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App Popularity: Where in the World Are Consumers Most Sensitive to Price and User Ratings?

Many companies compete globally in a world in which user ratings and price are important drivers of performance but whose importance may differ by country. This study builds on the cultural, economic, and structural differences across countries to examine how app popularity reacts to price and ratings, controlling for product characteristics. Estimated across 60 countries, a dynamic panel model with product-specific effects reveals that price sensitivity is higher in countries with higher masculinity and uncertainty avoidance. Ratings valence sensitivity is higher in countries with higher individualism and uncertainty avoidance, while ratings volume sensitivity is higher in countries with higher power distance and uncertainty avoidance and those that are richer and have more income equality. For managers, the authors visualize country groups and calculate how much price should decrease to compensate for a negative review or lack of reviews. For researchers, they highlight the moderators of the volume and valence effects of online ratings, which are becoming ubiquitous in this connected world.

Keywords: price sensitivity, rating sensitivity, mobile apps, dynamic panel model, Hofstede's cultural factors

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Expanding into other countries offers companies many opportunities, including a wealth of potential new customers (Burgess and Steenkamp 2006; Chao, Samiee, and Yip 2003). However, it also involves risk and uncertainty, partially because consumers' responses may differ across countries depending on economic, social, and cultural factors (Douglas and Craig 2011; Hofstede 1980). For example, when PopCap Games' *Plants vs. Zombies* cut its price from $2.99 to $.99, it gained a top-5 rank in countries such as Israel, Turkey, Italy, Hong Kong, Malaysia, and India, but only a top-25 sales rank in markets such as the United States, Germany, Brazil, Colombia, Canada, and the Netherlands. Different reaction patterns also appear when consumer ratings change. When features of ZeptoLab's *Cut the Rope* game app began to malfunction, consumer ratings plummeted within hours across the globe. App popularity dropped 35%–50% in countries such as China, the Czech Republic, Italy, Hungary, and Venezuela, forcing the developer to run price promotions to secure a top-100 ranking spot. However, app popularity dropped by less than 15% in countries such as Denmark, the United Arab Emirates, Brazil, and Vietnam. What explains these different consumer reactions to price and user ratings? Can certain factors predict the impact of such changes in app popularity across the globe?

While both price and user feedback are key drivers of customer behavior and company success (Bijmolt, Van Heerde, and Pieters 2005; Godes and Mayzlin 2004), the literature offers little guidance on systematic differences across countries. Despite decades of research on price sensitivity, only a few studies have provided insights into emerging markets (Bolton, Keh, and Alba 2010; Hult, Keillor, and Hightower 2000), and the most recent meta-analysis fails to find significant differences among the (mature) markets for which price response has been quantified (Bijmolt, Van Heerde, and Pieters 2005). Likewise, Floyd et al. (2014) find no significant difference between U.S. and non-U.S. settings in the sales elasticity of user reviews, which are a key source of information for many customers (Chevalier and Mayzlin 2006; Moe and Trusov 2011). As a reflection of this common wisdom, managers of globally and online distributed products (e.g., apps) offer similar prices around the world despite their ability to differentiate across countries. Thus, there is both an academic and a managerial need for studies that compare marketing responses across countries (Burgess and Steenkamp 2006; Hult, Keillor, and Hightower 2000).

This study addresses two research questions: (1) How do countries differ in their markets' response to price and ratings? and (2) Which cultural, economic, and structural factors help explain these differences? We focus on global products with

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24/7 availability, similar product attributes globally, and mobile online distribution: apps for mobile devices (smartphones and tablets). Mobile app usage constituted the majority (57%) of total digital media usage in 2017, and 18–24-year-olds spend more than three hours a day on mobile apps (Lella and Lipsman 2017). Millions of developers market over 1.5 million apps, for a cumulative revenue of more than $40 billion in Apple's (2016) App Store, the largest market for apps. Since the platform's launch in 2008, over 100 billion apps have been sold to more than 750 million customers. Smartphone users spend, on average, 82% of their mobile minutes on apps and just 18% on web browsers (S. Gupta 2013). Although most apps are free and monetized through in-app sales, most gross income comes from paid apps (approximately $72 billion) rather than in-app purchases (Statista 2015a). Moreover, many free apps monetize with the freemium strategy of in-app purchases, whose price points are similar to those of paid apps. App developers are typically start-ups or small companies with little contact with international users, making it difficult for them to set prices and interpret what ratings mean for their performance in different countries (Statista 2015a).

This study is the first to analyze the sensitivity of sales to price and user ratings across a wide variety of countries, including developing and developed markets. Our conceptual framework highlights the measurable cultural, economic, and structural factors expected to systematically affect these sensitivities (Burgess and Steenkamp 2006). We formulate a dynamic panel model that explicitly accounts for endogeneity and explains the variation in the price and ratings effect coefficients of these systematic factors. The empirical study is based on 276 days' worth of daily data on app popularity (sales rank), price, star ratings, ratings volume, and product updates for 20 top-selling mobile apps in 60 countries.

The results show substantial differences in price and ratings sensitivity across countries. In particular, price sensitivity is higher in countries with higher masculinity and uncertainty avoidance. Ratings valence sensitivity and ratings volume sensitivity are higher in countries with higher individualism and uncertainty avoidance. When ratings valence or volume drops in a country, the model quantifies how much managers should reduce price to achieve the same app popularity. The results also enable managers to predict marketing sensitivities for almost any country worldwide, using publicly available data on the country's specific cultural, economic, and structural factors.

Research Background

A key input into marketing decisions to globalize or localize is the extent to which consumers' responses to marketing actions differ across countries (Douglas and Craig 2011; Steenkamp and Geyskens 2012). The diffusion of innovation models shows cultural differences in consumer innovativeness (Steenkamp, Ter Hofstede, and Wedel 1999) and in the importance of social contagion and word of mouth (WOM; Tellis, Stremersch, and Yin 2003; Van den Bulte and Stremersch 2004; Yaveroglu and Donthu 2002). In contrast with this extensive literature on (the diffusion of) innovation, empirical evidence of differences in marketing-mix effectiveness is scarce. Using surveys of master of business administration (MBA) students enrolled in mature markets (but representing 38 nationalities), Dawar and Parker (1994) find little evidence of the varying importance of price and product attributes. However, researchers have found substantial differences in the weight given to attribute information compared with consensus cues (Aaker and Maheswaran 1997), in consumer reactions to advertising appeals (Alden, Hoyer, and Lee 1993), in consumer tipping decisions (Lynn, Zinkhan, and Harris 1993), and in brand market share (Roth 1995).

The cross-country literature falls short of quantifying differences in consumer sensitivity to price and ratings globally. With regard to price, Bijmolt, Van Heerde, and Pieters (2005) find no significant differences in price elasticities among the studied (mature) markets and call for further research in emerging markets. For branded (vs. unbranded) sales per capita in beverages, Bahadir, Bharadwaj, and Srivastava (2015) find that price is less important in markets with fewer resources and weaker infrastructures such as emerging markets. With regard to the opinion of others, Aaker and Maheswaran (1997) find that consumers in China care more about consensus signals, whereas consumers in the United States care more about attribute quality information in product purchases. This finding is consistent with the broader findings that social contagion (personal WOM) is more important for new product diffusion in collectivist than individualist cultures (Van den Bulte and Stremersch 2004; Yaveroglu and Donthu 2002). However, given the differences between online and offline WOM (Baker, Donthu, and Kumar 2016), it is unclear whether these results generalize to anonymous online ratings (Dellarocas 2003). Indeed, in their online WOM meta-analysis, Floyd et al. (2014) find no significant impact of geographic setting (U.S. vs. non-U.S. markets). As Table 1 details, the literature lacks research linking cultural, economic, and structural dimensions to price and ratings effectiveness across countries.

In addition, published research on mobile apps is mostly descriptive (see Web Appendix W1). The exceptions analyze platform choices by developers (Bresnahan, Orsini, and Yin 2014), in-app purchases (Ghose and Han 2014), and the impact of updates, price changes, and reviews on the likelihood of staying in the top 300 of an app store ranking (Lee and Raghu 2014). Hyrynsalmi et al. (2015) show that higher consumer ratings correlate with higher sales and that this relationship is stronger for paid (vs. free) apps. Finally, several recent studies have analyzed how adopting a company-owned free app makes customers more likely to purchase from or return to the company (Gill, Sridhar, and Grewal 2017; Narang and Shankar 2017). However, each study uses data from only one country, and none considers differences in marketing sensitivities across countries.

Practically, the two important players in the app business model are the download platform (e.g., Apple's App Store) and app developers. While the platform operator manages the download platform, the developers plan, design, program, and market the apps. In the current business model, the platform operator receives 30% of the app's gross income, while the developer receives 70%. In contrast with classic software markets, app developers are many and heterogeneous. Only 10% of apps are developed by large and experienced software companies, with the remainder designed, manufactured, and launched by individual people or small start-ups (Statista 2015a). As in many other product categories,

TABLE 1
Empirical Cross-Country Studies Quantifying Moderators on Price and Ratings Sensitivity

Study	Price	Ratings	Panel Data	Data Interval	Systematic and Cultural Analysis	Economic and Structural Factors	Countries	Continents	Products	Categories
Bahadir, Bharadwaj, and Srivastava (2015)	Yes	No	Yes	Quarterly	No	Yes	14	4	4	Beverages
Bijmolt, Van Heerde, and Pieters (2005)	Yes	No	N.A. (meta-analysis)	N.A.	No	No	7	3	1,851 elasticities	Durables versus groceries
Chintagunta and Desiraju (2005)	Yes	No	Yes	Quarterly	No	No	5	2	3	Pharmaceuticals
Erdem, Zhao, and Valenzuela (2004)	Yes	No	Yes	Daily	No	No	3	2	32	Detergents and margarine
Farley, Hayes, and Kopalle (2004)	Yes	No	No	N.A.	No	No	2	2	Not specified	Financial services
Floyd et al. (2014)	No	Yes	N.A.	N.A.	No	No	2	2	443 elasticities	Durables versus nondurables
Katsikeas, Samiee, and Theodosiou (2006)	Yes	No	No	N.A.	No	Yes	4	3	91	Finance, durables, automotive, and health care
Lages, Jap, and Griffith (2008)	Yes	No	No	N.A.	No	No	16	3	519 respondents	Not specified
Luo et al. (2014)	No	Yes	No	N.A.	Individualism	No	2	2	274 respondents	Not specified
Pauwels, Erguncu, and Yildirim (2013)	Yes	No	Yes	Monthly	Individualism	Yes	2	2	16	Personal care
Steenkamp, Van Heerde, and Geyskens (2010)	Yes	No	No	N.A.	No	No	23	4	Not specified	63 fast-moving consumer goods categories
Van den Bulte and Stremersch (2004)	No	No	Yes	N.A.	Individualism, masculinity, power distance, and risk avoidance	Yes	28	5	52	Consumer durables
Yaveroglu and Donthu (2002)	No	No	No	N.A.	All Hofstede dimensions	No	19	3	7	7 white goods categories
You, Vadakkepatt, and Joshi (2015)	No	Yes	N.A.	N.A.	No	No	Not specified	Not specified	339 elasticities	Not specified
This study	Yes	Yes	Yes	Daily	Individualism, masculinity, power distance, and risk avoidance	Yes	60	6	20	4 app categories

Notes: N.A. = not applicable.

developers face substantial investment risks and potential returns from the strong growth, market dynamism, and competition of apps. Their average investment exceeds $140,000 per app until marketability (Neagu 2017), while the average monthly per app revenue ranges from $3,200 to $8,100. Furthermore, 35% of all apps in the market generate less than $1,100 per month (Statista 2015b). To stimulate sales, developers consider price a key weapon (AdrianM 2015), and most developers update their products frequently.

Potential customers must own a mobile device (i.e., a cell phone, tablet, or iPod) and have Internet access to connect with an app store. This requirement for app market participation is not as limiting as latest-model prices suggest, because secondhand iOS (Apple's mobile operating system) devices and older smartphone generations provide many consumers with access to apps. When buying apps, consumers see app stores localized to their country, with corresponding language, currency, and product ranges. Customers who buy apps are frequently asked to rate (on a five-star scale) and review their purchase. The individual feedback and mean star rating are then displayed on the particular site of the app. Thus, each app site provides customers with information on (1) price, (2) app category, (3) update and version, (4) app size, (5) app description and screenshots, (6) new features of the latest update, (7) customer average rating, (8) customer number of ratings, and (9) detailed feedback. Price and ratings tend to be the most significant influence on sales (Carare 2012; Hao et al. 2011).

