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IJRM

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Full Length Article

On the monetary impact of fashion design piracy[☆]

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ARTICLE INFO

Article history:

First received on February 26, 2017 and was under review for 9½ months
Available online 16 August 2018

Senior Editor: Bernd Skiera

Keywords:

Counterfeits
Design piracy
Diffusion of innovations
Fashion
Knockoffs
Uniqueness

ABSTRACT

Whether to legally protect original fashion designs against piracy is an ongoing debate among legislators, industry groups, and legal academic circles, which has gained little exposure in the marketing literature. We combine data on the growth of fashion designs, price markups, and industry statistics to develop a formal analysis of the essential questions at the base of the debate. We distinguish between three effects: Acceleration, whereby the presence of a pirated design increases the awareness of the design; Substitution, which represents the loss of sales due to consumers who would have purchased the original design, yet instead buy the knockoff; and loss because of Overexposure of the design resulting from the design's ubiquity. Using data-driven simulation analysis, we find that for the items analyzed (handbags and apparel), overexposure emerged as having a stronger negative effect (on average) on the original's profitability than the positive effect of acceleration. Both effects are considerably larger than that of substitution. This result is of particular interest given that industry groups have consistently focused on the damage caused by substitution. We also show that the effect of a legally mandated postponement on the introduction of a knockoff is non-monotonic for short lag: A short time lag may not affect the original design's NPV, and in fact may even damage it. For the ranges we analyzed, the positive effect of the protection period is observed primarily for time lags of over one year.

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1. Introduction

Fig. 1 depicts several apparel items designed and manufactured by the high-end fashion firm Trovata, alongside nearly identical items produced by the clothing retail chain Forever 21. While Trovata sued Forever 21 for copying these items, the lawsuit was eventually settled out of court (Odell, 2009). This may not be surprising, given the failure of numerous lawsuits against major US firms, including more than 50 lawsuits against Forever 21 by well-known fashion designers such as Diane von Furstenberg, Gwen Stefani, and Anthropologie, claiming that their designs were copied (Tse, 2016). The reason for these failures is that unlike the EU, the US does not provide legal protection against fashion design piracy: a situation in which a firm creates a copy, or “knockoff”, of another firm's design without its logo.¹

[☆] The authors would like to thank Roland Rust, Bernd Skiera and reviewers, On Amir, Eyal Biyalogorsky, Margaret Campbell, Michael Haenlein, Liraz Lasry, Irit Nitzan, Raphael Thomadsen, the participants in the Marketing Science and EMAC conferences, and the participants in the seminars of the business schools of University of Maryland, University of California at Davis, University of California at San Diego, and Stanford University for a number of helpful comments and suggestions. Partial financial support of the Israeli Science Foundation is gratefully acknowledged.

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¹ The EU offers protection for unregistered designs that have exclusive rights covering the outward appearance of the designed product for a period of 3 years (Tse, 2016). In the US, the logo, trademark, or packaging may be protected under Trade Dress protection, but the design itself is not protected (Schutte, 2011; Tsai, 2005).



Fig. 1. Trovata's original fashion designs (below) vs. Forever 21's knockoffs (above).

Because of its possible impact on the US fashion industry, and due to large scale and low cost of copying, design piracy has drawn much attention and lobbying efforts on the part of the US fashion industry. It has become a major issue for policy makers, and the source of an on-going debate in the legal literature, with some calling for protection in the US to accord with that provided by the EU (Cotropia & Gibson, 2010; Diamond, 2015; Hemphill & Suk, 2009; Tsai, 2005). Yet much of this discussion has surrounded conceptual arguments that lack structured, data-based analysis of the issue. It has also drawn much attention in the global fashion market, as fast fashion design imitation has become a flourishing industry in various countries (OECD/EUIPO report, 2016). In recent years, several bills designed to protect US fashion items from design piracy – mainly via a legal protection period such as that instituted in the European Union – were introduced in the US Congress. Despite the fact that none of the bills have been successful, owing to their high financial stakes, design copying cases continue to be heard, including a Supreme Court case in 2016 of alleged design copying of a cheerleader uniform (Kendall, 2016).

Some aspects of this debate relate to its industry-level effects, such as innovation and the issue of affordability to mainstream consumers (Raustiala & Sprigman, 2006; Tse, 2016). However, an essential part of the debate, which is our focus here, regards the knockoff's possible influence on the demand for the original design. Opponents of knockoff restrictions cite the role of acceleration, whereby the pirated design's ubiquity increases awareness thereof, which might actually spur the original's growth (Givon, Mahajan, & Muller, 1995; Qian, 2014; Raustiala & Sprigman, 2012). Stakeholders in favor of knockoff restrictions cite the damage to original designs caused by substitution, which causes loss of sales due to consumers who would have purchased the original design, yet instead buy the knockoff (Lamb, 2010).

A third factor to be considered is the negative consequences for an original design stemming from a larger user base created by a knockoff. This effect, labeled overexposure, implies that fashion items that become too popular might cause a loss in their users' uniqueness, suppressing adopters and potential adopters. This effect stems from the fact that we use fashion to signal to others, as well as to ourselves, our social status and distinctiveness from others. Research strongly supports the idea that for many products, and fashion items in particular, uniqueness considerations play a significant role in consumers' adoption and attrition decisions (Amaral & Locken, 2016; Chan, Berger, & Van Boven, 2012), and in turn in aggregate market demand (Berger & Le Mens, 2009; Joshi, Reibstein, & Zhang, 2009). Overexposure has received less attention in the knockoff debate, and we will show here that it plays a critical role that must not be neglected when considering its effect on an original design.

While much of the knockoff debate has been conducted qualitatively in the legal literature, the question raised – of profitability in the interdependent growth of brands – is first and foremost a marketing issue. Thus, our aim here is to build a model that will enable us to investigate the effect of a fashion knockoff on the original design, and in particular to elicit the relative roles of acceleration, substitution, and overexposure; and to discover whether a legal protection period as proposed by several US lawmakers and academics (Schutte, 2011; Tsai, 2005) alleviates damages to the original.

Exploring how the dynamics of acceleration, substitution, and overexposure combine to create the overall effect of one brand on another is challenging in particular given the multiple social influences involved. An adoption or disadoption of the original design can affect both adoption and disadoption of the knockoff due to the interaction of word-of-mouth effects and overexposure. To untangle these issues, we use a data-driven simulation that has proven useful in helping managers and policy makers predict outcomes of marketing-related actions and policies phenomena that are non-linear and do not necessarily result in a closed-form solution to the model (Franses, 2006).

