glitches, represent serious threats to the health and well-being of consumers and to the reputations of doctors, hospitals, and medical device firms. All medical device recalls are recorded by the FDA.

A review of FDA's records indicates that most product recalls are undertaken voluntarily by manufacturers. However, rarely, the FDA may order the recall of a product, if it deems that it poses a significant health risk. Following a product recall issued by a manufacturer, the FDA evaluates the recalled product's health risk and classifies the recall as a 1) class I recall: where a reasonable probability that the use of or exposure to the violative product will cause serious adverse health consequences or death, 2) class II recall: where the use of or exposure to the violative product may cause temporary or medically reversible adverse health consequences or where the probability of serious adverse health consequences is remote, or 3) class III recall: where the use of or exposure to the violative product is not likely to cause adverse health consequences.

In sum, majority of new medical devices in the U.S. do not require clinical testing before the FDA clears them for market introduction. At the other end, majority of product-harm crises, which are caused by product recalls, are voluntary actions taken by firms, suggesting that product-harm crises represent strategic choices for firms, such that their leadership, including the CEO and powerful departments in the TMT, may be expected to play an important role.

[9] https://khn.org/news/heart-device-failure-medicare-spent-1-5b-over-10-years-to-replace-defective-implants/ accessed on November 13, 2017.

[10] https://www.fda.gov/medicaldevices/deviceregulationandguidance/postmarketrequirements/recallscorrectionsandremovals/default.htm#2 accessed on November 1, 2017.

Appendix B

Table B1: Instruments' Exclusion Restriction

Variable	Number of product-harm crises@
Marketing CEO_Peer^ × Marketing department power_Peer	.33 (1.76)
Marketing CEO_Peer × Finance department power_Peer	.86 (1.22)
Marketing CEO_Peer × Operations department power_Peer	3.47 (2.69)
Marketing CEO_Peer × R&D department power_Peer	.71 (2.22)
Marketing CEO_Peer × CEO's stock option pay†	.03 (.08)
Marketing CEO_Peer	-412.82 (265.43)
CEO's stock option pay†	-.005 (.03)
Marketing department power_Peer	.40 (.62)
Finance department power_Peer	.33 (.50)
Operations department power_Peer	-.90 (.92)
R&D department power_Peer	-.13 (.75)
GM department power_Peer	-1.42 (1.13)
Marketing CEO_Peer × GM department power_Peer	5.30 (3.15)*
R&D intensity	1.96 (1.12)*
Labor intensity	-197.87 (104.47)*
Firm age	-.67 (.25)***
Slack resources	.01 (.04)
Assets†	-.01 (.01)
ROA	-1.56 (.74)**
Sales change	-.59 (.36)*
Financial leverage	.04 (.16)
Financial distress	.01 (.02)
Patents	.001 (.0003)**
Reputation†	.005 (.03)
Size of TMT	.21 (.08)***
CEO age	.002 (.01)
CEO duality	-.10 (.15)
CEO-founder	.07 (.37)
CEO tenure	-.02 (.01)
CEO TC†	-.004 (.02)
CEO TCC†	-.96 (.59)
CEO marketing education	-.15 (.35)
Year- and Firm-FEs	YES
Inflate - Intercept	-39.44 (.20)***
Observations	*557*
Log pseudolikelihood	*-845.11*

*Notes: *p < .10. **p < .05. ***p < .01.* ^ Peer denotes peer firms. Unstandardized parameter estimates and standard errors in parenthesis. @ The model is a zero-inflated negative binomial model and includes a constant and robust standard errors. † Coefficient × 10^3.