Developers can decide whether to address each country separately by, for example, setting different prices for each country or setting the same price worldwide. Likewise, they can run price promotions by country or decide not to market an app in a particular country. Thus, developers make decisions not only on how to market their product but also on where to market it. This task is daunting for most developers, which may explain the current practice of charging the same price for a given app across countries. Given their digital character and distribution through single-source platforms, apps are a pacesetter for many other digital goods such as software, games, and other digital entertainment products.

Conceptual Framework

Price, ratings valence, and ratings volume are key drivers of demand in general (e.g., Babić Rosario et al. 2016; Bijmolt, Van Heerde, and Pieters 2005) and for apps specifically (Guzman and Maalej 2014; Jung, Baek, and Lee 2012). Building on prior theory and empirical research on cross-country differences in consumer response, we propose that cultural, economic, and structural factors influence consumer sensitivity to these drivers.

Price

Price sensitivity likely depends on economic factors, such as average income in a country: consumers in richer countries (e.g., France vs. Malaysia) have more disposable income on average, which means that any given price represents a lower relative cost in their budget (Burgess and Steenkamp 2006; Hult, Keillor, and Hightower 2000).

Price sensitivity may also depend on cultural factors, such as uncertainty avoidance (Dawar and Parker 1994). Uncertainty about the value of an app could be either reduced with a high price (if used as a quality cue) or increased because the consumer is uncertain about whether the app will be worth the high price (Kirmani and Rao 2000; Lichtenstein, Ridgway, and Netemeyer 1993). Moreover, price sensitivity is higher among expert consumers, who are less likely to use the price cue as a quality signal (Kirmani and Rao 2000). Previous research has suggested that price sensitivity is higher for categories stereotypically associated with consumers' gender identity. For example, women are assumed to excel in caring and feeding the family, and they indeed show higher price search, knowledge, and sensitivity for grocery items (Carlson and Gieseke 1983; Kolodinsky 1990; Maruyama and Wu 2014). Likewise, men are assumed to excel at navigation, games, and technology (Chou, Wu, and Chen 2011; Gutierrez and García-López 2012; Padilla et al. 2015). Given that apps are technological products that often involve games or navigation, we expect men to be more price sensitive than women. At the country level, this may translate into higher price sensitivity in cultures in which traditionally masculine values are given higher priority than traditionally feminine values (e.g., Japan vs. Peru).

Ratings

Currently, consumers have easy access to more direct indicators of quality: volume and valence of online ratings. While both components are expected to increase app popularity, the effects of moderating factors may differ.

As to ratings volume, social influence is widely believed to be the main driver of consumers' purchase decisions because other consumers have higher perceived trustworthiness than paid spokespeople for a company's offering (Nielsen 2013). The trustworthiness of face-to-face WOM depends on the strength of ties between the giver and the receiver, such that family and close friends are trusted more than casual acquaintances (Brown and Reingen 1987; Zhang, Feick, and Mittal 2014). However, raters in online environments are typically strangers, sometimes even anonymous to the consumer (Dellarocas 2003). Trust in those ratings requires "generalized trust," or trust in strangers that arises when "a community shares a set of moral values in such a way as to create regular expectations of regular and honest behavior" (Fukuyama 1995, p. 153). A large number of reviews carries more weight when (most of) these reviews are from people "like myself." Among all studied cross-country determinants of generalized trust, income equality is the strongest and most robust (Bjørnskov 2007). Therefore, we expect higher online ratings volume sensitivity in countries with higher rather than lower income equality (e.g., Austria vs. Saudi Arabia).

As to ratings valence, the directional opinion of other product users is especially important when consumers want to reduce purchase uncertainty (Berger and Calabrese 1975; Ho-Dac, Carson, and Moore 2013). Thus, a stronger desire to reduce uncertainty should increase the importance of the rating signal. Indeed, Erdem, Zhao, and Valenzuela (2004) find higher importance of brand credibility in cultures with high uncertainty avoidance. Thus, the higher the uncertainty avoidance, the more the valence of online ratings should drive app popularity.

For the other cultural dimensions, consumers in collectivist cultures give more weight to the opinion of others in their buying decisions and thus should be more sensitive to personal

WOM (Aaker and Maheswaran 1997), whereas those in individualist cultures tend to "go their own way" (Hofstede 1980). The easy availability and anonymity of online reviews allow individualist consumers to pick and choose the specific details of the attributes about which they care most. Thus, it is unclear in which direction individualism affects ratings sensitivity. Finally, the status of the user who gives the feedback matters more in cultures with high power distance (Hofstede 1980). Consistent with this argument, prior research has shown a higher impact of personal WOM in high-distance cultures (e.g., Van den Bulte and Stremersch 2004). Again, it is unclear whether these cultural influences on person-to-person WOM generalize to online ratings (volume and valence) given by strangers (Dellarocas 2003). This is a key empirical question for the many industries in which online ratings are proliferating. For theory, this important distinction represents a boundary condition on how offline WOM implications generalize to online WOM settings.

Data

We collect data from the Apple App Store.[1] The App Store is a truly global market. During our data collection period, country-specific App Stores were available in 60 countries. Stores feature the local language and currency and contain both local and global apps. Beyond games, many apps give users the functionality of navigation devices, pulse monitors, personal digital assistants, and so on. We use daily data from the official overall app rankings of Apple's App Store. We developed a web crawler to collect data for 276 consecutive days from June 25, 2011, to March 27, 2012. Table 2 provides an overview of the variables and their operationalization. Web Appendix W2 gives a detailed overview of the included 20 apps, their average rank, ratings valence (star ratings), ratings volume (number of reviews), and price. Twelve apps are games, among them popular apps such as Angry Birds, FIFA 12 by EA Games, and Plants vs. Zombies. Five apps are from the leisure category, featuring popular apps such as Camera+ and Hipstamatic; the remaining three apps are business (e.g., Apple's Pages) and health (e.g., Nike+ Run Club) related.

The data set contains app-level information for 60 countries. These countries represent every inhabited continent and cover the majority of the world's surface area and population. The least-covered continent is Africa, for which we could obtain data only for South Africa. The sample includes major mature (e.g., the United States, Germany) and emerging (e.g., Brazil, India, Russia, China) markets and has a wide variety of scores across cultural, economic, and structural factors (see Web Appendix W3).

We obtained information on the cultural dimensions directly from the Geert Hofstede Center's online database (https://www.hofstede-insights.com/models/national-culture/). Dozens of studies have updated this information, beginning with Hofstede (1980), and the actual scores for each country come from the 1990–2008 period. We thus assume that cultural differences among countries still apply, consistent with the definition of culture as a set of stable norms and beliefs (Tse et al. 1988) and with empirical evidence that culture adapts slowly and maintains its distinction across countries (Inglehart and Baker 2000). For the economic factors, we operationalize average income and income inequality with, respectively, gross domestic product (GDP) per capita and the Gini index of income inequality (World Bank 2010).

We operationalize structural (social and infrastructure) differences with respect to the product category. First, apps are commonly believed to appeal to a target group aged between 15 and 44 years (P. Gupta 2013). We therefore operationalize "age distribution" as the percentage of a country's inhabitants between the ages of 15 and 44 years. Second, we operationalize "educational achievement" as spending on education as a percentage of the national budget, following the Central Intelligence Agency's (CIA's) World Factbook operationalization. For infrastructure, we collect data on all countries for the penetration of smartphones (i.e., the hardware required to run apps) from Google's (2013) new media report. We also considered other operationalizations of infrastructure but could only obtain information for 35 countries on network speed, Wi-Fi distribution, and the penetration of iOS devices such as the different versions of iPhone, iPod touch, and iPad.[2]

To resolve concerns about multicollinearity among the explanatory variables, Table 3 provides the correlation matrix and descriptive statistics for the variables used in our model. The strongest correlation (–.68) occurs for individualism and power distance. Furthermore, GDP per capita is correlated with power distance (–.58), individualism (.60), and phone penetration (.61). Education is also correlated with individualism (.59). All other correlations are below .5 in absolute value. Web Appendix W4 reports the variance inflation factors (VIFs), with the highest value for individualism (3.41) and an average VIF of 1.93, implying that multicollinearity is not a serious issue.

For our dependent variable, we track information for every app that appears in the top-100 ranking of paid apps in at least 80% of our observed countries and remains in this ranking during our observation period.[3] This choice leads to a data set of 20 unique apps, with 308,844 observations. Web Appendices W5 and W6 show the number of apps, observations, and observed price changes for each country.

To operationalize our dependent variable of app popularity, sales rank data are typical for online products (e.g., Chevalier and Goolsbee 2003; Chevalier and Mayzlin 2006) and are the most often-used performance measure in studies calculating review elasticities (Floyd et al. 2014). Similar to Chevalier and Mayzlin (2006), we apply the log-log model specification for our sales rank data. According to their work, this choice is robust under the assumption that the relationship between log sales rank and log sales is close to linear.

[1]We could not obtain data for other platforms such as Android. Although the average price and ratings sensitivity may differ across platforms (e.g., Ghose and Han 2014), we believe that our substantive results on differences across countries will not differ for those platforms. The App Store is by far the most profitable market for developers and is technically separate from other platforms (Franko and Tirrell 2012).

[2]Of the 35 countries for which we observe iOS and smartphone penetration, we find a correlation of 85%, indicating that smartphone penetration is a suitable proxy for iOS penetration.

[3]The App Store provides three types of rankings: (1) paid apps, (2) free apps, and (3) gross paid. Users are likely to use these rankings as a starting point when searching for apps. Because price effects are a key focus of this study, our sample consists solely of apps in the paid apps listing.

TABLE 2
Variable Description and Operationalization

Variable	Definition	Coding	Scale	Source
App-Specific Variables				
Sales rank	Sales rank of app j at time t in country i	Metric	From 1 (worst) to 100 (best)	Country-specific App Store ranking
Free version rank	Rank of free version of app j at time t in country i in top100 free ranking	Metric	From 1 (worst) to 100 (best); 0 in case there is no observation of a free app version	Country-specific free App Store ranking
Price	Price of app j at time t in country i	Metric	U.S. dollars	Country-specific app site
Ratings valence	Mean star rating of all ratings for app j at time t in country i	Metric	Star rating from 1 (worst) to 5 (best)	Country-specific app site
Ratings volume	Number of reviews for app j at time t in country i	Metric		Country-specific app site
Update	Indicates if there is an update for app j at time t in country i	Nominal	0 = no update, 1 = update	Country-specific app site
Dispersion	$h = \sum_{i=1}^{5}\left[(s_i \times i)/(\sum_{i=1}^{5} s_i \times i)\right]^2$ for app j at time t, where s_i is i-star rating, and i is the weight	Metric		Country-specific app site
Category dummy	Four category dummies with games as reference category	Categorical	0/1	Country-specific app site
Cultural Factors				
Power distance	Extent to which the less powerful members of organizations and institutions accept that power is distributed unequally	Metric	From 0 (low power distance) to 120 (high power distance)	Hofstede's database
Individualism	Degree to which people are integrated into groups	Metric	From 0 (high collectivism) to 120 (high individualism)	Hofstede's database
Masculinity versus femininity	Society's preference for achievement, heroism, assertiveness, and material reward for success	Metric	From 0 (very feminine culture) to 120 (very masculine culture)	Hofstede's database
Uncertainty avoidance	Society's tolerance for uncertainty and ambiguity	Metric	From 0 (low uncertainty avoidance) to 120 (high uncertainty avoidance)	Hofstede's database
Economic Factors				
GDP per capita	GDP divided by population	Metric	U.S. dollars	International Monetary Fund database 2011
Gini index	The extent to which income among individuals derives from an equal distribution	Metric	From 0 (absolute equal distribution) to 100 (absolute unequal distribution)	World Bank database 2008–2012
Structural (Demographic and Infrastructural) Variables				
Age distribution	Share of a country's inhabitants between the ages of 15 and 44 years	Metric	From 0 to 1	CIA Factbook
Education	Country-specific spending on education as a percentage of the national budget	Metric	From 1 to 0	CIA Factbook
Smartphone penetration	Country-specific smartphone penetration	Metric	From 0 to 100	Google Mobile Planet Survey 2010
Deterministic Components				
Trend	Linear trend		t = 1, …, T	Authors
Seasonal dummies	Indicates the day of the week: d = 1 if Monday, 0 otherwise (Friday is the left-out benchmark)		0/1	Authors