While historically the use of simulation in marketing has been limited compared to that in other disciplines, researchers are increasingly using simulations to understand the effects of various firm actions (Gielens, Gijsbrechts, & Dekimpe, 2014); examine structural modeling of markets (Bronnenberg, Rossi, & Vilcassim, 2005), and to study via agent-based models how individual level behavior aggregates to market phenomena (Rand & Rust, 2011). Simulations are particularly relevant to issues of the diffusion of innovations due to the complexity, multi agent interactions, and nonlinear effects that characterize such phenomena (Franses, 2006; Rand & Rust, 2011).

Aided by various data on prices and the availability of knockoffs, and on growth of fashion items, we can set the boundaries to the simulation parameters, and examine the effect of design piracy on an original design's NPV. Our major results are as follows:

- The overall effect of a knockoff: We find an overall negative effect of a knockoff entry on the revenues of an original, which is larger when the price ratio between the original and knockoffs is large (handbags) in comparison to small (apparel items).
- Relative role of acceleration, substitution, and overexposure: Overexposure has a slightly stronger negative effect on the original's NPV than the positive effect of acceleration, and both effects are considerably stronger than that of substitution.
- The effects over time: Initially, the original design may benefit from the existence of a knockoff. Later on, as the number of adopters continues to rise, overexposure becomes the strongest effect, leading to an overall negative impact on the original's NPV.
- The role of a legal protection period: We find that a short protection period might harm the original, due to the opposing effects of overexposure and acceleration. For longer protection periods, we observe a positive effect.

Fig. 2 depicts the framework that serves as a basis for our analysis. Consistent with this framework, the paper is divided into three parts: First, we develop a multi-product fashion growth model that includes an original design and a knockoff, and where the joint effects of acceleration, substitution, and overexposure are tracked. This model's goal is to help us examine the effect of the knockoff on the original's NPV's growth.

In the second part, we calibrate the model parameter drawing on information from fashion markets. We combine industry statistics, information collected from fashion blogs on price difference between knockoff items and originals, and data collection from

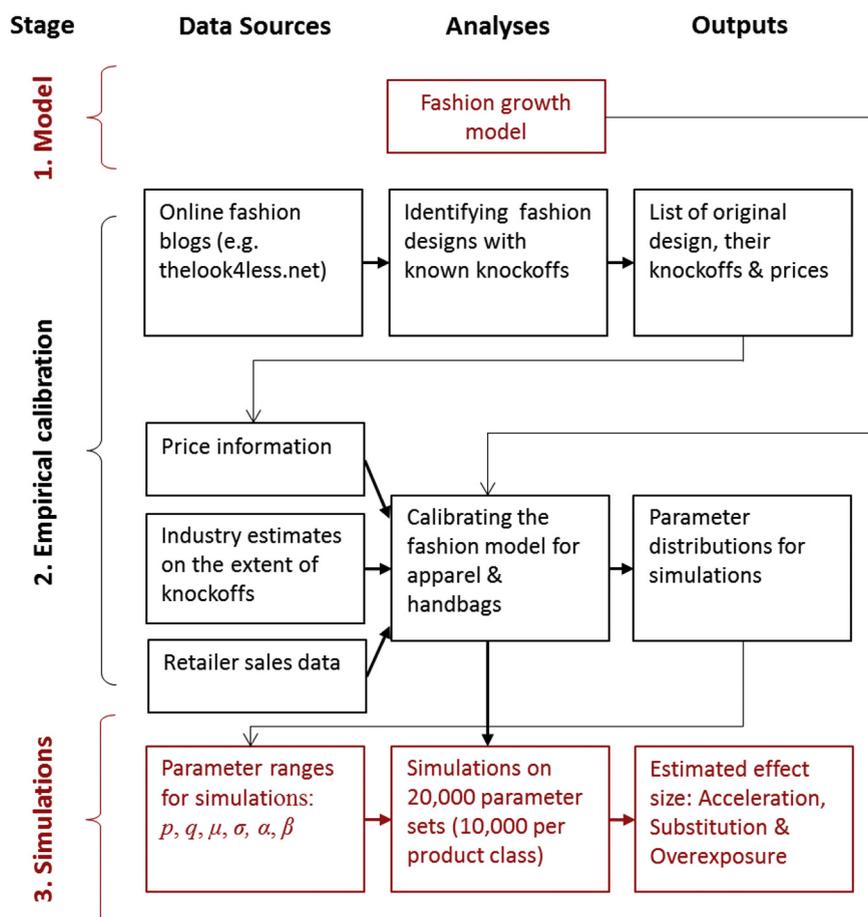


Fig. 2. Flow chart of the analysis process.

a large online retailer on the growth of specific items. We looked in particular at two different product classes identified in the data: handbags and apparel that differ considerably in price between the original and the knockoff.

The third part of the paper is a large-scale simulation study that uses the model and the parameter estimates to assess the knockoff's monetary effect on the original design's NPV, and in particular the effect size of acceleration, substitution, and overexposure. Note that while we use the case of 20 original designs to create the range of parameters for this simulation, the actual number of scenarios we cover within this range is much larger. The simulation results help us assess not only what drives the overall effect, but also its dynamics over time, which help to discern the outcome of a legal protection period.

Note the distinction that we follow here between counterfeits, which impersonate a brand including the brand's logo, and knockoffs, which copy design and appearance (e.g., [Rosenbaum, Cheng, & Wong, 2016](#)). A counterfeit is "a nearly exact duplicate of an item sold with the intent to be passed off as the original," while a knockoff is "a close copy of the original design, mimicking its elements, but is not sold in an attempt to pass as the original," ([Tse, 2016, pp. 418–9](#)). The EU protection for unregistered design extends exclusive rights to the outward appearance of original resulting from "the features of, in particular, the lines, contours, colors, shape, texture, and/or materials of the product itself and/or its ornamentation" for a period of 3 years. Registered designs are covered for a period of 10 years ([Diamond, 2015; Tse, 2016](#)).

The size of the markets for apparel counterfeits and knockoffs is considerable. Using CFDA (Council of Fashion Designers of America) estimates reported in [Ellis \(2010\)](#) and extrapolated, as well as the [OECD/EUIPO \(2016\)](#) report, the latest available estimates (for 2012–2013) for the knockoffs market in the USA, and the counterfeits market in Europe, are \$11.3b and \$17.5b respectively. While the CFDA does not provide any methodology to justify their estimate, the OECD report relies on customs seizures, then correlates these to overall imports into the EU. This appears to be an underestimate of the true value, as it relies on customs seizures that almost exclusively target trademark infringements rather than copyright, patent, and design infringements.² In addition, the OECD methodology disregards local design piracy in the EU that despite legal protection is likely to occur ([Hemphill & Suk, 2009](#)). Lastly, the OECD estimate is an underestimate as it relies on replacement value for mostly established products. Thus, it implicitly calculates substitution while ignoring the damages due to overexposure. We found the latter to be significantly larger than the former in our findings.