Table B2: Instruments' Relevance

Variable	Dependent Variable: Marketing CEO Column 1	Marketing department power Column 2	Finance department power Column 3
Marketing CEO_Peer × Marketing department power_Peer	-.16 (.12)	-.39 (.21)*	-.13 (.17)
Marketing CEO_Peer × Finance department power_Peer	.50 (.10)***	.14 (.18)	-.08 (.15)
Marketing CEO_Peer × Operations department power_Peer	1.03 (.18)***	.47 (.30)	-.12 (.25)
Marketing CEO_Peer × R&D department power_Peer	-.09 (.20)	-.81 (.33)**	.38 (.29)
Marketing CEO_Peer × CEO's stock option pay†	-.001 (.007)	.003 (.01)	-.03 (.01)**
Marketing CEO_Peer^	-181.01 (17.42)***	-41.31 (30.02)	6.04 (26.13)
CEO's stock option pay†	.0007 (.003)	-.001 (.005)	.009 (.004)**
Marketing department power_Peer	.04 (.04)	-2.01 (.08)***	.10 (.06)
Finance department power_Peer	-.17 (.04)***	-.02 (.08)	-2.80 (.06)***
Operations department power_Peer	-.34 (.07)***	-.17 (.11)	.06 (.09)
R&D department power_Peer	.01 (.07)	.30 (.13)**	-.15 (.11)
GM department power_Peer	-.57 (.07)***	-.30 (.13)**	.08 (.12)
Marketing CEO_Peer × GM department power_Peer	1.72 (.18)***	.92 (.34)***	-.04 (.31)
R&D intensity	.06 (.07)	.09 (.10)	-.01 (.10)
Labor intensity	-1.12 (4.00)	9.86 (11.40)	-21.29 (8.83)**
Firm age	-.07 (.02)***	.29 (.04)***	3.18 (.03)***
Slack resources	-.001 (.002)	.003 (.004)	-.01 (.004)**
Assets†	.0005 (.001)	.002 (.002)	.005 (.002)**
ROA	.03 (.03)	.07 (.06)	-.08 (.06)
Sales change	.02 (.01)	.02 (.03)	-.02 (.02)
Financial leverage	.01 (.01)	.004 (.02)	.04 (.02)**
Financial distress	-.0003 (.001)	-.002 (.002)	.001 (.002)
Patents	-.00004 (.00004)	.00005 (.00004)	-.0001 (.0001)
Reputation†	-.006 (.002)***	-.005 (.003)	.002 (.004)
Size of TMT	-.003 (.004)	-.004 (.01)	.01 (.01)
CEO age	.00003 (.001)	.0002 (.001)	-.0003 (.001)
CEO duality	.01 (.01)	.02 (.02)	.05 (.02)**
CEO-founder	-.02 (.02)	.05 (.05)	-.04 (.03)
CEO tenure	-.0004 (.001)	-.001 (.001)	-.001 (.001)
CEO TC†	.001 (.001)	.004 (.003)	-.002 (.003)
CEO TCC†	-.02 (.03)	-.12 (.05)**	-.02 (.05)
CEO marketing education	.02 (.02)	.06 (.03)*	.003 (.02)
Year- and Firm-FEs	YES	YES	YES
Observations	*557*	*557*	*557*
R-sq	*.99*	*.99*	*.99*

*Notes: *p < .10. **p < .05. ***p < .01.* ^ Peer denotes peer firms. Unstandardized parameter estimates and standard errors in parenthesis. @ All models include a constant and robust standard errors. † Coefficient × 10^3.

Table B3: Instruments' Relevance (Cont.)