TABLE 3
Data Descriptive Statistics and Correlation Matrix

	Sales Rank	Price	Ratings Volume	Ratings Valence	Free App Rank	Individualism	Power Distance	Uncertainty Avoidance	Masculinity	GDP	Gini	Smartphone Penetration	Age	Education
Sales rank	1													
Price	−.250	1												
Ratings volume	.296	−.025	1											
Ratings valence	.244	−.108	.218	1										
Free app rank	.402	−.227	.051	.063	1									
Individualism	−.032	−.031	.193	.266	−.030	1								
Power distance	.034	.013	−.094	−.176	.036	−.683	1							
Uncertainty avoidance	−.025	−.004	−.094	−.124	.038	−.266	.236	1						
Masculinity	−.009	−.022	.078	.045	−.012	.117	.119	.025	1					
GDP	−.059	−.048	.077	.157	−.071	.598	−.581	−.260	−.163	1				
Gini	.066	.085	.024	−.043	.025	−.431	.282	.099	.093	−.480	1			
Phone pen.	−.026	−.048	.097	.168	−.082	.319	−.308	−.445	−.203	.605	−.281	1		
Age	.053	.019	−.106	−.183	.025	−.537	.524	.008	.094	−.307	.276	.160	1	
Education	−.009	.005	.045	.133	−.025	.589	−.625	−.171	−.265	.386	−.311	.190	−.477	1
M	71.373	1.619	5.069	4.656	10.683	46.263	59.355	66.485	50.629	30,763.120	36.620	29.263	.444	4.808
SD	24.96	1.785	26.982	.677	23.010	24.844	23.705	23.467	19.465	25,702.450	8.361	14.763	.055	1.478
Min	1	.712	0	1	0	6	11	8	5	1,164.113	23.900	6.000	.356	1.100
Max	100	12.990	1769	5	100	91	104	112	110	122,272.300	63.100	73.000	.681	8.700

Notes: For sales rank and free apps rank variables, correlations are Spearman correlations. All correlations are significant at the 5% level.

For app price, ratings valence,[4] and ratings volume, we obtain daily data from the publicly available information on each app's page in Apple's App Store. As Table 3 shows, the average rating valence is 4.66, with a minimum of one star and a maximum of five stars, and the average rating volume (daily number of reviews) is 5.07, with a daily minimum of 0 and a maximum of 1,769. Regarding dispersion (Godes and Mayzlin 2004), app ratings follow the typical J-shaped distribution. One-star ratings represent 12%, with two-, three-, and four-star ratings representing only 1%, 3%, and 8%, respectively, of all ratings; five-star ratings are most common (76% of the total, on average).

To decrease uncertainty about a paid app's quality, some developers launch free versions of an app. These free versions commonly contain limited content; users who want to have unlimited content then need to buy the full version. Eight of the 20 observed apps offered a free version for testing. To control and account for the presence of a free app version, we further crawled the free app top-100 rankings and collected for each of the free apps the daily free app ranking position for each of our 60 countries.

App release dates are identical across countries in our data. Conversations with app developers revealed that it is easiest to keep release dates the same and that sequential launches may lead to illegal downloads and, thus, lost revenue opportunities (as happened to Pokémon Go in 2016). Similarly, we find that updates for these apps are introduced simultaneously in the App Store and are immediately available in all countries. Thus, neither consumers nor developers learn from reactions to the app in other countries before it launches in a given country.

Methodology

Table 4 outlines our modeling approach in four steps. First, we examine whether the variables are stationary. Second, we build a dynamic panel data (DPD) model, treating endogeneity explicitly by using (1) the exclusion restrictions and control function approach (external instrumenting) and (2) the lagged variables within the generalized method of moments (GMM) estimation (internal instrumenting). Third, we perform diagnostics checks for the DPD model specification. Fourth, we use weighted least squares (WLS) regression to demonstrate how the countries' cultural, economic, and infrastructural factors explain the price, ratings volume, and ratings valence sensitivities.

Step 1: Panel Unit Root Tests

The stability of the DPD model requires that the dependent variable (sales rank) is stationary. To this end, we perform Fisher-type panel unit root tests (Choi 2001).

[4]App Store users can post and read written reviews, which often consist of only two or three brief sentences. Because of dynamic updating, our web crawler cannot observe which reviews a particular buyer accessed before making the buying decision. Previous research on user-generated content, however, has found a strong correlation between numeric ratings and the valence expressed in written reviews (Hoon et al. 2013). To verify the ratings–text relationship, we used the Linguistic Inquiry and Word Count sentiment analysis tool (www.liwc.net) and found a strong correlation (.87) between the obtained text-based valence of the review and its numerical star rating.

Step 2: DPD Model Specification

Our final DPD model specification requires careful delineation of premodeling steps, including endogeneity, optimal lag length, stability, and variable selection. First, we explain the sources of endogeneity and show how our model deals with them explicitly. We need to accommodate two likely sources of endogeneity in the model: (1) endogenous regressors (price, ratings volume, ratings valence, and product update) and (2) unobserved app quality. Second, we describe how we tackle the optimal lag length and stability of the model as well as the variable selection. Finally, we discuss the model estimation strategy.

Endogenous regressors. Our independent variables may not be strictly exogenous. For example, it is possible that price and product update decisions are made strategically on the basis of sales rank expectations and that past information (e.g., previous sales rank) drives customer ratings. Ratings in a country may also influence pricing or product updates in that country (i.e., app developers likely increase prices with high ratings and release updated versions of the app when ratings decrease). Thus, these variables' correlations might be nonzero with past and current realizations of the model's error term (i.e., they are endogenous). This type of endogeneity can be overcome using exclusion restrictions (i.e., instrumenting the price, ratings volume, ratings valence, and product update variables). We subsequently explain how we derive these exclusion restrictions and then use the control function approach to account for this source of endogeneity for our data set that includes multicountry data (Papies, Ebbes, and Van Heerde 2017; Wooldridge 2015).

For each endogenous variable, we use its weighted combination in similar countries as an instrument in focal country i. The rationale is that ratings/price in focal country i should be correlated with ratings/price in similar countries and that ratings/price in similar countries should not be formed by either sales rank expectations or past sales ranks of focal country i (i.e., they should not be correlated with the error term of the sales rank of focal country i). To find similar countries, we carry out factor analysis with the k-means clustering method (Hastie, Tibshirani, and Friedman 2009), using Hofstede's (1980) cross-country cultural dimensions (see the "Data" section for further details on the variables). Because the number of clusters is unknown a priori, we compute and compare several k-means solutions (k = 1, …, 10). To determine the optimal number of clusters (k*), we look for a kink in the scree plot (see Web Appendix W7) that is generated from the within-sum-of-squares measure (Makles 2012).

Thus, assuming that there are M countries within cluster k and denoting i, j, and t as the indices for country, app, and time, respectively, we compute our instrumental variables (IVs) as

$$(1)\quad z_{i,j,t} = \frac{1}{M-1}\sum_{\substack{m=1 \\ m \neq i}}^{M} x_{m,j,t}\ \ i \in M,\ m \in M,\ m = \{1, \ldots, M\},$$

$$\text{for } j = \{1, \ldots, J\} \text{ and } t = \{1, \ldots, T\},$$

where $x_{m,j,t}$ denotes the endogenous variable (i.e., ratings volume, ratings valence, price, and update) for app j at period t in country m within cluster k and $z_{i,j,t}$ is the resulting IV for country i, app j, at period t.

TABLE 4
Overview of Methodological Steps

Modeling Step	Test/Methodology	Relevant Literature	Research Question
1. Panel Unit Root Tests	Fisher-type test	Choi (2001)	Are variables stationary or evolving?
2. DPD Model			
Endogeneity	Exclusion restriction and control function	Papies, Ebbes, and Van Heerde (2017); Wooldridge (2015)	How should the model account for the endogeneity explicitly?
Lag length selection and stability	Autocorrelation check; roots of AR polynomial check	Pauwels, Erguncu, and Yildirim (2013)	How many lags should be used for the lagged DV? Is the model stable?
Variable selection	VIF and likelihood ratio tests; information criteria: AIC and BIC.	Greene (2012)	Which variables should be used in the model?
Model estimation	System GMM	Arellano and Bond (1991); Blundell and Bond (1998); Roodman (2009)	How does app rank respond to price changes, ratings volume, ratings valence, and other variables over time, while accounting for the unit root and cointegration results?
3. DPD Model Diagnostics			
Autocorrelation	Arellano–Bond test	Arellano and Bond (1991)	Do the residuals of the DPD model show autocorrelation?
IV exogeneity and overidentification	Hansen-J test	Hansen (1982)	Are instruments exogenous (i.e., valid)? Is the model overidentified owing to use of many instruments?
IV test for the subset of instruments	Difference-in-Hansen test of exogeneity of instrument subsets	Roodman (2009)	Are subsets of instruments valid?
Sensitivity analysis for number of instruments	Change the number of instruments in the DPD estimation	Roodman (2009)	Are the DPD estimates sensitive to a reduction in number of instruments?
4. WLS regression model	WLS estimation	Wooldridge (2015)	Do the price, ratings volume, and ratings valence slopes obtained from DPD model vary depending on countries' cultural, economic, and infrastructural traits?

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion.

The next step is to decompose the observed variation into exogenous and endogenous variation components by using the created IVs. This method is known as auxiliary regression (Papies, Ebbes, and Van Heerde 2017). The underlying mechanism is that the IVs should capture the exogenous variation in the endogenous variables. As such, we regress the endogenous variable (x) on all the IVs (z) and other exogenous variables in the data set (w):

$$x_{jt} = \underbrace{\gamma_0 + \gamma_z z_{jt} + \gamma_w w_{jt}}_{\text{Exogenous variation}} + \underbrace{\theta_{jt}}_{\text{Endogenous variation}}. \quad (2)$$

At this point, we can either compute the predicted values $(\hat{x}_{jt} = \hat{\gamma}_0 + \hat{\gamma}_z z_{jt} + \hat{\gamma}_w w_{jt})$ and use these instead of x_{jt} in the main model, because $\hat{x}_{jt}$ is exogenous by construction, or compute the predicted residuals $(\hat{\theta}_{jt} = x_{jt} - \hat{x}_{jt})$ and include these as additional regressors in the main model. We opt for the latter approach, known as control function because it is superior when using the interaction effects (see Ebbes, Papies, and Van Heerde 2011; Wooldridge 2015).

Unobserved apps quality. Apps likely differ in quality levels, which we cannot observe completely. Higher-quality apps are ranked higher, receive higher ratings, and can charge higher prices. Moreover, apps can have different privacy settings (not observed in our data), which affect both their popularity and price (Kummer and Shulte 2016). This leads to a correlation among price, rating, and the error term. Therefore, we need to account for unobserved app-level effects. We do so by including time-invariant fixed effects, v_j, in our dynamic panel model:

$$y_{jt} = c + \sum_{p=1}^{P} \alpha_p y_{j,t-p} + \beta x_{jt} + \gamma \hat{\theta}_{jt} + \delta r_{jt} + \lambda d_{jt} + v_j + u_{jt} \quad (3)$$
$$\text{with } j = \{1, \ldots, N\} \; t = \{p+1, \ldots, T\},$$

where j, t, and p are the subscripts for app, time, and lag length, respectively; y_{jt} is the sales rank in logarithm; $y_{j,t-p}$

is the lagged sales rank in logarithm up to lag p; and x_{jt} is a vector of variables (price, ratings volume, ratings valence, and update; all in logarithm) to account for endogeneity.[5]

Note that we use lagged ratings volume and lagged ratings valence, which is in line with prior research (e.g., Godes and Mayzlin 2004) and produces better model fit. The control function $\hat{\theta}_{jt}$ captures the endogenous part of x_{jt}. With $\hat{\theta}_{jt}$, we can control for the variation that makes rating volume, ratings valence, and update variables endogenous. The term r_{jt} is a vector of variables that includes the free rank apps variable used to control for the effects of free apps and rating dispersion, and d_{jt} is a vector of deterministic components that includes trend component and seasonal dummies (day-of-the-week effects). The term v_j captures the unobserved app-level effects, and u_{jt} is white noise. In addition, c is the constant term, and α, β, γ, δ, and λ are vectors of parameters to be estimated. Finally, we assume that $(u_{jt}) = E(v_j) = E(v_{i,t}\ u_{i,t}) = 0$ and that there is no correlation between u_{jt} and all the exogenous regressors.