Our framework, as depicted in [Fig. 2](#), could be applied to counterfeits as well, and thus one can consider what we propose here as a framework for estimating the effects of knockoffs and counterfeits. In this work, while we apply the framework to data that we obtained on knockoffs, given appropriate data, one can apply it to counterfeits as well.

2. Acceleration, substitution, and overexposure

To facilitate the discussion on the effects of knockoffs, consider the following example of Primp's Anchor hoodie and its corresponding low-cost knockoff by Forever 21. The website www.thelook4less.net, along with many other sites, offers a collection of high-priced apparel and accessories, often showing a celebrity wearing the fashion item, matched to a low-priced knockoff, pointing to the website at which the latter is available. [Fig. 3](#) shows the actress and singer Hayden Panettiere wearing a Primp's Anchor Hoodie, together with the matching knockoff by Forever 21.

[Fig. 3b](#) depicts the sales of this fashion item in the dataset that we discuss in [Section 4](#) of this paper. The figure shows the rapid increase and decline of this original fashion design. Though it was still selling well after four years, about 75% of the ultimate sales occurred in the first two years.³ We next use this example to facilitate the discussion on the three effects of knockoff on the original fashion design: acceleration, substitution, and overexposure.

2.1. Acceleration⁴

If one thinks about the growth of the Anchor Hoodie in terms of classical diffusion theory where word-of-mouth communications, imitation, and other contagion effects play a major role, then contingent on the Forever 21 design being a close copy of the original Primp design, adoption of Forever 21's knockoff will accelerate the diffusion of the original design ([Van den Bulte & Stremersch, 2004](#)).

Thus if a knockoff is a close copy of the original design, adoption of the knockoff will accelerate the diffusion of the original. This argument does not require the knockoff and original to be identical; the acceleration effect will simply be larger the more similar are the two products. It does require, however, that adopters be influenced by the ubiquity of knockoffs, even if they can tell by observing the knockoff that it is not an original.⁵

Thus, opponents of legal intervention argue that original design owners can actually benefit from design piracy due to the above-described contagion process ([Raustiala & Sprigman, 2012](#)). It has further been argued that these effects are especially beneficial in fashion items, whose collective character is important for the creation of a trend or "flocking" toward a particular fashion

² Over 95% of the 327,000 customs seizures for intellectual property infringement into the EU in 2011–2013 (that served as a basis for the estimate) were for trademark infringements, while less than 1.5% were for design infringement.

³ This is typical of our fashion sample, discussed in [Section 4](#), where 75% of the diffusion curves are left skewed (see [Table 1](#)).

⁴ While it might appear that we argue for linearity in the theorizing for acceleration, substitution, and overexposure, this is not the case, as we show later (in [Section 3.3](#)): These effects are inherently nonlinear.

⁵ An interesting complexity can be added if there is a group of users (called "patricians" by [Han et al., 2010](#)) defined as consumers who buy the original items; and can differentiate between knockoffs and originals, yet do not care about, and are not affected by, the number of knockoffs in the market, possibly because they mingle only with other patricians (who only buy the originals).

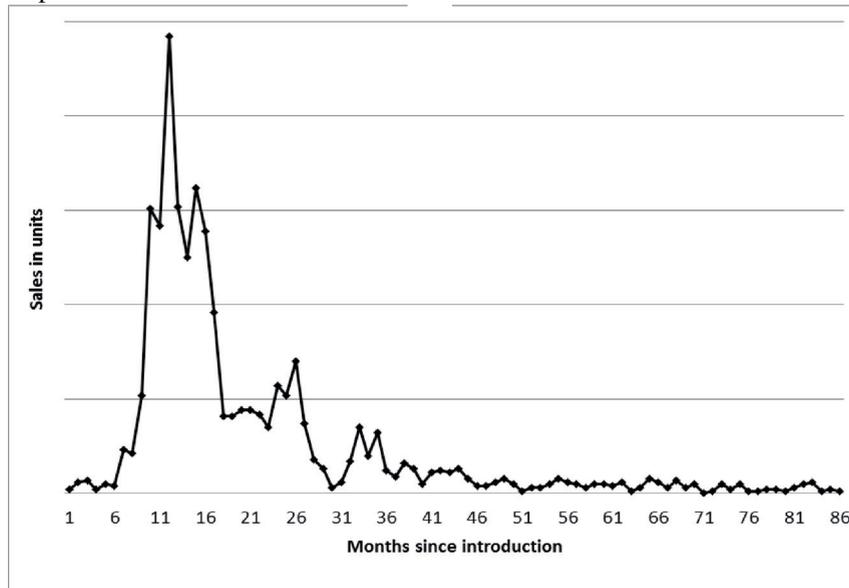
a: Primp Anchor Hoodie and Forever 21 knockoff**b:** Primp Anchor Hoodie unit sales

Fig. 3. a: Primp Anchor Hoodie and Forever 21 knockoff. b: Primp Anchor Hoodie unit sales.

(Cotropia & Gibson, 2010; Hemphill & Suk, 2009). Indeed, Qian (2014) demonstrated the acceleration effect (called “advertising effect”) in the context of counterfeiting of shoes in the Chinese market.

2.2. Substitution

As websites such as TheLook4Less become popular, more potential adopters might consider buying the hoodie from Forever 21 rather than the original Primp. This is especially true if the price markup of the original is not too large. Some of the individuals who now buy the Forever 21 knockoff would have bought the original Primp if the former would not have copied the Anchor design. Thus, substitution effect refers to the monetary effect of individuals who purchased the knockoff, yet would have purchased the original, absent the knockoff. As in the previous effect, we cannot simply count the number of such individuals, due to their complex effect on the Primp Anchor hoodie’s diffusion of via word of mouth, imitation, and other contagion effects. That is, while fashion designers see this issue as a real threat to their sales, its magnitude is debatable, as many knockoffs are sold for a much lower price, and so target a market that would not have purchased the original (Raustiala & Sprigman, 2006). This effect

may depend on the manufacturers' abilities to create knockoffs that are similar in terms of look and quality. Industry reports suggest that knockoffs are becoming considerably similar to original designs, to the extent that they confuse even sophisticated shoppers, especially when sold online (Holmes, 2011; Wilson, 2007).