	Dependent Variable		
Variable	Operations department power Column 1	R&D department power Column 2	GM department power Column 3
Marketing CEO_Peer^ × Marketing department power_Peer	-.19 (.22)	-.04 (.20)	.12 (.22)
Marketing CEO_Peer × Finance department power_Peer	.31 (.17)*	-.003 (.17)	-.20 (.17)
Marketing CEO_Peer × Operations department power_Peer	-1.44 (.31)***	-.19 (.32)	-.07 (.26)
Marketing CEO_Peer × R&D department power_Peer	-.84 (.30)***	-2.10 (.43)***	.46 (.28)
Marketing CEO_Peer × CEO's stock option pay†	-.008 (.01)	.007 (.02)	-.005 (.01)
Marketing CEO_Peer	81.79 (29.99)***	36.25 (32.04)	48.63 (27.28)*
CEO's stock option pay†	.003 (.004)	-.002 (.007)	.001 (.004)
Marketing department power_Peer	.07 (.08)	.03 (.08)	-.03 (.09)
Finance department power_Peer	-.13 (.07)*	.03 (.08)	.12 (.06)**
Operations department power_Peer	-1.52 (.11)***	.06 (.12)	.06 (.09)
R&D department power_Peer	.27 (.11)**	-1.36 (.18)***	-.19 (.11)*
GM department power_Peer	.19 (.13)	-.01 (.14)	-2.29 (.13)***
Marketing CEO_Peer × GM department power_Peer	-.64 (.34)*	.22 (.34)	-1.00 (.32)***
R&D intensity	.10 (.13)	.04 (.12)	-.08 (.10)
Labor intensity	11.42 (7.50)	-4.15 (8.51)	1.21 (7.39)
Firm age	.76 (.03)***	-.53 (.05)***	-.87 (.03)***
Slack resources	.0001 (.004)	.04 (.003)	.001 (.004)
Assets†	.004 (.002)*	.003 (.003)	-.002 (.002)
ROA	.10 (.06)*	.05 (.08)	.01 (.06)
Sales change	-.01 (.03)	.09 (.03)***	-.06 (.03)**
Financial leverage	.002 (.02)	-.02 (.02)	.03 (.02)*
Financial distress	.001 (.002)	-.004 (.002)**	.003 (.002)
Patents	-.0001 (.0001)	-.0002 (.0001)*	-.00001 (.0001)
Reputation†	-.002 (.004)	-.004 (.004)	.004 (.004)
Size of TMT	-.01 (.01)	.01 (.01)	.03 (.01)***
CEO age	-.0002 (.001)	.001 (.002)	-.00004 (.001)
CEO duality	.01 (.02)	-.01 (.02)	-.02 (.02)
CEO-founder	-.07 (.04)*	.03 (.06)	.01 (.04)
CEO tenure	.002 (.001)	-.001 (.002)	.001 (.001)
CEO TC†	-.002 (.003)	.007 (.004)*	-.002 (.003)
CEO TCC†	.02 (.05)	-.08 (.06)	.08 (.05)
CEO marketing education	-.04 (.03)	.05 (.03)*	-.06 (.04)
Year- and Firm-FEs	YES	YES	YES
Observations	*557*	*557*	*557*
R-sq	*.99*	*.99*	*.99*

*Notes: *p < .10. **p < .05. ***p < .01.* ^ Peer denotes peer firms. Unstandardized parameter estimates and standard errors in parenthesis. [@] All models include a constant and robust standard errors. † Coefficient × 10^3.

Appendix C
Table C1: Model Results Expressed as Incidence Rate Ratios (IRRs)

Variable	Main Model	IRR
MKT CEO × Marketing department power (H_1)	-.25 (.14)*	.78 (.11)*
MKT CEO × Finance department power (H_2)	-.31 (.12)***	.74 (.09)***
MKT CEO × Operations department power (H_3)	.04 (.12)	1.04 (.12)
MKT CEO × R&D department power (H_4)	-.25 (.11)**	.78 (.09)**
MKT CEO × CEO's stock option pay† (H_5)	-.01 (.005)**	.99 (.005)**
MKT CEO	.01 (.22)	1.01 (.22)
CEO's stock option pay	.007 (.003)**†	1.00 (.003)**
Marketing department power	-.18 (.08)**	.83 (.07)**
Finance department power	-.14 (.09)	.87 (.08)
Operations department power	-.13 (.08)*	.87 (.07)*
R&D department power	-.002 (.07)	1.00 (.07)
GM department power	-.10 (.12)	.91 (.11)
MKT CEO x GM department power	-.20 (.18)	.82 (.15)
R&D intensity	1.66 (1.08)	5.28 (5.69)
Labor intensity	-135.01 (98.32)	.00 (.00)
Firm age	.06 (.03)**	1.06 (.03)**
Slack resources	.002 (.05)	1.00 (.05)
Assets	-.002 (.01)†	1.00 (.00001)
ROA	-1.81 (.70)**	.16 (.11)**
Sales change	-.49 (.35)	.61 (.21)
Financial leverage	.04 (.17)	1.05 (.17)
Financial distress	.004 (.02)	1.00 (.02)
Patents	.0001 (.0003)	1.00 (.0003)
Reputation	.02 (.03)†	1.00 (.00003)
Size of TMT	.20 (.07)***	1.22 (.09)***
CEO age	.01 (.01)	1.01 (.01)
CEO duality	-.11 (.14)	.89 (.13)
CEO-founder	.08 (.38)	1.08 (.41)
CEO tenure	-.02 (.01)*	.98 (.01)*
CEO TC	.01 (.02)†	1.00 (.00002)
CEO TCC	-1.51 (.49)***†	1.00 (.0005)***
CEO marketing education	-.33 (.34)	.72 (.24)
Error_MKT CEO	1.09 (.98)	2.98 (2.93)
Error_Marketing department power	1.92 (.50)***	6.85 (3.45)***
Error_Finance department power	-.08 (.46)	.93 (.42)
Error_Operations department power	.13 (.43)	1.14 (.50)
Error_R&D department power	.06 (.34)	1.06 (.36)
Error_GM department power	1.65 (.58)***	5.20 (3.03)***
Year- and Firm-FEs	YES	YES
Inflate - Intercept	-37.82 (.14)***	-37.82 (.14)***
Observations	*557*	*557*
Log pseudolikelihood	*-824.73*	*-824.73*