Optimal lag length, stability, and variable selection. Our model incorporates the dynamics of the sales rank, due to the autoregressive (AR) term in Equation 3 (i.e., the current sales rank depends on the previous sales rank assessments). When the model includes an AR term, we need to ensure that the model specifies the dynamics well and that it is parsimonious and stable. For the AR term, we investigate (1) the optimal number of lags and (2) the roots of the AR polynomial. To determine the optimal lag length for the AR term, we evaluate the GMM estimator assumption that the data present first-order serial correlation, but not second-order serial correlation if one lag is used in the estimation (see the "Step 3: Model Diagnostics" subsection).

To ensure the stability of the dynamic process, we check whether the roots of the AR polynomial are outside the unit circle (i.e., the AR term coefficient complies with $\left|\sum_{j=1}^{J}\alpha_j\right| < 1$).[6] Finally, we determine which variables to use and whether the model overfits the data, based on the Akaike and Bayesian information criterion model fit statistics, and use the VIF statistics to check for multicollinearity.

Model estimation. Dynamic panel bias (also known as Nickell's [1981] bias) exists when the lagged dependent variable $(y_{j,t-1})$ is an explanatory variable in the model and there is app-level unobserved heterogeneity (v_j) at the same time (see Equation 3), because $y_{j,t-1}$ is correlated with v_j. Therefore, ordinary least squares estimators are inconsistent. Within-group estimators are also biased because the first regressor $y_{j,t-1} - \bar{y}_j$ is correlated with $u_{jt} - \bar{u}_j$, due to the common term $\bar{u}_j$. One solution to this problem is to take the first differences for both sides and eliminate the specific app effects. Assuming one lag for the dependent variable, our DPD model becomes

(4)

$$\Delta y_{jt} = \alpha\Delta y_{j,t-1} + \beta\Delta x_{jt} + \gamma\Delta\hat{\theta}_{jt} + \delta\Delta r_{jt} + \lambda\Delta d_{jt} + \Delta u_{jt},$$
$$\text{with } j = \{1,\ldots,N\}\ \ t = \{p+1,\ldots,T\}$$

Now, $\Delta u_{jt} = u_{jt} - u_{jt-1}$ is correlated with $\Delta y_{j,t-1} = y_{j,t-1} - y_{j,t-2}$ because $y_{j,t-1}$ in $\Delta y_{j,t-1}$ is a function of u_{jt-1}. However, Δu_{jt} is uncorrelated with $\Delta y_{j,t-p}$ for $p \geq 2$, so lagged variables can be used as instruments (Anderson and Hsiao 1982). For example, $y_{j,t-2}$ is uncorrelated with Δu_{jt}; therefore, we can use $y_{j,t-2}$ as an instrument for $\Delta y_{j,t-1}$. Arellano and Bond (1991) suggest an alternative approach, GMM (also known as difference GMM), that can exploit all the information available in the sample and thus produce more efficient estimates of the dynamic panel. All other regressors can be instrumented in the same way (i.e., the instruments for x_{jt} are $x_{jt-2}, x_{jt-3}, \ldots$). Their model is further augmented by Arellano and Bover (1995) and Blundell and Bond (1998) as "system GMM." System GMM uses the original equation as well as the transformed one (first-differenced). In this study, we apply the system GMM approach that uses moment conditions in which lags of the dependent variable and first differences of the exogenous variables are instruments for the first-differenced equation as well as moment conditions in which lagged first differences of the dependent variable are instruments for the level equation. Specifically, we employ the xtabond2 procedure in Stata (Roodman 2009). The estimation is a one-step GMM and uses robust standard errors. In our empirical application, we also report the number of instruments used and how sensitive our results are to the reduction in the number of instruments. Web Appendix W8 details how the app specific intercept term (v_j) can be computed after the model estimation.

Step 3: Model Diagnostics

We perform several tests to diagnose the robustness of our model and to show whether the results comply with the model assumptions. The diagnostics reported in Web Appendix W9 include (1) autocorrelation, (2) IV exogeneity (Hansen-J test), and (3) an IV test for the subset of instruments (difference-in-Hansen test).

Step 4: WLS Regression

After we estimate the DPD model, we pool the estimated price, ratings volume, and ratings valence coefficients across K countries and regress them on the proposed cultural, economic, and infrastructural variables: individualism, power distance, uncertainty avoidance, masculinity, GDP, Gini index, age, education, and phone penetration. Because the dependent variables are estimated parameters, we need to account for variance of the estimates and to obtain heteroskedasticity-corrected estimates (e.g., Wittink 1977). Thus, we perform WLS regression for three slope parameters estimated through the DPD model: price, ratings volume, and ratings valence:

[5]We also considered the inclusion of interaction variables (see the "Results" section). The model fit measures indicated the highest likelihood and lowest information criteria for the model without the interaction variables.

[6]Alternatively, we could check whether the eigenvalues of the companion matrix are inside the unit circle.

TABLE 5
Model Fit Statistics

Model	Model Definition	Log-Likelihood	AIC	BIC	RMSE
Model 1	Base model: AR(1) + Price + Ratings volume (t – 1) + Ratings valence (t – 1) + Free apps rank + Update + Dispersion+ Category dummies	–134,693.53	269,407.06	269,506.31	.590193
Model 2	Base model + Seasonal dummies	–134,680.16	269,392.31	269,551.13	.59014
Model 3	Base model + Seasonal dummies + Trend	–134,106.27	268,246.53	268,415.25	.587903
Model 4	Base model + Seasonal dummies + Trend + Interactions	–253,901.44	507,848.88	508,077.16	1.299287

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion; RMSE = root mean squared error.

(5)
$$\hat{\beta}_k^{(\text{price})} = [\phi_1 \quad \phi_2 \quad \phi_3 \quad \phi_4 \quad \phi_5 \quad \phi_6 \quad \phi_7 \quad \phi_8 \quad \phi_9] \begin{bmatrix} \text{Individualism}_k \\ \text{Power Dist.}_k \\ \text{Uncertainty Av.}_k \\ \text{Masculinity}_k \\ \text{GDP}_k \\ \text{Gini}_k \\ \text{Age}_k \\ \text{Education}_k \\ \text{Phone Pen.}_k \end{bmatrix} + \varepsilon_k^{(\text{price})}, \quad k = \{1, \ldots, K\},$$

(6)
$$\hat{\beta}_k^{(\text{rat. volume})} = [\psi_1 \quad \psi_2 \quad \psi_3 \quad \psi_4 \quad \psi_5 \quad \psi_6 \quad \psi_7 \quad \psi_8 \quad \psi_9] \begin{bmatrix} \text{Individualism}_k \\ \text{Power Dist.}_k \\ \text{Uncertainty Av.}_k \\ \text{Masculinity}_k \\ \text{GDP}_k \\ \text{Gini}_k \\ \text{Age}_k \\ \text{Education}_k \\ \text{Phone Pen.}_k \end{bmatrix} + \varepsilon_k^{(\text{rat.volume})},$$
$$k = \{1, \ldots, K\}, \qquad \text{and}$$

(7)
$$\hat{\beta}_k^{(\text{rat. valence})} = [\zeta_1 \quad \zeta_2 \quad \zeta_3 \quad \zeta_4 \quad \zeta_5 \quad \zeta_6 \quad \zeta_7 \quad \zeta_8 \quad \zeta_9] \begin{bmatrix} \text{Individualism}_k \\ \text{Power Dist.}_k \\ \text{Uncertainty Av.}_k \\ \text{Masculinity}_k \\ \text{GDP}_k \\ \text{Gini}_k \\ \text{Age}_k \\ \text{Education}_k \\ \text{Phone Pen.}_k \end{bmatrix} + \varepsilon_k^{(\text{rat. valence})},$$
$$k = \{1, \ldots, K\}.$$

Generalizability Across Markets

Although our study has implications for app marketers (e.g., changing price has different sales rank effects in the United States vs. India), generalizing the findings to other industries would prompt the question of whether app consumers differ across countries in other ways (i.e., not captured by our explanatory factors). In other words, do app consumers represent the "average" citizen in, for example, the United States but not India? This question is also relevant in cross-country studies (e.g., almost all U.S. households are in the market for laundry detergent, whereas many households in emerging markets are not) and cultural studies: for example, Hofstede (1980) established four cultural dimensions in a sample of only IBM managers, and Dawar and Parker (1994) surveyed MBA students enrolled in mature markets. We address this question conceptually and empirically.

First, our conceptual focus is on how differences across countries affect price and user rating sensitivities. To demonstrate this impact, it is not necessary that the people in the market for a particular product fully represent the country's population. Hofstede (1980) assumes, for example, that although high-earning Indian managers may differ from other people in the country, they are still influenced by the country's culture and thus likely differ on the four cultural dimensions from high-earning managers in other countries. Likewise, we assume that, in general, people in the market for apps in India differ in individuality, power distance, uncertainty avoidance, and masculinity from app consumers in, for example, the United Kingdom in a way that reflects the differences found in other samples of their countries.

Second, we offer empirical reasoning that barriers to using iOS-based apps are not as high as the prices of new Apple products suggest. During our observation window, four older generations of iOS-based smartphones and iPods were available to users on the secondhand market. In addition, users could choose between three different versions of iOS-based tablets, of which generations 1 and 2 were already discontinued and only available on the secondhand market. A Vendio.com-based web research study of historical prices reveals that such discontinued, older iOS devices are sold for up to 85% cheaper than their original price. Such price reduction holds for all types of models and countries.

Finally, our model accommodates differences across markets in modeling Step 4, incorporating the country-specific price and rating effects across markets. Moreover, we explicitly account for different income and demographic distributions across countries in our model, which includes GDP, the Gini index, age distribution, and smartphone penetration.

In summary, app market consumers do not represent the population for any country, and managers should evaluate their own industries (with our generalizable methodology) to obtain and compare marketing sensitivities among consumers. For any such study, random-effects model specifications and adequate controls enhance the validity of the resulting insights.

Results

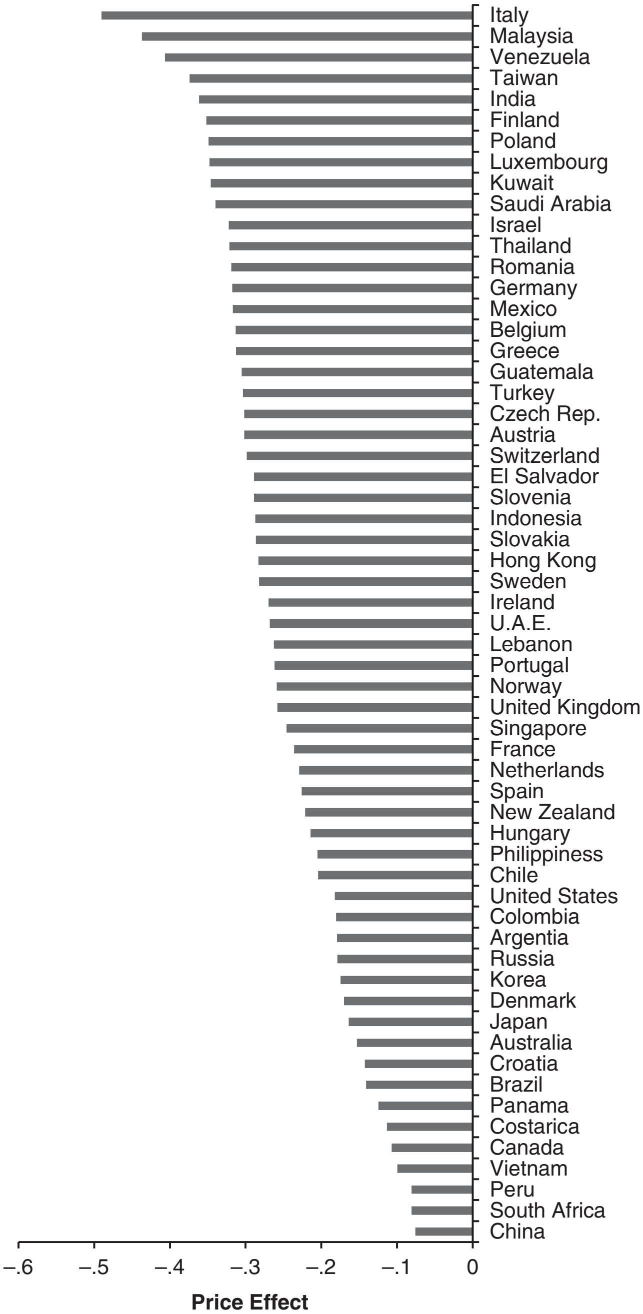
Model Fit, Estimates, and General Findings

The Fisher-type panel unit root test results reveal that the rank data were stationary for all the countries. We opt for a log-log model specification to smooth the series and reduce the impact of the outliers, and we find a linear pattern in the resulting variables.[7] We estimate four nested models that progressively add the explanatory variables. Model 1 (the baseline model) includes the sales rank autoregression (AR[1]), price, lagged ratings volume, lagged ratings valence, free apps rank, update, dispersion, and category dummies. Model 2 adds the seasonal dummies, Model 3 adds a trend, and Model 4 adds the interactions among the marketing variables. As shown in Table 5, all three fit criteria favor Model 3, with the trend and seasonal dummies but without interactions.