2.3. Overexposure

It is not straightforward to determine to what extent the Anchor Hoodie contributes to its wearer's sense of uniqueness.⁶ Yet if it does, then overexposure to hoodies with an anchor design evenly spread across it, be it original or knockoff, might decrease this sense of uniqueness, and therefore would likely cause some potential adopters to decide not to adopt the anchor design, and some adopters to stop wearing the hoodie.

Consumers' need for uniqueness manifests in our drive to differentiate oneself from others through the acquisition of consumer products, which serve to develop and enhance our social image. The need for uniqueness is recognized as a major driver of consumer behavior in the context of fashion as well as other markets (Berger & Heath, 2007; Chan et al., 2012; Morvinski, Amir, & Muller, 2017; Smaldino, Janssen, Hillis, & Bednar, 2017; Timmor & Katz-Navon, 2008). Studies in this area have investigated the role of uniqueness in increasing certain products' desirability (Berger & Shiv, 2011), moderating consumers' word-of-mouth levels in publicly consumed products (Cheema & Kaikati, 2010), and affecting consumers' preferences on brand visibility (Han, Nunes, & Drèze, 2010).

Thus, overexposure to fashion items that become too popular might very well cause a loss to their users' sense of uniqueness, in turn triggering fewer adopters and potential adopters (Berger & Le Mens, 2009). Indeed, some legal researchers have recognized by that the ubiquity of knockoffs can damage sales of the originals, due to the loss of utility of the original design by some consumers (Hemphill & Suk, 2009; Raustiala & Sprigman, 2012). Yoganarasimhan (2012) demonstrated how these dynamics drive some fashion firms to restrict information on the brand's ubiquity, while other firms make this information highly available. Yet there is no evidence on the magnitude of the effect. Note that while overexposure is also driven by the continuing existence of the original in the market (internal overexposure), when we consider overexposure, we examine the effects of external overexposure, where an increase in the number of users of a knockoff affects the adoption of the original.

The need for uniqueness is not inconsistent with the need for belongingness that is well recognized as a factor of human behavior in general, and brand consumption in particular (Baumeister & Leary, 1995; Stokburger-Sauer, Ratneshwar, & Sen, 2012). Consumers adopting a fashion brand do so (partly) because they wish to be a part of the segment associated with it, even if that segment is small (Han et al., 2010). Yet at the same time, once the number of adopters becomes too large, and passes a certain threshold, the need for uniqueness takes over. Any formal exploration of fashion markets should take the tension between these two factors into account.

2.4. Combined effects of acceleration, substitution, and overexposure

The current findings are ambiguous with respect to a knockoff's overall effect: On the one hand, the size of the user base may drive acceleration of new fashion growth due to increasing social influence. On the other hand, the size of the user base above a certain level may have a negative effect, in that it creates deceleration due to the negative effect of design ubiquity. In addition, substitution may "poach" demand from the original design. In one of the few structured papers on this question, Qian (2014) utilized a Chinese dataset on original design before and after 1995, a time when piracy dramatically increased in China. Utilizing this natural experiment setting, and an OLS regression, coupled with a clever use of instrumental variable to address endogeneity issues, Qian found an overall positive effect of piracy on sales of high-end products, and negative effect on low-end ones; attributing the difference to differing size effect of acceleration and substitution. However, her work did not measure each effect separately as we do here, and neither did it consider the effect of overexposure.

While acceleration and substitution have been studied in the past, and may be easier to quantify, overexposure is an important effect that has been understudied so far. It is also hard to measure: Acceleration could be quantified through the post-hoc calibration of a Bass-type diffusion model; substitution could be studied using simulation and preference elicitation methods such as conjoint analysis; but the impact of overexposure remains elusive, especially as consumers whose choices are impacted might not be fully aware themselves of their own underlying motivations. Thus, the overall effect has not been formally assessed to date, and it is not clear what the dominant factor may be. We next provide the framework that will help us to separate the monetary consequences of the three main effects of design piracy discussed above.

3. Modeling the impact of knockoffs on the growth of fashion items

3.1. The framework

To examine the questions raised above, we move in three phases: First, we present a new product growth model that takes into account the conflicting effects of acceleration and overexposure, and use it to assess their respective effects on the net present value (NPV) of the revenues of an original design facing a knockoff. Second, we gather empirical data to calibrate the model's

⁶ Primp's website advertises the brand as "...designed for the girl who is someone who is carefree, whimsical, feminine, artsy, and sometimes quirky".

parameter distributions. We then use these parameter distributions to run simulations that will help us to study a knockoff's effect on an individual original design.

The use of simulation studies in this case helps in a number of ways: Firstly, due to model complexity, one cannot obtain a closed-form solution, and simulation helps us examine the overall impact as well as the effects of various parameters on the final outcome. In particular, we need to conduct a number of sensitivity analyses to explore “what-if?” scenarios in the basic analysis itself, as well as when examining questions such as the efficacy of a legal protection period. Secondly, while we could follow the growth of 20 products with corresponding knockoffs, their cases represent only a small subset of the possible market conditions. Using a simulation, we can analyze a more extended world in which scenarios can be created from the various parameters that we observed for the 20 cases. The use of a simulation based on a combination of parameters from actual products thus enables us to explore a wide range of scenarios while still using a realistic parameter range. The model is based on the following assumptions:

3.1.1. Timing of the introduction of the knockoff

We assume that the knockoff is introduced at the same time as the original. This is consistent with market reports indicating that knockoffs are often introduced into the market concurrently with or very shortly after original designs (Tan, 2010). We later examine the case of knockoffs introduced after a time lag.

3.1.2. Perception of uniqueness

A fundamental issue relates to how original design adopters and potential adopters are affected by others' use. Here we assume that they are affected both by the number of originals and by the number of knockoffs that they see in the market. While the former is obvious, an explanation is called for the latter.

The owner, who paid for the product, is of course likely to be aware of the source of that product, as s/he could closely inspect it, and determine its originality from the point of purchase and from the price. Yet this is much harder when one needs to assess the originality of an item that another individual uses. Often the interaction between the parties is brief, and occurs from a distance (e.g., walking down the street) rendering the ability to inspect the item closely, and even more so to determine where it was purchased and for how much. This is especially true as pirated items become ever more similar to originals, and consumers find it hard to distinguish between originals and knockoffs (Gentry, Putrevu, & Shultz, 2006; Holmes, 2011).

However, even if some original design buyers identify the pirated design as coming from another manufacturer, it is not evident that this can help much in terms of loss of uniqueness. In fact, even if the original design's owner identifies the source and cares about it, it is not necessarily the case that others can discern it as well. Therefore, we assume that consumers are affected in their quest for uniqueness by a user-base, which includes both the original design and its knockoff.