*Notes: *p < .10. **p < .05. ***p < .01*. ^ Peer denotes peer firms. Unstandardized parameter estimates and standard errors in parenthesis. @ All models include a constant and robust standard errors. † Coefficient × 10^3.

Appendix D. Table D1: Results for Finance CEO, Operations CEO, and R&D CEO instead of Marketing CEO

	Dependent Variable		
Variable	Number of Product- harm crises Column 1[@]	Number of Product- harm crises Column 2	Number of Product-harm crises Column 3
Finance CEO × Marketing dept power	.04 (.13)		
Operations CEO × Marketing dept power		-.09 (.13)	
R&D CEO × Marketing dept power			.40 (.18)**
Finance CEO × Finance dept power	.16 (.12)		
Operations CEO × Finance dept power		-.11 (.12)	
R&D CEO × Finance dept power			.10 (.14)
Finance CEO × Operations dept power	.11 (.11)		
Operations CEO × Operations dept power		-.07 (.11)	
R&D CEO × Operations department power			-.08 (.11)
Finance CEO × R&D department power	.04 (.09)		
Operations CEO × R&D department power		-.11 (.09)	
R&D CEO × R&D department power			.12 (.17)
Finance CEO × CEO's stock option pay†	.006 (.004)		
Operations CEO × CEO's stock option pay†		.004 (.005)	
R&D CEO × CEO's stock option pay†			-.008 (.007)
Finance CEO	.19 (.17)		
Operations CEO		.49 (.17)***	
R&D CEO			.21 (.30)
CEO's stock option pay†	.003 (.003)	.003 (.003)	.006 (.003)*
Marketing department power	-.29 (.10)***	-.25 (.11)**	-.33 (.08)***
Finance department power	-.32 (.10)***	-.21 (.09)**	-.30 (.09)***
Operations department power	-.19 (08)**	-.13 (.09)	-.18 (07)***
R&D department power	-.06 (.08)	-.01 (.08)	-.08 (.07)
GM department power	-.17 (.14)	-.05 (.15)	-.25 (.12)**
Finance CEO × GM department power	-.01 (.17)		
Operations CEO × GM department power		-.29 (.16)*	
R&D CEO × GM department power			-.21 (.20)
R&D intensity	2.12 (1.06)**	1.93 (1.09)*	1.79 (1.06)*
Labor intensity	-125.21 (99.35)	-152.92 (100.89)	-148.07 (100.44)
Firm age	.06 (.03)**	.04 (.03)	.04 (.03)
Slack resources	.01 (.05)	-.01 (.05)	-.02 (.05)
Assets†	-.004 (.01)	.01 (.01)	.008 (.01)
ROA	-1.36 (.74)*	-1.89 (.72)***	-1.46 (.71)**
Sales change	-.60 (.37)	-.57 (.37)	-.55 (.37)
Financial leverage	.11 (.15)	.05 (.16)	.14 (.16)
Financial distress	.01 (.02)	.02 (.03)	.02 (.02)
Patents	.0002 (.0003)	.0001 (.0003)	.0004 (.0003)
Reputation†	.01 (.03)	.007 (.03)	.01 (.03)
Size of TMT	.23 (.07)***	.21 (.07)***	.24 (.07)***
CEO age	.003 (.01)	.001 (.01)	.01 (.01)
CEO duality	-.03 (.14)	-.13 (.14)	-.15 (.14)
CEO-founder	.26 (.43)	.15 (.44)	-.62 (.37)*
CEO tenure	-.02 (.01)	-.002 (.01)	-.002 (.01)
CEO TC†	.0002 (.02)	.005 (.02)	.003 (.02)
CEO TCC†	-1.11 (.54)**	-1.22 (.46)***	-1.24 (.51)**
CEO marketing education	-.18 (.33)	-.58 (.26)**	-.30 (.31)
Year- and Firm- FEs	YES	YES	YES
Inflate - Intercept	-38.45 (.19)***	-39.39 (.15)***	-38.51 (.17)***
Observations	*557*	*557*	*557*
Log pseudolikelihood	*-834.50*	*-825.72*	*-828.60*