Figures 1 and 2 show the country ordering of the estimated price and ratings effects, respectively, on sales rank, obtained from the DPD estimation.[8] Malaysia has the second-highest price sensitivity for apps, consistent with its consumer-reported price importance compared with France for each of the studied categories of groceries, clothing, and cars (Hult, Keillor, and Hightower 2000). However, the highest price sensitivity is reported for Italy, and the top ten most price-sensitive countries are a mix of emerging markets, such as India and Venezuela, and mature markets, such as Finland and Luxembourg. A similar story emerges for ratings sensitivities: Japan, the United States, and Italy give most weight to ratings valence, while Luxembourg, the Czech Republic, and El Salvador are most sensitive to ratings volume. Thus, we do not find a simple pattern along a single difference dimension. Consistent with our conceptual framework, a more comprehensive model is required to reveal any systematic patterns and aid managers in predicting market sensitivities.

Using Equation 3, we present the findings of the first-stage DPD model estimates for each country in Table 6 and Web Appendix W10. Sales rank success carries over to future periods, with a significant AR coefficient of .50, on average, across countries This magnitude is intuitive for daily-level data (Trusov, Bucklin, and Pauwels 2009; Wiesel, Pauwels, and Arts 2011). The sign and significance of the main marketing

FIGURE 1
Country Ordering (Strongest to Weakest) of Estimated Price Effects on App Popularity



effects of marketing on sales rank are consistent with those of previous research. Price has a significant and negative direct effect on rank, with an average magnitude (–.25) consistent with the reported low price elasticity for apps in the United States (Ghose and Han 2014). Higher valence ratings imply higher sales rank (.03 on average), with a magnitude at the lower end of the range provided by Floyd et al. (2014). Likely explanations include the nature of apps as low-ticket durables and the nature of the reviews by nonexperts on sellers' websites (both factors

[7]Assuming that the relationship between log rank and log sales is close to linear, we could also convert the estimated coefficients of the log rank model by scaling the parameters by a constant (see Chevalier and Mayzlin 2006).

[8]Price did not vary in Pakistan enough for estimation. South Africa and Costa Rica had nonsignificant price coefficients. Thus, we do not include these (5% of studied) countries in Figures 1–3, Table 6, or our second-stage estimation.

FIGURE 2
Estimated Ratings Valence and Volume Effects on App Popularity

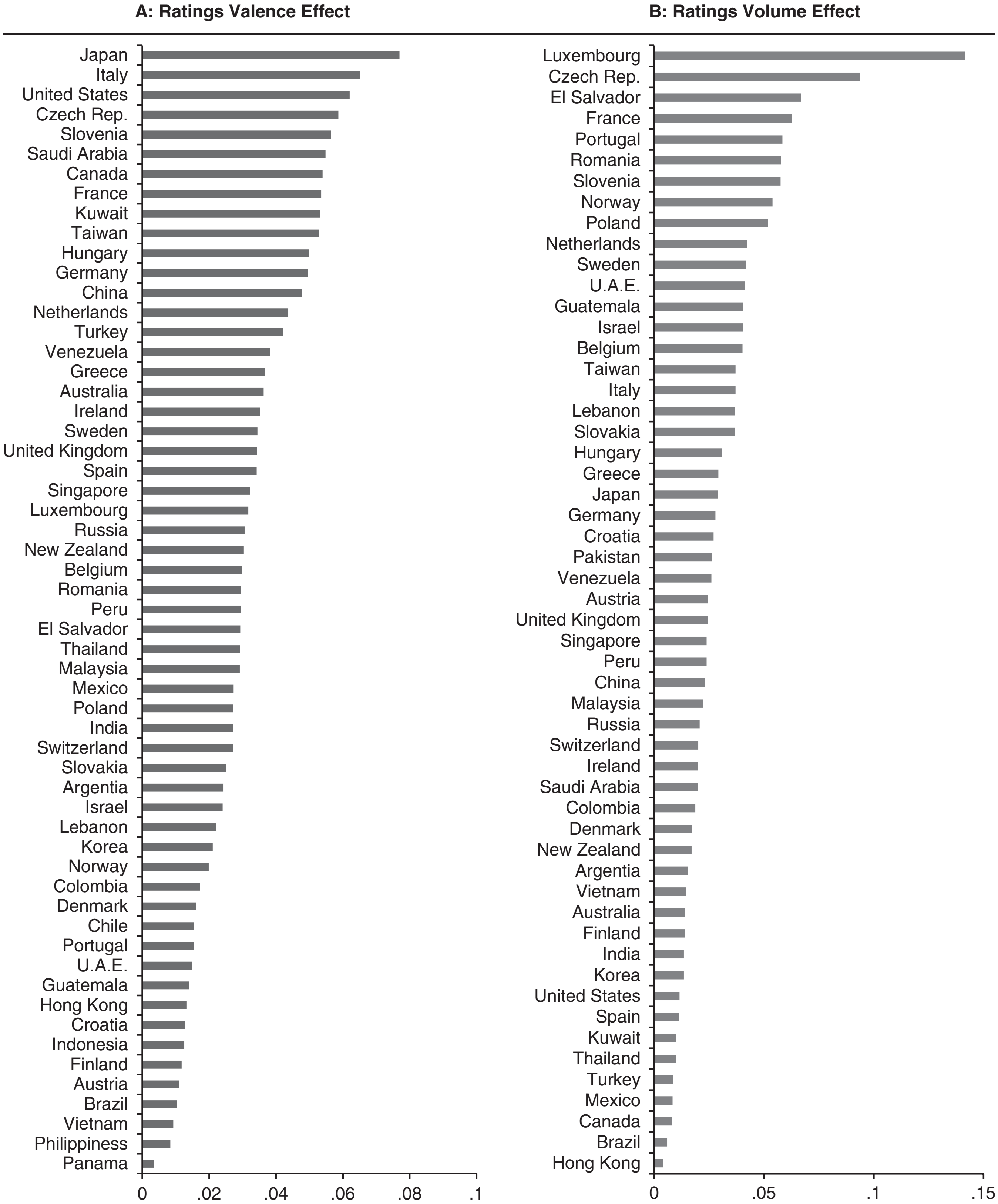


TABLE 6
First-Stage Model Coefficients

Country	Constant	AR(1)	Price	Volume	Valence	Update	Free Rank	Dispersion
Argentina	2.280***	.376***	−.168***	.011	.021**	.056*	.014	.071
	(.485)	(.031)	(.040)	(.010)	(.009)	(.031)	(.011)	(.051)
Australia	.501	.905***	−.154*	.014	.036	−.011	−.006	.009
	(.481)	(.110)	(.082)	(.011)	(.025)	(.025)	(.017)	(.034)
Belgium	2.134***	.548***	−.309***	.040***	.029***	.042	.023	.028
	(.821)	(.048)	(.085)	(.014)	(.010)	(.030)	(.028)	(.020)
Brazil	1.400***	.662***	−.141**	.005**	.010**	−.032	.005	.013
	(.128)	(.033)	(.007)	(.002)	(.005)	(.030)	(.005)	(.014)
Canada	1.092***	.678***	−.108***	.009	.054**	.021	−.007	−.038
	(.347)	(.021)	(.036)	(.009)	(.023)	(.016)	(.021)	(.027)
Chile	1.652	.374*	−.185***	−.015	.007	.021	.031**	.131
	(3.054)	(.200)	(.064)	(.028)	(.023)	(.028)	(.014)	(.164)
China	1.552***	.659***	−.074	.022**	.045***	.040**	.009	.028
	(.588)	(.140)	(.050)	(.009)	(.015)	(.021)	(.016)	(.040)
Colombia	2.549***	.360***	−.172***	.014	.014**	−.021	.020	.048*
	(.251)	(.053)	(.074)	(.009)	(.007)	(.047)	(.014)	(.027)
Croatia	2.615***	.395***	−.141***	.029*	.013**	−.076	.008	.033
	(.226)	(.052)	(.054)	(.016)	(.006)	(.053)	(.010)	(.028)
Czech Republic	2.421***	.396***	−.298**	.092***	.057***	.048	.043***	.022
	(.569)	(.040)	(.121)	(.025)	(.014)	(.037)	(.016)	(.039)
Denmark	1.149***	.679***	−.166***	.014**	.014*	.062	.004	.032
	(.226)	(.061)	(.036)	(.007)	(.008)	(.040)	(.017)	(.021)
Germany	1.232***	.708***	−.317***	.028***	.049**	.119**	−.005	.006
	(.131)	(.022)	(.095)	(.011)	(.021)	(.060)	(.009)	(.030)
Spain	1.610***	.591***	−.226***	.010	.032**	.019	−.001	.023
	(.350)	(.049)	(.058)	(.012)	(.015)	(.033)	(.025)	(.029)
Finland	2.441***	.361***	−.348***	.012	.011	.059**	.013	.027
	(.230)	(.043)	(.111)	(.015)	(.008)	(.030)	(.020)	(.028)
France	1.649***	.564***	−.236**	.062***	.051***	−.014	.019	.037
	(.204)	(.043)	(.105)	(.021)	(.020)	(.035)	(.023)	(.042)
Greece	2.394***	.367***	−.314***	.029	.036***	.150***	.033	.002
	(.318)	(.060)	(.081)	(.025)	(.010)	(.031)	(.025)	(.060)
Guatemala	1.906***	.437***	−.300**	.041	.013	.016	.017	.046
	(.428)	(.048)	(.139)	(.047)	(.010)	(.035)	(.011)	(.044)
Hong Kong	1.793***	.583***	−.274***	.002	.011	.072*	.027	.057**
	(.232)	(.045)	(.035)	(.010)	(.007)	(.041)	(.022)	(.025)
Hungary	2.921***	.295***	−.210**	.028	.049***	−.025	−.017	.025
	(.343)	(.053)	(.108)	(.023)	(.014)	(.041)	(.021)	(.035)
India	2.618***	.401***	−.354***	.012	.026**	−.036	.032	.028
	(.404)	(.098)	(.078)	(.009)	(.011)	(.060)	(.022)	(.033)
Indonesia	2.731***	.348***	−.276***	−.007	.011*	.060*	.024*	.063
	(.185)	(.041)	(.078)	(.009)	(.007)	(.034)	(.013)	(.050)
Ireland	2.567***	.399***	−.258***	.014	.031***	−.001	−.004	.101
	(.428)	(.069)	(.091)	(.013)	(.011)	(.043)	(.014)	(.060)
Israel	2.526***	.426***	−.322***	.040*	.024**	.043	.013	−.001
	(.227)	(.062)	(.043)	(.022)	(.011)	(.039)	(.015)	(.035)
Italy	1.815***	.602***	−.490***	.037***	.063***	.065	−.003	.026
	(.267)	(.043)	(.087)	(.012)	(.016)	(.068)	(.045)	(.045)
Kuwait	2.005***	.451***	−.292*	−.010	.031	.051	.006	.375***
	(.219)	(.053)	(.161)	(.025)	(.023)	(.126)	(.022)	(.141)
Lebanon	2.728***	.377***	−.257***	.041**	.023**	−.077	−.002	.008
	(.231)	(.056)	(.070)	(.021)	(.012)	(.056)	(.012)	(.053)
Mexico	1.854***	.510***	−.314***	.007	.026*	.037	.030*	.041*
	(.341)	(.066)	(.090)	(.006)	(.014)	(.026)	(.018)	(.023)
Philippines	2.096***	.489***	−.185***	−.001	.005	.001	.034	.241**
	(.508)	(.103)	(.037)	(.009)	(.009)	(.033)	(.022)	(.121)
Russia	1.670***	.600***	−.178***	.020**	.030**	.002	.012	.019
	(.187)	(.034)	(.046)	(.009)	(.014)	(.044)	(.009)	(.039)
Turkey	2.261***	.477***	−.286***	.005	.039***	.025	.037**	.079**
	(.248)	(.048)	(.087)	(.010)	(.013)	(.031)	(.019)	(.035)
United States	.632***	.790***	−.182***	.012	.062**	.022	.012	−.007
	(.214)	(.063)	(.061)	(.010)	(.031)	(.016)	(.013)	(.062)