3.1.3. Sales of the knockoff

While our interest is the original's NPV, we model the growth of both the original and the knockoff while their market potentials differ (which can be attributed to a price difference, as we elaborate presently). We assume that the adopters of the original design may affect the knockoff adopters and vice versa in two contrasting ways: On one hand, the inter-market interactions will increase the positive social influence through the number of perceived consumers, thus accelerating adoption. On the other hand, this reciprocal effect will cause more current and potential adopters of the original design to disadopt the product due to their loss of uniqueness.

3.2. The model

3.2.1. Three populations to follow

Consider Fig. 4 below, which defines the following three segments of interest for the original design as well as the knockoff: Current Users - those who adopted the fashion item and still use it; Disadopters - those who adopted, yet stopped using, wearing, or displaying it due to extensive adoption by others; and Avoiders - those who have not yet adopted, and will not adopt the design due to extensive adoption by others. Formally, at each point in time t we consider the following three segments for the design broken down to the original design ($i = o$) and the knockoff ($i = k$): x_{it} - the number of current users; y_{it} - the cumulative number of disadopters; and z_{it} - the cumulative number of avoiders.



Fig. 4. Fashion diffusion framework flow chart.

3.2.2. Individual threshold

The negative effect of others is modeled via a uniqueness threshold model, where each individual has a threshold for the number of product users s/he is willing to tolerate before avoiding or disadopting the product. In the context of product use, while threshold models have largely been used to model adoption dynamics (Goldenberg, Libai, & Muller, 2010; Granovetter, 1978; Valente, 1995), they can be also used to describe attrition processes (Granovetter & Soong, 1986). Let the current fraction of adopters be x/M , where x is the number of adopters, and M is the market potential. If H is the uniqueness threshold level with a given distribution in the population, then the effective market potential for rejections at time t , i.e., the total number of those in the market segment whose threshold has been surpassed is given by $M \cdot \text{prob}(H \leq x/M)$. When there are multiple segments, the analysis becomes more intricate, as we presently show.

It becomes clear now why disadopters are central to the process: Indeed, their direct effect is not economically important, as they had already generated revenue to the firm. This, however, does not take into account their indirect effect in that they reduce the number of current users, the latter which are central to the diffusion process in two ways: Firstly, they add to the word-of-mouth and other contagion effects, and secondly, they enter the individual threshold level directly, thereby influencing future adopters and avoiders.

The collective action literature, where threshold models have been extensively used, has largely assumed thresholds with normal distributions (Macy, 1991; Valente, 1995; Yin, 1998), which are actually truncated normal, as negative thresholds are assumed to be zero (Granovetter & Soong, 1986). We follow this literature and assume that H follows a truncated normal distribution with mean μ and a standard deviation of σ , i.e., $H \sim N(\mu, \sigma^2)$.⁷ Notice that the individual threshold is fixed and not a function of the number of adopters. While this might not be an innocuous assumption, it is the prevalent one for thresholds in this context (Macy, 1991; Valente, 1995).

3.2.3. Disadopters and avoiders

Let M_{it} be the market potential for the original ($i = o$) and the knockoff ($i = k$). We will address the exact specification of these market potentials shortly. To calculate the number of consumers who have passed their own threshold at time t , we need to take all consumers whose uniqueness threshold (M_{it} multiplied by the probability of passing the threshold) has been passed, and subtract from this all consumers who have already disadopted or avoided the fashion, i.e., y_{it} and z_{it} , to obtain the following equation ($i = o, k$ for the original and knockoff fashion item respectively):

$$d(y_{it} + z_{it})/dt = M_{it} \cdot \text{prob}(H \leq (x_{ot} + x_{kt})/M) - y_{it} - z_{it} \quad (1)$$

We divide the number of adopters by M and not by M_{it} , as consumers care about the design as a whole and not of the adoption of an item (original or knockoff). As the markets interact, each consumer observes the sum of adopters $x_{ot} + x_{kt}$, i.e., the adoptions of the design, when considering attrition.

3.2.4. Separating disadopters and avoiders

While Eq. (1) describes the change in overall rejections, as we wish to evaluate the change in each population separately, we need to find a way to decouple the two. For this reason, we examine the threshold distribution between the current user population and the potential consumer population. As the individual threshold is independent of the adoption probability, the adoption process acts like a process of sampling from a population with a conditional uniqueness threshold distribution. Thus, the proportion of users whose uniqueness threshold has been passed, and the proportion of individuals in the remaining market potential whose uniqueness threshold has been passed, will converge to the same mean, that is:

$$E(\text{ratio}_{it}) = \frac{dy_{it}/dt}{x_{it}} = \frac{dz_{it}/dt}{M_{it} - x_{it} - y_{it} - z_{it}} \quad (2)$$

with standard deviations depending on the sizes of the two populations. Substituting from Eq. (1), the number of disadopters in each time period t is given by:

$$dy_{it}/dt = \frac{M_{it} \cdot \text{prob}(H \leq (x_{ot} + x_{kt})/M) - y_{it} - z_{it}}{M_{it} - y_{it} - z_{it}} \cdot x_{it} \quad (3)$$

3.2.5. Current users

The next phase needed for the model is to find the change in the number of users (x_{it}). Following the diffusion modeling paradigm, we view adoption as a growth process with diffusion parameters p (representing external influence such as advertising), q (internal influence such as word of mouth), and long-range market potential (Peres, Muller, & Mahajan, 2010). However, in each time period t , the current remaining market potential is the share of the market that did not adopt, or avoids the item. The adoption pattern captures the change in the number of users and the change in the number of disadopters in each time period t , and to separate the two, we need to subtract the change in disadoptions from the number of new adoptions:

$$dx_{it}/dt = (p + q \cdot (x_{ot} + x_{kt})/M) \cdot (M_{it} - x_{it} - y_{it} - z_{it}) - dy_{it}/dt \quad (4)$$

⁷ For robustness purposes, we also considered a beta distribution and found that it does not change the substantive results presented in what follows.

Hence, word-of-mouth communication is assumed to occur between adopters (captured by $x_{ot} + x_{kt}$) and consumers who have not yet adopted, have disadopted, or have avoided the fashion within each market segment. Note that when $\mu = 1$ and $\sigma = 0$, no one abandons the fashion, and the model reduces to the classic Bass diffusion model.

3.2.6. The market equations

The total market potential for the design (original and knockoff) is denoted by M . If α is the share of potential knockoff adopters in M , then the market potential for the knockoff (k) and the original (o), are given by $M_k = \alpha M$ and $M_o = (1 - \alpha)M$.