Notes: $*p < .10$. $**p < .05$. $***p < .01$. Unstandardized parameter estimates and standard errors in parenthesis. [@] All models are zero-inflated negative binomial models and include a constant and robust standard errors. † Coefficient × 10^3. Errors from instrumental variables' regressions are included but not reported here for brevity

Appendix E

Table W1: Descriptives and Correlation Matrix of Marketing Department Power's Indicators

	Mean	Std. dev	1.	2.	3.	4.	5.
1. Proportion of marketing executives	.08	.12	1.00				
2. Proportion of marketing executives' pay	.06	.10	.89*	1.00			
3. Highest ranking of marketing executives	2.17	1.64	.81*	.75*	1.00		
4. Cumulative ranking of marketing executives	6.92	2.28	.72*	.64*	.81*	1.00	
5. Cumulative responsibilities of marketing executives	.76	1.15	.80*	.73*	.78*	.73*	1.00

*Note: *p<0.05*

Table W11: Factor Loadings of Marketing Department Power's Indicators

	Factor 1	Uniqueness
1. Proportion of marketing executives	.94	.12
2. Proportion of marketing executives' pay	.89	.20
3. Highest ranking of marketing executives	.92	.15
4. Cumulative ranking of marketing executives	.86	.26
5. Cumulative responsibilities of marketing executives	.90	.20

Table W2: Descriptives and Correlation Matrix of Finance Department Power's Indicators

	Mean	Std.dev	1.	2.	3.	4.	5.
1. Proportion of finance executives	.30	.14	1.00				
2. Proportion of finance executives' pay	.23	.14	.76*	1.00			
3. Highest ranking of finance executives	3.87	1.16	.38*	.37*	1.00		
4. Cumulative ranking of finance executives	10.05	3.06	.57*	.40*	.63*	1.00	
5. Cumulative responsibilities of finance executives	4.25	2.27	.80*	.59*	.36*	.74*	1.00

*Note: *p<0.05*

Table W21: Factor Loadings of Finance Department Power's Indicators

	Factor 1	Uniqueness
1. Proportion of finance executives	.89	.21
2. Proportion of finance executives' pay	.78	.40
3. Highest ranking of finance executives	.64	.59
4. Cumulative ranking of finance executives	.82	.32
5. Cumulative responsibilities of finance executives	.88	.22

Table W3: Descriptives and Correlation Matrix of Operations Department Power's Indicators

	Mean	Std.dev	1.	2.	3.	4.	5.
1. Proportion of operations executives	.12	.11	1.00				
2. Proportion of operations executives' pay	.11	.12	.84*	1.00			
3. Highest ranking of operations executives	2.86	1.98	.75*	.74*	1.00		
4. Cumulative ranking of operations executives	7.61	2.69	.69*	.65*	.86*	1.00	
5. Cumulative responsibilities of operations executives	1.16	1.31	.84*	.78*	81*	.77*	1.00

*Note: *p<0.05*

Table W31. Factor Loadings of Operations Department Power's Indicators

	Factor 1	Uniqueness
1. Proportion of operations executives	.91	.17
2. Proportion of operations executives' pay	.88	.22
3. Highest ranking of operations executives	.92	.15
4. Cumulative ranking of operations executives	.88	.23
5. Cumulative responsibilities of operations executives	.93	.13

Table W4: Descriptives and Correlation Matrix of R&D Department Power's Indicators