TABLE 6
Continued

Country	Constant	AR(1)	Price	Volume	Valence	Update	Free Rank	Dispersion
El Salvador	1.104***	.630***	−.284***	.064	.028	.035	−.020	.101
	(.307)	(.097)	(.038)	(.089)	(.020)	(.050)	(.022)	(.096)
Japan	.993***	.766***	−.166***	.027	.080***	.313*	.034*	.011
	(.181)	(.039)	(.050)	(.018)	(.020)	(.168)	(.022)	(.029)
Korea	2.496***	.439***	−.176***	.012	.019	−.062	.030	.055*
	(.398)	(.079)	(.023)	(.009)	(.013)	(.045)	(.019)	(.034)
Luxembourg	2.924***	.289***	−.347***	.145**	.032**	−.073	.002	.015
	(.153)	(.030)	(.086)	(.072)	(.016)	(.057)	(.013)	(.026)
Malaysia	2.672***	.305***	−.438***	.022*	.029**	.012	.034***	−.002
	(.582)	(.083)	(.115)	(.013)	(.012)	(.043)	(.009)	(.048)
Netherlands	1.390***	.632***	−.226***	.041***	.042***	.041*	.005	.037**
	(.173)	(.041)	(.049)	(.012)	(.012)	(.025)	(.012)	(.016)
New Zealand	1.676***	.509***	−.208**	.012	.026***	−.006	.0001	.087**
	(.318)	(.065)	(.085)	(.012)	(.009)	(.030)	(.012)	(.042)
Norway	2.376***	.574***	−.256**	.053**	.019**	.010	−.038	.042
	(.562)	(.160)	(.126)	(.021)	(.008)	(.024)	(.033)	(.073)
Austria	1.551***	.621***	−.293***	.023***	.009	.057	.018	.057**
	(.186)	(.039)	(.028)	(.009)	(.008)	(.050)	(.014)	(.027)
Panama	.740***	.742***	−.125***	.013	.004	.011	.009	.008
	(.240)	(.038)	(.032)	(.073)	(.011)	(.033)	(.007)	(.031)
Peru	2.089***	.437***	−.077	.017	.027**	.007	.027***	.070**
	(.295)	(.062)	(.081)	(.011)	(.012)	(.047)	(.010)	(.032)
Poland	2.468***	.383***	−.347***	.051***	.027***	−.013	.032*	.015
	(.216)	(.051)	(.073)	(.014)	(.008)	(.047)	(.018)	(.028)
Portugal	2.448***	.339***	−.254***	.055***	.014	.038	.037*	.069**
	(.296)	(.048)	(.069)	(.020)	(.009)	(.037)	(.020)	(.036)
Romania	3.330***	.241***	−.321***	.058**	.029***	.039	.015**	−.006
	(.338)	(.046)	(.063)	(.029)	(.009)	(.041)	(.007)	(.036)
Saudi Arabia	2.413***	.435***	−.327***	.017	.053*	−.029	.008	.041
	(.299)	(.060)	(.044)	(.037)	(.029)	(.064)	(.023)	(.054)
Singapore	2.781***	.379***	−.242***	.023	.030**	.026	.013	.034*
	(.223)	(.044)	(.085)	(.014)	(.012)	(.026)	(.016)	(.022)
Slovakia	2.356***	.379***	−.278***	.030*	.024***	.037	.031***	.066***
	(.289)	(.042)	(.057)	(.018)	(.008)	(.027)	(.011)	(.024)
Slovenia	1.559***	.599***	−.292***	.060	.057***	.027	.016	.064
	(.249)	(.041)	(.112)	(.094)	(.022)	(.038)	(.012)	(.086)
Switzerland	1.876***	.527***	−.294***	.019	.026*	.070*	.010	.055***
	(.264)	(.058)	(.077)	(.016)	(.016)	(.040)	(.012)	(.021)
Sweden	1.172***	.661***	−.277***	.040**	.033**	.010	−.006	.038
	(.175)	(.046)	(.092)	(.016)	(.014)	(.018)	(.019)	(.028)
Taiwan	1.851***	.562***	−.362***	.031**	.047**	.084	.021	.071
	(.230)	(.063)	(.143)	(.013)	(.019)	(.057)	(.014)	(.046)
Thailand	2.410***	.500***	−.324***	.011	.029***	.046*	.028	.003
	(.300)	(.077)	(.074)	(.015)	(.009)	(.025)	(.019)	(.077)
United Arab Emirates	2.285***	.486***	−.260***	.037	.011	−.036	.019	.073**
	(.420)	(.097)	(.041)	(.023)	(.008)	(.095)	(.017)	(.034)
United Kingdom	.695***	.758***	−.258***	.024	.032	.055***	.009	.044*
	(.205)	(.023)	(.088)	(.018)	(.024)	(.021)	(.012)	(.025)
Venezuela	2.627***	.335***	−.392	.019	.034**	−.251**	.020	.089
	(.220)	(.051)	(.273)	(.035)	(.014)	(.127)	(.014)	(.057)
Vietnam	2.861***	.341***	−.098***	.014	.009	−.070	.002	.012
	(.230)	(.044)	(.026)	(.023)	(.006)	(.059)	(.008)	(.029)

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.
Notes: We provide the full set of estimates, including the other variables' coefficients in Web Appendix W10. Robust standard errors are in parentheses.

significantly reduce review elasticities in Floyd et al. [2014]). Higher ratings volume also indicates higher sales rank (.03 on average). The remaining variables had a weaker impact, with fewer countries showing a significant effect. Product updates increase sales rank (.02 on average), and the rank of the free version of the app increase the sales rank of the paid app,

TABLE 7
Impact of Cultural, Economic, and Structural Factors on Price and Ratings effects

	Price		Ratings Volume		Ratings Valence	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Individualism	.001	.001	.001	.001	.004***	.001
Power distance	−.001	.001	.003**	.001	.001	.001
Uncertainty avoidance	.001***	.001	.002**	.001	.001*	.001
Masculinity	.008**	.001	.000	.001	.001	.001
GDP	.001	.001	.002*	.001	.001	.001
Gini	.002	.001	−.006***	.001	.001	.001
Age	.001	.001	.000	.001	.001	.001
Education	−.006	.005	.001	.002	−.002	.001
Smartphone penetration	.122	.154	−.011	.038	−.001	.029

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

suggesting complementarity rather than substitution for the ten countries in which the effect is significant.

How Marketing Responses Differ by Cultural, Economic, and Structural Factors

Table 7 shows our second-stage WLS estimates. The higher a country's masculinity, the higher is the price sensitivity of sales rank. As we explained in the conceptual framework, this finding is likely driven by the nature of the studied technology product, whose content (mostly games) aligns with stereotypically masculine values. Price sensitivity is also higher in countries with higher uncertainty avoidance (e.g., Greece and Thailand vs. Spain and Denmark).

Ratings valence sensitivity is higher in countries with higher uncertainty avoidance, which we expected from the greater importance consumers in such cultures attach to the opinion of others. Ratings reduce uncertainty, and high-uncertainty-avoidant consumers should hesitate in buying products that are not highly rated by others. Individualism is also associated with higher sensitivity to ratings valence. This finding accentuates how anonymous ratings by strangers may differ from face-to-face WOM, which is influential in collectivist cultures. User ratings allow prospective customers to make up their own minds drawing on the opinion of others, without requiring strong ties or personal interaction.

Ratings volume sensitivity is higher in countries with higher uncertainty avoidance but also in countries with high power distance, high income, and low income inequality. The cultural factors are consistent with the argument that popularity reassures consumers uncertain about how buying an app would affect their status in society (Aaker and Maheswaran 1997; Bughin, Doogan, and Vetvik 2010; Pauwels, Erguncu, and Yildirim 2013). The economic factors follow from the theory that generalized trust increases the importance of online ratings. Although the ratings are from strangers and are mostly anonymous, prospective buyers trust that their numbers reflect the actual popularity of the app among real users. The difference between valence and volume sensitivities is intriguing, and we illustrate the log ratio of these estimates in Figure 3.

The United States, Japan, and Canada show the highest ratio of valence to volume importance. Emerging countries such as Saudi Arabia, Turkey, and China are close behind. In these countries, app marketers should be primarily concerned with the star rating of their apps. By contrast, sales ranks in Luxembourg, Portugal, and El Salvador depend more on ratings volume than on valence. These countries tend to be smaller, making it more difficult for apps to gather a substantial number of local reviews.

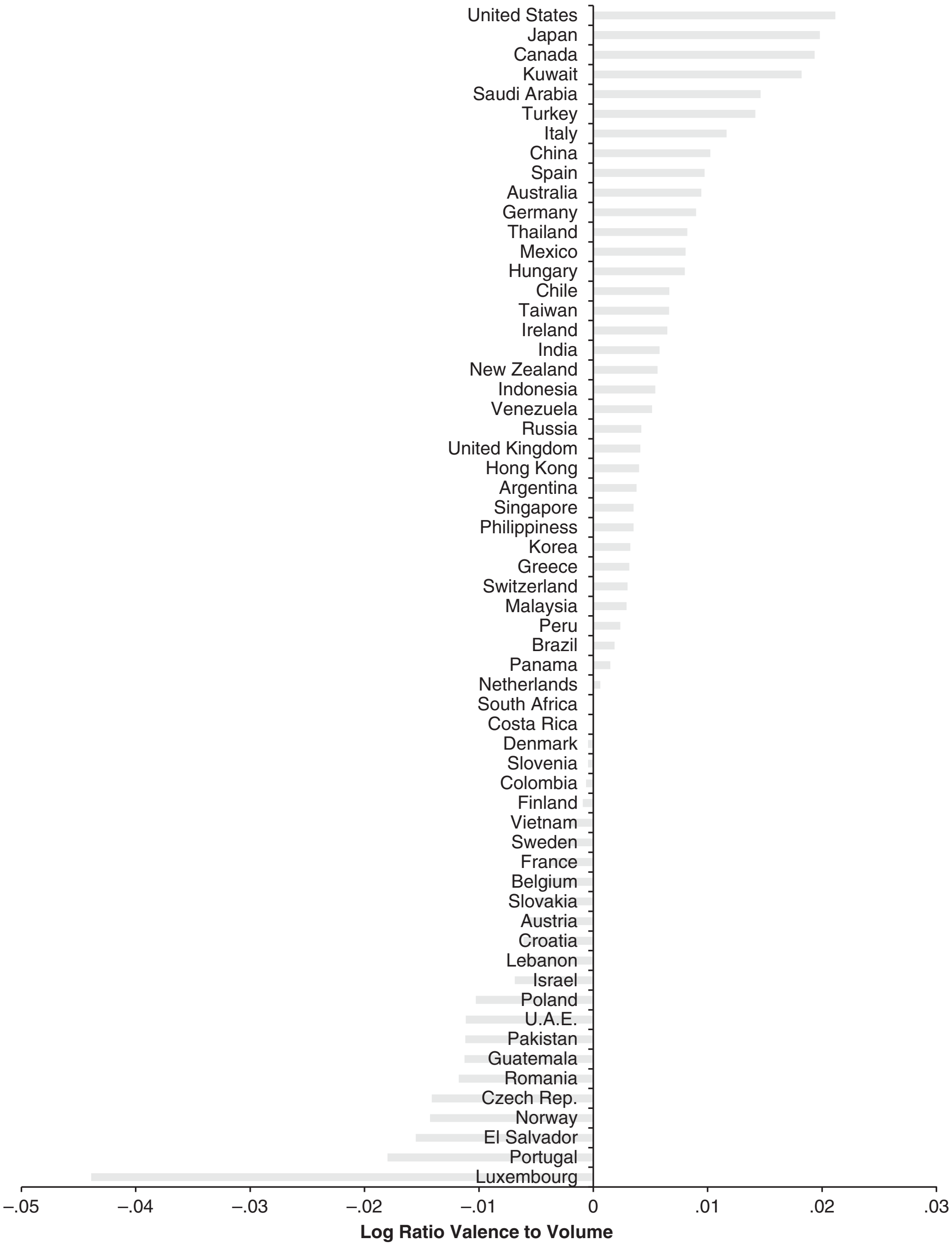
Because uncertainty avoidance and income inequality are the main drivers among the cultural and economic factors, we juxtapose them in a median split analysis in Table 8. We find the highest price and ratings volume sensitivities for countries high in uncertainty avoidance but low in income inequality (e.g., Thailand), whereas we find the lowest price and ratings volume sensitivities for countries low in uncertainty avoidance but high in income inequality (e.g., Spain). Ratings valence sensitivity (.029 on average in low-uncertainty-avoidance countries) increases with uncertainty avoidance when income inequality is low (e.g., Argentina vs. Thailand) but decreases with uncertainty avoidance when income inequality is high (e.g., Spain vs. New Zealand).