However, the effective market potential of the original fashion design at period t (M_{ot}) must take into account the substitution effect. Hence, we define the share of the knockoff potential market that would have purchased the original if knockoffs had not been available as β . The larger β , the smaller the actual market potential that the original firm faces. We multiply this factor by the number of people that have already adopted the knockoff ($x_{kt} + y_{kt}$) to adjust the effective market potential (where o and k denote the original and knockoff fashion item):

$$M_{ot} = (1 - \alpha) \cdot M - \beta \cdot (x_{kt} + y_{kt}) \quad (5)$$

There can be a difference between the substitution factor β , and the eventual effect of substitution on NPV, as the former represents the potential loss due to substitution, or the share of the market potential that the original potentially loses to those who instead buy the knockoff. The latter is largely based on β , yet takes into account the consequences of the overexposure and acceleration effects (e.g., some of the lost potential adopters may not have adopted anyhow due to overexposure effect). Therefore, the substitution parameter and the substitution effect will not necessarily be the same.

3.3. Operationalization of the main factors

Our interest here is not only in the overall effect, but also in its breakdown into the three factors described above, i.e., acceleration, substitution, and overexposure. Note that what we described in the model is a complex system where adopters and potential adopters affect each other via word of mouth, imitation, and other contagion mechanisms, as well as collectively via the individual threshold level. Thus, when trying to measure the effect of changing a parameter that results in a single consumer not adopting the product, this individual no longer generates word of mouth about the product, and is not counted in the threshold levels of the adopters. This local change causes a shock to the system, and therefore has implications for the information flow through the entire system. As a result of that consumer's influence, some people may purchase the product at a different time, and some who would not otherwise have purchased the product may adopt it. These effects will translate into a change in profits due to this single parameter change.

Moreover, this system has an inherent nonlinear element. To see it, consider a threshold normal distribution with a high mean and a low variance. An additional user(s) (who might have adopted because of a small change in any of the parameters), having a threshold level at or near the inflection point, will have a large positive effect on the threshold level, and thus fewer potential adopters will become users, while more will become avoiders and disadopters. Thus, to measure the effect, we form several scenarios and measure the difference among them. Therefore, we examine the following five scenarios that enable us to isolate the respective effect of each on the original design's NPV:

- Scenario A: The basic fashion model with no knockoffs. We completely removed knockoffs and their effects by setting α (the share of potential knockoff adopters) to zero.
- Scenario B: Full model: All effects described in Eqs. (1)–(5). The case of a knockoff where acceleration, substitution, and overexposure occur.
- Scenario C: Overexposure + acceleration: In this model, we remove the substitution effect by setting β (the substitution parameter) to zero.
- Scenario D: Acceleration alone: In this scenario, every segment considers its segment only when disadopting or avoiding the design, while considering both segments when adopting. This way, the only effect one segment has on the other is to accelerate sales.
- Scenario E: Substitution alone: In this scenario, we use Eqs. (1)–(5) with one change: Each segment (original and knockoff adopters) considers only its segment (the level of x_{it}) when considering attrition or adoption.

With these scenarios, we are now in the position to define the three main factors described above, i.e., acceleration, substitution, and overexposure.

- Acceleration effect = (Scenario D – Scenario A) / Scenario A
- Substitution effect = (Scenario E – Scenario A) / Scenario A
- Overexposure effect = (Scenario C – Scenario D) / Scenario A

We also computed an interaction effect of the three main effects, defined as the difference between the overall effect ((Scenario B – Scenario A) / Scenario A) plus the sum of the three effects (acceleration effect + substitution effect + overexposure effect), yet found it to be small with a median (and mean) of less than 1%. As it does not affect the substantive results that we describe next, we focus on the results for the three main effects and the overall effect.

4. Empirical parameter calibration

Our next task is to calibrate the model parameters to help us create the parameter distributions used in the simulation. To this end, we use three sources of information: Fashion growth data on original designs, online data on price differences between originals and knockoffs, and industry statistics on the extent of knockoffs.

4.1. The selection process of the fashion items

We were able to follow the growth of a number of original fashion designs with the help of a dataset of a major US online retailer as follows: In the first phase, we aimed to find original fashion designs that face a knockoff. Online search helped us to identify fashion blogs dedicated to matching original designs and their knockoff counterparts. In order to avoid bias originating from our perceptions of fashion, we turned to leading fashion blogs dedicated to matching original designs and their knockoff counterparts. Such blogs were found using Google's image search function, looking for images that match the search phrases "Cheap vs. Steep", "Real vs. Steal", and similar phrases. To add an item to our list, we required a photo comparing the two items and their respective prices. We gathered the names and price levels of 300 pairs of original-knockoff design items.

In the second phase, we searched for sales data for these design items using the dataset of the online retailer that is one of the largest traders in the U.S., where designer clothing and fashion in general, are among its most prominent categories. We construct the growth of some of the items on our list. This demanded very large-scale data analysis, going through hundreds of millions of transaction particulars, to identify the relevant brands we were looking for as parts of the transactions. We restricted the cases as follows:

First, we looked only for the monthly transactions of the new originals over time. The reason we did not look for knockoffs in the dataset is that knockoffs may appear under differing listing titles and as part of the collection (e.g., of chains such as Forever 21), and not necessarily in a design-identifiable form. Thus, while one can expect originals to be frequently sold on the website of this retailer on a regular basis, much cheaper knockoffs may not be as ubiquitous.

Second, we only considered data for sales transacted in the US and only to US citizens, in order to minimize geographical, cultural and regulatory biases.

Third, we looked only for original designs that had a minimum substantive sales data in our database. We looked for specific items, and thus obtaining continuous sales data over time in sufficient numbers was not straightforward. In particular, we looked for items that survived at least 4 years (48 months) of continuous data points, sales having already reached a first peak, selling more than 10 items per month on average. Similarly, we also avoided data with strong seasonality effects such as boots, coats, or swimsuits.

This selection process has an impact on the types of products analyzed: The fashion world has been traditionally divided into fads that stay only a few weeks, fashion products that last for a few years, and classics that may stay for a very long time (Sproles, 1981). Our data focuses on the second group (and possibly the third), and thus does not capture the dynamics of fast-fashion products that would not last more than a season or two, which somewhat limits the generalizability of our results. We further discuss the difference between fast and slow growth products in the Discussion section, yet a few issues should be noted in this regard.

- Not all designs are pirated: It is reasonable to assume that pirated products are those that are expected to be more successful and established, and stay longer in the market.
- Much of the fashion market (and our data) is bought online. In the online world, even if a product has long passed peak sales, purchases are still made, as there is no rush to take it off the shelf. Thus, the fact that our designs lasted 48 months does not imply long-range substantial demand. For about a third of our products demand peaked at 14 months or less (see Table 1).
- We show in Appendix A that when analyzing several products that lasted less than 48 months, our results did not change substantially.