	Mean	Std.dev	1.	2.	3.	4.	5.
1. Proportion of R&D executives	.06	.10	1.00				
2. Proportion of R&D executives' pay	.04	.09	.81*	1.00			
3. Highest ranking of R&D executives	1.81	1.35	.87*	.66*	1.00		
4. Cumulative ranking of R&D executives	6.46	2.09	.70*	.53*	.80*	1.00	
5. Cumulative responsibilities of R&D executives	.66	1.20	.86*	.69*	85*	.76*	1.00

*Note: *p<0.05*

Table W41. Factor Loadings of R&D Department Power's Indicators

	Factor 1	Uniqueness
1. Proportion of R&D executives	.95	.10
2. Proportion of R&D executives' pay	.82	.33
3. Highest ranking of R&D executives	.94	.13
4. Cumulative ranking of R&D executives	.84	.29
5. Cumulative responsibilities of R&D executives	.93	.14

Table W5: Descriptives and Correlation Matrix of GM Department Power's Indicators

	Mean	Std.dev	1.	2.	3.	4.	5.
1. Proportion of GM executives	.46	.22	1.00				
2. Proportion of GM executives' pay	.58	.20	.83*	1.00			
3. Highest ranking of GM executives	5.41	1.35	.21*	.29*	1.00		
4. Cumulative ranking of GM executives	15.14	6.45	.69*	.63*	.50*	1.00	
5. Cumulative responsibilities of GM executives	5.05	2.60	.71*	.67*	.37*	.80*	1.00

*Note: *p<0.05*

Table W51: Factor Loadings of GM Department Power's Indicators

	Factor 1	Uniqueness
1. Proportion of GM executives	.88	.23
2. Proportion of GM executives' pay	.86	.26
3. Highest ranking of GM executives	.51	.74
4. Cumulative ranking of GM executives	.90	.20
5. Cumulative responsibilities GM executives	.89	.21

Appendix F. Table W1: Control Variables and Reason for Inclusion

Variable	Reason for Inclusion
R&D intensity	R&D efforts may attenuate the chances of a product failure, and, as a result, reduce the likelihood of product-harm crises, or may indicate the firm's innovation orientation, which may increase the likelihood of product-harm crises (Thirumalai and Sinha 2011).
Labor intensity	The chances of error, and therefore of product-harm crises, may vary with increased use of labor (Thirumalai and Sinha 2011).
Firm age	Older firms may have distinct risk-taking tendencies (Chatterjee and Hambrick 2011).
Slack resources	Resource availability may affect strategic behaviors, in general, and risk-taking, in particular (Kashmiri et al. 2017).
Assets	Larger firms may have distinct risk-taking tendencies (Chatterjee and Hambrick 2011). Larger firms have more resources but are also more bureaucratic, which may affect innnovation outcomes (Kashmiri et al. 2017).
ROA	Firm profitability affects the availability of resources.
Sales change	Variations in sales affect both the availability of resources and risk-taking.
Financial leverage	Higher financial leverage may decrease the firm's capability to invest in innovation and product safety (Kashmiri and Brower 2016).
Financial distress	Financial distress increases risk-taking and affects the firm's capability to invest in innovation and product safety.
Patents	More innovative firms may be more likely to experience product-harm crises.
Reputation	Firms with higher reputation may display lower risk-taking and be therefore less likely to experience product-harm crises.
Size of TMT	Large TMTs include diverse interests and opinions and promote innovation (Li et al. 2013), which may increase the occurrence of product-harm crises.
CEO age	CEO's strategic behaviors and capability to influence firm outcomes vary with seniority (Chatterjee and Hambrick 2011).
CEO duality	CEO's strategic behaviors and capability to influence firm outcomes vary with structural power (Chatterjee and Hambrick 2011; Finkelstein 1992).
CEO-founder	CEO's strategic behaviors and capability to influence firm outcomes vary with structural power (Chatterjee and Hambrick 2011).
CEO tenure	CEO's strategic behaviors and capability to influence firm outcomes vary with seniority (Chatterjee and Hambrick 2011).
CEO marketing education	Having received a formal marketing education may impact CEO's risk-taking tendencies.
CEO TC	CEO's compensation affects the CEO's structural power and therefore his/her strategic behaviors as well as his/her capability to influence firm outcomes (Chatterjee and Hambrick 2011).
CEO TCC	Changes in CEO's compensation affect CEO's structural power and therefore his/her strategic behaviors as well as his/her capability to influence firm outcomes (Chatterjee and Hambrick 2011).