Finally, none of the structural factors included in the model (average age, education and phone penetration) significantly affect price, ratings volume, or ratings valence sensitivity in our sample. Thus, our findings appear robust with respect to these structural factors.

Model Diagnostics and Robustness Checks

Sensitivity analysis. In the "Methodology" section, we discussed that the practice of using more instruments than strictly necessary is often a good idea in a system GMM because the additional instruments can help increase the precision of the estimates (efficiency). However, using a very large number of instruments relative to the sample size may result in estimation bias, especially if some or many of the instruments are only weakly correlated with the endogenous variables. Thus, we need to trade off less efficiency for less bias. We perform a sensitivity analysis by reducing the number of instruments and show the results in Table 9.

FIGURE 3
Log Ratio of Estimated Ratings Valence and Volume Effects on App Popularity



Halving the time length T and reducing the instrument count from 1,105 to 557 decreases the estimate of the price parameter in absolute terms by .02 (from –.2536 to –.2330). The decrease for the ratings volume estimate is .01 (from .0269 to .0169), while that for the ratings valence is .007 (from .0296 to .0224). The estimate for the update variable decreases by .006. These variations do not alter our substantive findings; thus, our results are robust to variation in number of instruments.

Instrument validity. We also provide the test results for the validity of the instruments using Hansen-J and difference-in-Hansen tests (see model diagnostics in Web Appendix W9). The Hansen-J test shows that the moment conditions are jointly valid (i.e., the instruments are exogenous and valid). The difference-in-Hansen test results also confirm the validity of the subset of instruments for the lagged dependent variable.

Autocorrelation. We further check the optimal number of lags for the first-stage DPD estimation and test the roots of the AR polynomial. For all countries, except China and Ireland, one lag is sufficient (Web Appendix W9). For China and Ireland, the

TABLE 8
Price and Ratings Sensitivities Across Income Inequality (Gini) and Uncertainty Avoidance (UAV)

	Gini Low		Gini High	
UAV Low	Mean ratings volume effect:	.035	Mean ratings volume effect:	.014
	Mean ratings valence effect:	.029	Mean ratings valence effect:	.029
	Mean price effect:	–.255	Mean price effect:	–.230
	Example country:	Argentina	Example country:	Spain
UAV High	Mean ratings volume effect:	.036	Mean ratings volume effect:	.024
	Mean ratings valence effect:	.037	Mean ratings valence effect:	.028
	Mean price effect:	–.266	Mean price effect:	–.246
	Example country:	Thailand	Example country:	New Zealand

autocorrelation test (Arellano and Bond 1991) is significant for AR(2). Therefore, we use two lags for these countries in the DPD estimation. We also find that the root of the AR polynomial is outside the unit circle for all the countries, ensuring the stability of the dynamic process.

Sample with 100% coverage. Our data set represents 80% overlap of similar apps across countries. As a robustness check, we limit the empirical analysis to apps that are present in all countries, which results in 19 apps in 24 countries. Our DPD model estimates show similar and robust findings. The correlations for price, ratings volume, and ratings valence coefficients from 80% and 100% coverage are .83, .94, and .81, respectively, lending additional support to our findings (for the first-stage estimates of the 100% coverage DPD model, see Web Appendix W11).

Category-specific differences. We estimated the model with (1) game apps and (2) other apps separately. We find significant differences in price sensitivities for games (–.283) versus other app categories (–.182) but do not find any significant difference for the app popularity effects of ratings volume and valence variables. With regard to the moderators, the effect of power distance on ratings volume sensitivity is not significant for games, while the effect of uncertainty avoidance on ratings volume sensitivity is not significant for nongame apps.

Discussion

Managerial Implications

We detail the managerial implications by (1) discussing the feasibility of changing prices on the basis of our results, (2) calculating how much managers would need to reduce price to maintain sales rank in the face of a ratings drop (to return to our examples in the opening paragraph), and (3) visualizing the predicted sensitivities for countries outside our app sample. Figures 2 and 3 show substantial cross-country differences in sales rank response. Do these large cross-country differences mean that managers need to devise a separate offer for each country? No; similar countries often have similar sensitivities, thus providing a means for grouping countries. East Asia (Malaysia, Indonesia, Thailand, Taiwan, Korea, and the Philippines) and continental Europe (Czech Republic, Luxembourg, Italy, Greece, and Poland) appear most price sensitive, while many countries in Middle and South America (Panama, Costa Rica, Brazil, and Peru) appear the least. Developers could thus consider charging lower prices or releasing cheaper versions of their apps in East Asia as compared with Latin America. The potential benefits (in light of our estimated price response differences) should be weighed against the costs of price discrimination, including physical costs and consumer fairness perceptions. In the case of apps, having different prices requires developers to register different products in the App Store. A rich body of literature has investigated the many reasons consumers accept or tolerate different price levels between countries (*The Economist* 2007; Isard 1977). Engel and Rogers (2001) find a strong correlation between distance and accepted price divergence between countries: the higher the perceived difference between countries, the more likely consumers are to accept different price levels. Our recommendations are consistent with this research stream. We advise different prices only between countries that substantially differ in culture and/or economic conditions.

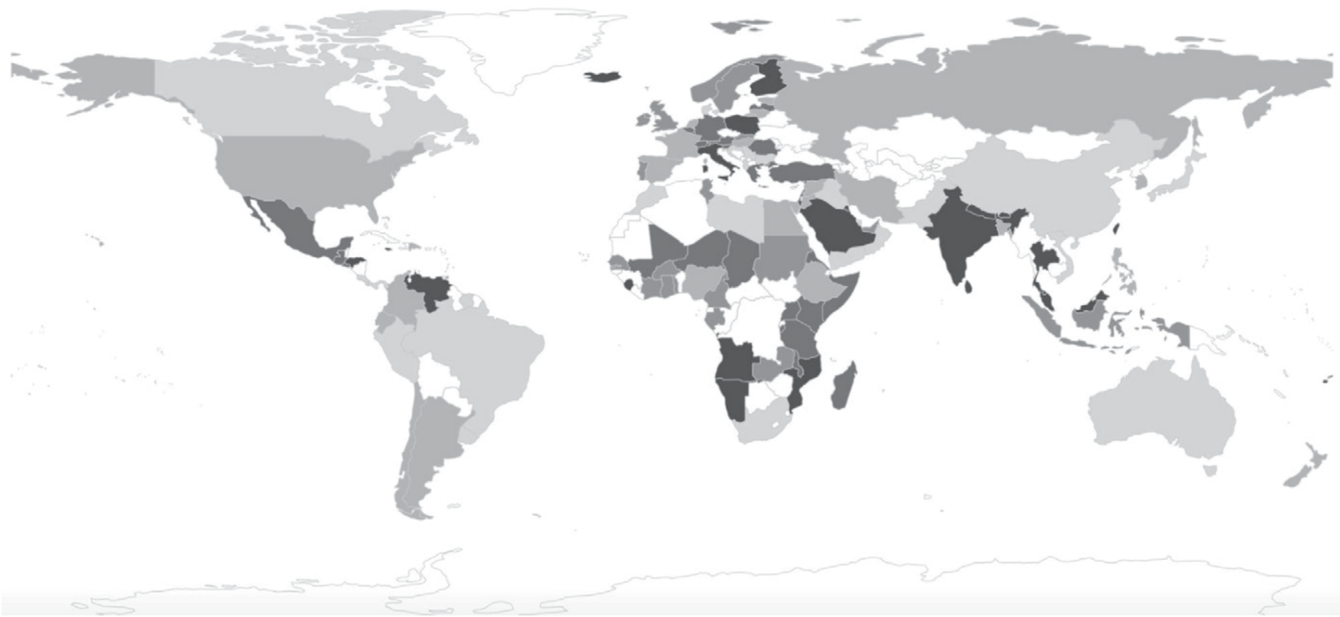
To quantify the performance implications of changing prices, we start from the scenario in which ratings valence has dropped (a common occurrence in our data) and the manager wants to restore sales rank to its previous level by decreasing the

TABLE 9
Sensitivity to Reduction in Number of Instruments

Time Length	Instrument Count	$\hat{\beta}^{price}$	$\hat{\beta}^{rat.\ volume}$	$\hat{\beta}^{rat.\ valence}$	$\hat{\beta}^{update}$
T = 276	1105	–.2536	.0269	.0296	.0195
T = 200	805	–.2385	.0195	.0246	.0150
T = 138	557	–.2330	.0169	.0224	.0138
T = 100	405	–.2275	.0146	.0196	.0163

Notes: For Korea, we had fewer time-series observations for some apps, lowering the total number of instruments.

FIGURE 4
World Map of Estimated and Predicted Price Sensitivities



Notes: Darker colors indicate higher price sensitivity; white indicates insufficient data on country factors to make prediction.

app price while keeping all other model variables constant (at their means for each country). Using the model estimates, we calculate how much we need to lower the price to return to the baseline sales rank. We do so for a range of ratings valence and prices (between \$.10 and \$2.25). Web Appendix W12 illustrates the findings for all countries and those for a similar simulation for ratings volume. For example, app developers can readily use price to make up for a lower ratings valence in price-sensitive Germany. When ratings valence drops from four stars (out of five) to two stars for an app priced at \$1, the app developer only needs to reduce price to \$.75 to reattain the previous sales rank. By contrast, in the more star-ratings-sensitive United States, the price needs to be reduced to \$.25 to reattain the previous sales rank. In countries with lower price sensitivity, such as China, even reducing the price to \$.10 does not restore the previous sales rank.

Finally, as the first study to quantify the price sensitivity effects of cultural, economic, and structural factors, an extra benefit of our approach is that we can predict price sensitivity for countries with data on these factors but no data on marketing and sales rank for the studied product. These out-of-country sample predictions thus offer price advice to managers for almost any country. By using different shades of gray to reflect the terciles of high, medium, and low sensitivity, Figures 4 (price), 5 (ratings valence), and 6 (ratings volume) depict these predictions together with our estimated elasticities in world maps.