Following this selection process, we were left with sales data on 20 fashion items out of our initial list – 11 clothing items, 2 footwear items, and 7 handbags – whose data we used to create the parameter distributions range using our fashion growth model (see the first column of Table 1, and an example of three pairs of originals/knockoffs designs in Fig. B1, Appendix B).

4.2. The magnitude of the price markup

The items we gathered represent a wide range of prices, and in particular, relative price differences between the original and the knockoff. For each individual fashion item in our list, we define the price markup ratio as the price of the original divided by the price of the knockoff. We observed two classes of items: handbags, with an average price markup ratio of 40.5; and apparel (clothing and footwear), which had a price markup ratio of about 5 on average (5.1 for footwear, and 5.03 for clothing). This is reflected also in differences in the absolute prices of the originals we examined: \$2191 for handbags, and \$224 for apparel. We incorporated the price markup ratio into our model by looking at the differential effects between apparel and handbags in two ways:

Firstly, the price markup between the original and the knockoff can help determine the extent of substitution, following the framework in Staake and Fleisch (2008). The idea is that the larger the relative price difference between the original and the knockoff, the less the knockoff can serve as a substitute for the more costly original. Based on experimental research, Staake

Table 1
Estimation results for the fashion items, by class.^a

	Time (months)	Time to reach sales peak (months)	External effect (p)	Internal effect (q)	Threshold mean (μ)	Threshold standard deviation (σ)	RSE
Fashion item - handbags							
Chloe Betty	83	5	0.0013	0.698	0.0048	0.01240	5.3
Chloe Paddington	95	14	0.0006	0.932	0.0087	0.03101	56.1
Fendi Spy	93	7	0.0058	0.303	0.1367	0.09570	96.3
Hermes Birkin	132	47	0.0009	0.058	0.1685	0.00538	19.1
Luella Gisele	111	17	0.0012	0.250	0.1854	0.04347	6.7
Marc Jacobs Stam	87	6	0.0029	0.232	0.0308	0.01046	37.8
Yves Saint Laurent Muse	87	7	0.0006	0.074	0.0177	0.00752	16.3
Average	98	15	0.0019	0.364	0.0790	0.0294	33.9
Fashion item – apparel							
BCBG Cotton Poplin Dress	115	63	0.00002	0.116	0.1942	0.0807	23.1
Black Halo Ruffle Dress	63	31	0.00285	0.081	0.2649	0.0047	5.9
Christian Louboutin Decollete (shoe)	84	24	0.00034	0.140	0.0104	0.0204	8.5
Citizens of Humanity Jeans	114	19	0.00016	0.137	0.0009	0.0117	484.3
Current Elliot Love Jeans	50	9	0.00088	0.258	0.0131	0.0145	8.5
Dr. Martens 1460 (shoe)	132	25	0.00016	0.001	0.9126	0.0740	90.7
DVF Wrap Dress	132	58	0.00001	0.159	0.0021	0.0121	115.6
Ed Hardy Tee	93	45	0.00010	0.138	0.2549	0.0888	276.3
J. Crew Eliza Cami	79	27	0.00008	0.569	0.0047	0.0516	15.1
Juicy Couture Terry Hoodie	130	30	0.00019	0.167	0.0299	0.0372	110.4
Primp Anchor Hoodie	86	12	0.00016	0.957	0.0377	0.0534	14.7
Seven For All Mankind Dojo Denim	119	31	0.00006	0.117	0.00005	0.0130	162.8
So Low Foldover Pants	99	42	0.00278	0.028	0.2495	0.0056	9.1
Average	100	32	0.00060	0.221	0.1519	0.0360	101.9

^a Since the number of observations differs between items, we state it in the Time column for each item.

and Fleisch (2008, p. 130) suggested that the substitution factor can be expressed as the inverse of the price markup factor. In the case of the products we studied, this means an average substitution factor $\beta = 0.025$ for handbags (i.e., 2.5% of the handbag knockoff's potential adopters would have purchased the original had a knockoff not been available); and $\beta = 0.198$ for apparel.

Secondly, we used the price markup ratio to assess the market share of potential knockoff buyers α . We were aided by industry data under which the US sales of pirated designs are estimated as accounting for 5% of monetary sales of the US fashion market (Ellis, 2010). Given this share, we can calculate the unit share of pirated design for a given item with a price markup ratio level using this simple conversion: Knockoff Market share = $(5\% * \text{price markup ratio}) / (95\% + 5\% * \text{price markup ratio})$. Given the price markup ratio, we can assess the average knockoff share of handbags at 68%, and 21% for apparel. This means that of every 100 fashion handbags sold, 68 are knockoffs; and for 100 apparels item sold, 21 are knockoffs. Given the large differences in prices as reflected in the price markup ratio measure between these product classes and the consequent implications for the parameters, we conduct the analysis separately on these two classes: handbags and apparel.

4.3. Parameters for the fashion items

In order to develop the range for the simulated model, we estimated the parameters of the fashion growth model, using Eqs. (1)–(5). We use these equations to express Eq. (4) just as a function of x , y , and z , and therefore the variables y and z were treated as latent variables whose changes over time follow Eqs. (1) and (3). To estimate a design's parameters, we apply the simulated annealing method, which allows for efficient optimization in a case where the estimated function has multiple local extrema. We applied this method using the GenSA package in R (Brusco, Cradit, & Stahl, 2002; Xiang, Gubian, Suomela, & Hoeng, 2013), selecting the parameter set that minimizes the sum of square error (SSQ). We report the results in Table 1. For a fashion design that belongs to the apparel class, we set the external parameters, $\alpha = 0.21$ and $\beta = 0.198$, and $\alpha = 0.68$ and $\beta = 0.025$ for handbag class.

We next ran simulations to estimate the effect of knockoffs on the original's NPV. The time horizon used was 132 months (periods), the maximum number of periods in our dataset. To translate the temporal adoptions into NPV, we assumed an annual discount rate of 10% (0.8% monthly rate), and one unit of revenue for each item upon adoption.

We evaluated the mean and covariance of p , q , μ , and σ to create a multivariate normal distribution of the parameters. We then took a random draw of 10,000 parameter sets from the parameter distribution for each product class. The parameter sets drawn from the multivariate distribution were limited to be within the parameter ranges described in Table 2. To obtain a range of α and β , we draw a random value in the range of the class mean, plus or minus 20% (i.e., if handbag average α is 0.68, the range would be between 0.544 and 0.816). For each parameter set we estimated the NPV of the growth patterns across the five scenarios, and then compared the NPV obtained at the end of the growth horizon. In Table 2, we report the resulting parameter range used to explore the monetary consequences of the introduction of a knockoff.