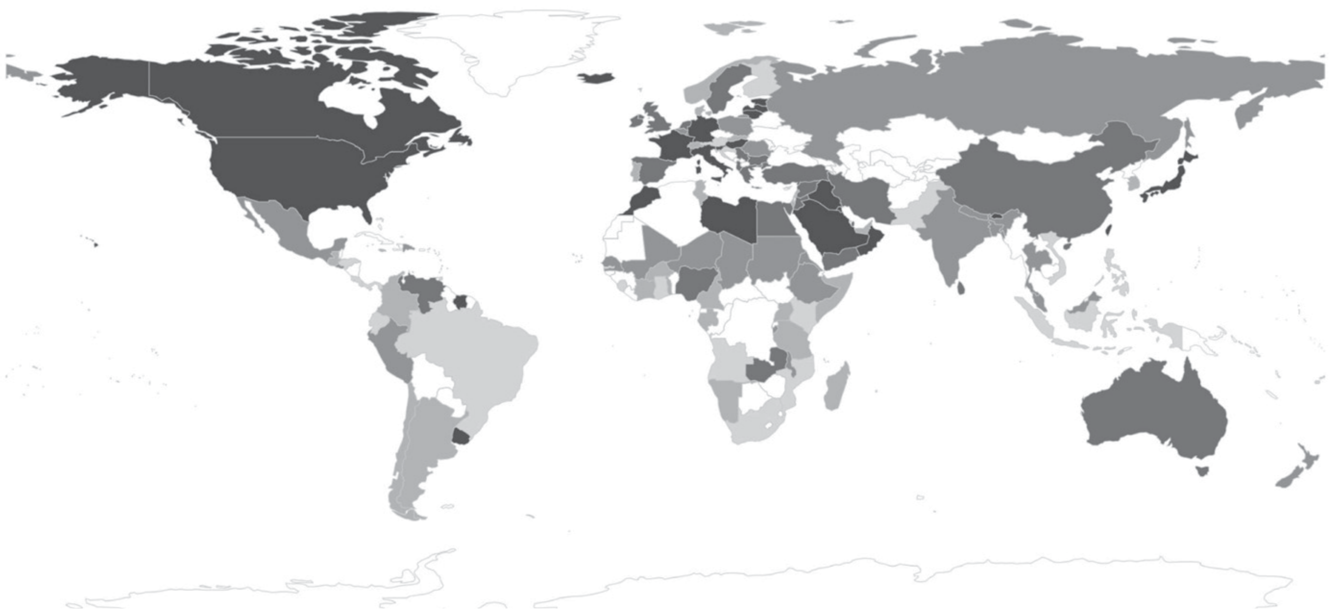
Figure 4 shows the high predicted price sensitivity in central Africa, similar to the high estimated price sensitivity in Southern Europe, the Middle East, Mexico, and India. Conversely, Morocco, Pakistan, and Guyana have low price sensitivity, similar to the estimated low price sensitivities of South Africa, China, and Brazil. Whereas ratings valence is crucial in countries such as the United Kingdom, the United States, China, and Japan (Figure 5), ratings volume is important in central Europe, Scandinavia, and several Middle Eastern countries. Although we cannot assess the accuracy of out-of-country-sample predictions, we note the high forecasting accuracy within our country sample (the root mean square error reported in Tables 5 and 6). After pricing an app in a new country, managers can observe the resulting sales rank and update the predictions accordingly.

Conclusion

Rapid advancements in technology and consumer-to-consumer contact (Web 2.0) have created dynamic global markets for products. Does this mean that the world has become one "global village"? Data across 60 countries reveal substantial and systematic differences in sales (rank) sensitivity to price, ratings valence, and ratings volume, as summarized in Table 10.

Price sensitivity is higher in countries with higher masculinity and uncertainty avoidance. Ratings valence sensitivity is higher in countries with higher individualism and uncertainty avoidance, while ratings volume sensitivity is higher in countries with higher power distance and uncertainty avoidance and those that are richer and have income equality. Although these insights are not directly actionable, they may help companies differentiate the sales benefits of incentivizing WOM in certain countries compared with others. Our findings imply that online ratings are a quality signal, which is more important in countries with high uncertainty avoidance, power distance, and generalized trust. This finding implies that online WOM (typically by strangers) is more important in

FIGURE 5
World Map of Estimated and Predicted Ratings Valence Sensitivities

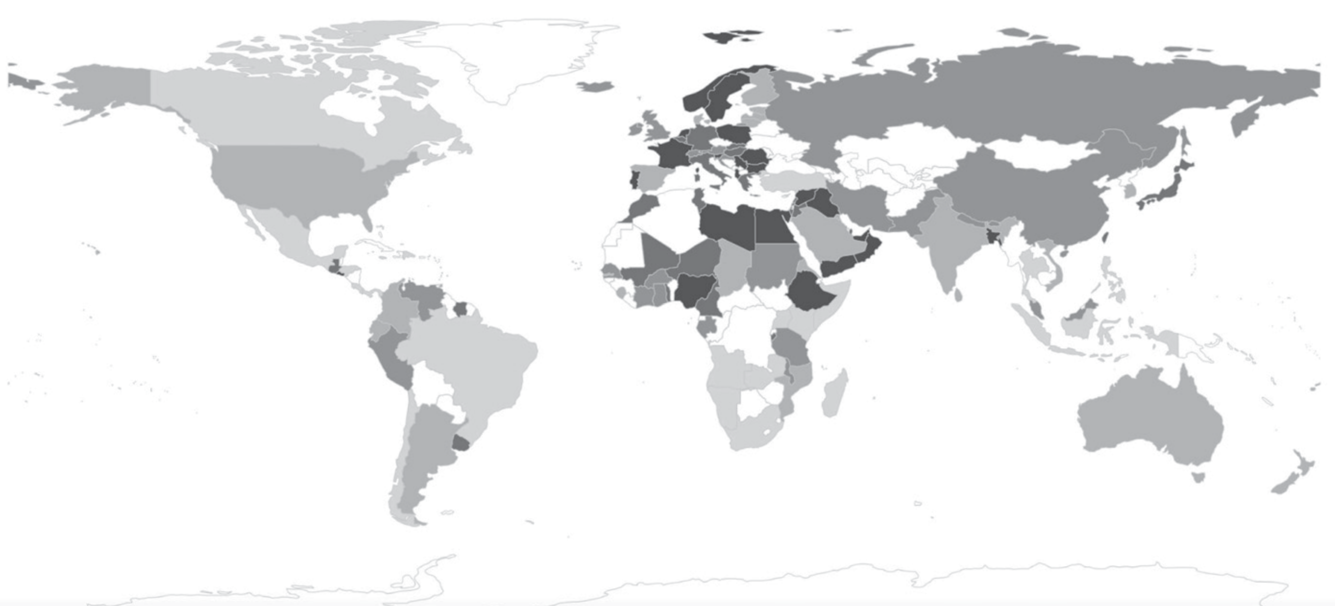


Notes: Darker colors indicate higher ratings valence sensitivity; white indicates insufficient data on country factors to make prediction.

individualist cultures and "mature markets" (with high average income and low income inequality), in contrast with the lower sensitivity to offline WOM reported in these markets.

In terms of international marketing theory, this study is the first to quantify the price and ratings effects across dozens of countries with time-series data and to show the relative importance of the cultural, economic, and structural drivers of these effects. Our findings both replicate previous studies, mostly based on surveys in a subset of countries, and put their interpretations into perspective. We replicate Hult, Keillor, and Hightower's (2000) interview evidence that Malaysian consumers attach higher importance to price than French

FIGURE 6
World Map of Estimated and Predicted Ratings Volume Sensitivities



Notes: Darker colors indicate higher ratings volume sensitivity; white indicates insufficient data on country factors to make prediction.

TABLE 10
Summary of Findings and Implications

Sensitivity of Column Variable to Row Variable	Price	Ratings Volume	Ratings Valence	Implications
Individualism			+	Ratings valence drives app popularity more in individualist cultures
Power distance		+		Ratings volume drives app popularity more in high-power-distance cultures
Uncertainty avoidance	+	+	+	Price, ratings valence, and volume drive app popularity more in high-uncertainty-avoidance cultures
Masculinity	+			Price drives app popularity more in high-masculinity cultures
GDP		–		Ratings volume drives app popularity more in poorer countries
Gini		–		Ratings volume drives app popularity more in countries with high income equality

consumers but also show that this does not apply to any emerging market (as their study's title implies). Instead, our findings indicate the need to more carefully consider the multiple dimensions in which markets differ (Burgess and Steenkamp 2006). Similar to us, Dawar and Parker (1994, p. 81) analyze a product category (consumer electronics) targeting "young, mobile, affluent and educated consumers." They find that MBA students from countries such as the United States and Denmark value product appearance over price. These countries also show a lower-than-median price sensitivity for apps in our findings. In contrast with their survey findings, however, we find substantial evidence of different price sensitivity in revealed preferences along country-level dimensions. The high price sensitivity for apps in mature markets such as Germany is consistent with the higher importance of price on branded beverage sales in markets with more resources and stronger infrastructures (Bahadir, Bharadwaj, and Srivastava 2015). Our framework explains such differences according to the different meanings of price and ratings under different cultural, economic, and structural circumstances. For example, we find that app price sensitivity is lowest for countries that score low on masculinity, such as Costa Rica, Peru, and Canada. For economic factors, ratings volume sensitivity is higher for countries with lower income inequality, including much of central Europe (e.g., Luxembourg, Czech Republic) and Asia (e.g., Korea, Kuwait, Lebanon). Thus, our findings run counter to the simple "developed versus developing" distinction, instead lending support to academic calls for a deeper investigation of consumers' purchase behavior and marketing effect differences along several cultural, economic, and structural dimensions (Bahadir, Bharadwaj, and Srivastava 2015; Burgess and Steenkamp 2006; Sheth 2011).

Two novel findings contradict common wisdom and stand out in providing impetus to future theory development. First, price sensitivity for apps is affected by cultural factors such as masculinity and thus is higher in several mature countries (e.g., Italy) than emerging countries (e.g., Peru). By contrast, a country's average income level has no significant impact in our sample. Thus, low average income levels may be less important than other facets in determining the market's price sensitivity for low-ticket items such as apps, and further research should expand our set of variables and categories to explain when this is the case. Second, ratings valence sensitivity is higher in countries with high uncertainty avoidance as well as in countries with higher individualism. Given the importance of offline WOM in collectivist countries (Bughin, Doogan, and Vetvik 2010; Pauwels, Erguncu, and Yildirim 2013), our findings suggest boundary conditions to the digitization of WOM (Dellarocas 2003). The distinction between (most) offline and (most) online WOM should inspire additional research.

Might our findings on paid apps apply to cross-country differences for other online products? Our interviews with app and game developers indicate that they likely would, for several reasons. Key market elements such as platform, ratings display, and even price levels and discounts are similar for paid apps, in-app purchase of free apps (currently the more popular way to monetize apps), and similar forms of digital products such as online music sales and online game sales on platforms such as the Steam network, the Xbox Games Store, and Sony's PlayStation Store. Recent research has revealed that game publishers can increase their revenues as well as the time consumers spend on a game by asking consumers to pay before they play, instead of offering their games as a freemium product (Rietveld 2018). Thus, the debate on the viability of paid versus free apps is far from settled—similar to the back-and-forth pendulum for other digitally distributed products and services, such as news and professional forums (e.g., Kumar et al. 2012; Pauwels and Weiss 2008). More broadly, the App Store structure is similar to other prominent online market platforms. Price and user-generated information are prominently displayed in online stores and platforms such as Amazon (Chevalier and Mayzlin 2006; Dellarocas 2003). Online platforms gain importance when targeting new markets abroad (e.g., Amazon's engagement in India; BBC 2013). Even in physical stores, consumers increasingly check prices and ratings online for products ranging from durables to apparel to food (Lecinski 2011). The increasing number of smartphones and tablets, which allow immediate and mobile access to online sales, further stimulates online search and shopping across a wide variety of categories (Wylie et al. 2012). We therefore call for more research on different categories, which have their own characteristics and could be affected to a different extent by cultural, economic, and structural factors.

Important limitations to generalizability include our examination of price and ratings sensitivity for paid apps only, not for free apps and their different monetization tools (e.g., in-app purchases, advertising). Moreover, we used sales rank (app popularity) as the dependent variable, not sales or market share, and absolute prices instead of purchasing power parity–adjusted prices. Within paid apps, researchers can expand the data beyond the top-performing apps and explore how best to launch an app in different countries. Indeed, research has shown that some conclusions on price promotion effects differ when going beyond the top three brands typically examined in price response studies (Slotegraaf and Pauwels 2008). We speculate that the sensitivity to both price and ratings should be higher for new than established apps but do not envision systematic differences in the moderating effect of cultural dimensions. Finally, researchers could expand our conceptual framework to include other cultural dimensions by Hofstede (2001), Inglehart (1997), and Schwartz (1999) and develop hypotheses on the impact of cultural, economic, and structural factors.

Has the world economy become a global village of similar consumer sensitivities, implying standardized marketing programs (Levitt 1983)? Our analysis shows a different story, even for a global technology product with 24/7 availability. Fortunately for marketers, these differences are largely predictable and are related to cultural and other systematic factors shared by groups of countries. Developers with knowledge of these factors can customize prices and choose where to stimulate positive ratings. Our research provides a first step toward such an understanding.

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