Table 2Parameter ranges for the simulation process.^a

	Parameter range handbags	Parameter range apparel
External effect (p)	0.0006–0.0058	0.000014–0.0029
Internal effect (q)	0.058–0.932	0.001–0.957
Threshold mean (μ)	0.0048–0.1854	0.00005–0.9126
Threshold standard deviation (σ)	0.0054–0.0957	0.0047–0.0888
Share of potential knockoff adopters (α)	0.544–0.816	0.168–0.252
Substitution factor (β)	0.02–0.03	0.158–0.238

^a Market size (M) is fixed at 10,000; time horizon (T) at 132 periods; and monthly discount rate is 0.8%.

5. Simulation results: knockoffs' effects on NPV

We next present the simulation results regarding the knockoff phenomenon. While the simulation framework strength is apparent for this complex, non-linear case, one should also consider the drawbacks, and in particular the dependency of the results on the range of parameters used. Note that here we use the calibrated parameters as boundaries to the simulations. We do not simulate based on one or a few items, but rather ask about possible scenarios in the range of parameters of what we see in practice. Table 3 presents the results of the three main effects – acceleration, substitution, and overexposure – as well their combined effect on the original's NPV in percentage of change. We discuss here the results in terms of the mean, and provide a confidence interval for the mean. In Web Appendix A, we provide the full density plots of the effects. Similar to the distribution of the real data, the distribution of time-to-peak of the simulations is left skewed, with an average of 9.6 (SD = 3.9) months in handbags and 26 (SD = 19.9) months in apparel (see Web Appendix B for the histograms of the time-to-peak distribution and the relationship between time-to-peak and the effects).

Looking at the mean effect on the NPV, the smallest effect is the negative impact of substitution, followed by the positive effect of acceleration, and the strongest effect is the negative effect of overexposure. The overall effect we observe is negative. On average across the two classes, the knockoff creates a 22.7% negative effect on the original's NPV. Though the results are consistent across the two classes, we do see a considerable difference in the effect size: For handbags, we see that the overall effect is stronger, with an average effect of –36.5%, versus –8.9% for apparel. In the case of handbags, the acceleration effect is higher than that of apparel, yet the overexposure effect jumps from –13.6% for apparel to –54.5% for handbags, thus driving the overall effect.

One might ask which of the parameters contributed the most to the effect. We apply the ω^2 index that measures the relative importance of factors, based on the results of an ANOVA (Green, 1973). ω^2 is calculated according to Eq. (6):

$$\hat{\omega}^2 = \frac{SS_{parameter} - df_{parameter} \cdot MS_{error}}{MS_{error} + SS_{Total}} \quad (6)$$

From Table 3, we can see that the share of potential knockoff adopters (α) has a substantive impact on the effects in handbags (which carries over to the overall calculation), but as the effects of acceleration and overexposure work against each other (as can be seen from their counterbalancing parameters), its influence on the overall effect is small. The internal and external effects (p and q respectively) tend to be more important on the overall effect, as they accelerate the overall rate of adoption.

Table 3Simulation results: The effects and importance of various factors on NPV.^a

	Mean	Mean confidence interval ^a		Relative importance of the parameter (ω^2)					
		Lower	Upper	p	q	μ	σ	α	β
Handbags									
Substitution	–1.7%	–1.7%	–1.6%	0.01	–	0.29	0.01	0.41	0.05
Acceleration	19.2%	18.9%	19.5%	0.04	0.28	–	0.02	0.21	–
Overexposure	–54.5%	–54.7%	–54.2%	0.14	0.10	0.05	0.04	0.55	–
Overall effect	–36.5%	–36.6%	–36.3%	0.04	0.14	0.03	0.21	0.15	–
Apparel									
Substitution	–3.0%	–3.1%	–3.0%	0.01	0.44	–	–	0.04	0.02
Acceleration	6.4%	6.2%	6.6%	0.05	0.28	0.01	0.01	0.01	–
Overexposure	–13.6%	–13.7%	–13.4%	–	–	0.25	0.02	0.06	–
Overall effect	–8.9%	–9.1%	–8.7%	0.04	0.28	0.03	0.03	0.01	–

$N = 10,000$ for each class; p and q are the external and internal effects; μ and σ are the threshold mean and standard deviation, α is the share of knockoff adopters, β is the substitution parameter; the index ω^2 follows Eq. (6).

^a Mean confidence interval is calculated by $\pm 1.96 \cdot SE$ (Standard Error).

Table 4

The parameters' effects on acceleration and overexposure.

	Overall effect	Overexposure	Acceleration
Handbags			
External effect (p)	-0.315	0.195	-0.386
Internal effect (q)	-0.601	0.266	-0.630
Threshold mean (μ)	-0.084	0.107	-0.137
Threshold standard deviation (σ)	0.733	0.309	0.214
Share of potential knockoff adopters (α)	-0.387	-0.739	0.453
Substitution factor (β)	-0.021*	-0.003 (NS)	-0.002 (NS)
Adjusted R ²	57%	87%	55%
Apparel			
External effect (p)	-0.189	0.028*	-0.218
Internal effect (q)	-0.540	0.042	-0.583
Threshold mean (μ)	0.079	0.438	-0.166
Threshold standard deviation (σ)	0.204	0.161	0.134
Share of potential knockoff adopters (α)	-0.097	-0.243	0.091
Substitution factor (β)	-0.017 (NS)	0.003 (NS)	0.002 (NS)
Adjusted R ²	38%	33%	36%

Parameters are standardized, and all are significant at p -value < .001, except those marked with * (p -value < .01), and NS (non-significant); $N = 10,000$.

While the average overall effect is negative, it is not negative in all cases, with an extent that differs across classes. According to our calculations, a small fraction of handbags actually benefits from knockoffs (0.3%), and the percentage increases to 9.1% for the apparel class. Certainly, we cannot say categorically that a knockoff always creates a negative effect.

Result 1. Taking into account acceleration, substitution, and overexposure, the expected overall effect of the introduction of a knockoff is a reduction in the NPV of the original design. Yet the extent of this reduction can considerably vary across product classes.

Result 2. Among the three effects – acceleration, substitution, and overexposure – the (negative) effect of overexposure on the NPV of the original is the strongest on average, followed by (positive) acceleration effect, and then a small (negative) substitution effect.

5.1. Are the dynamics consistent across product classes?

We have observed that the overall effect of a knockoff differs between handbags and apparel. One might ask if this difference is manifested in terms of the effect size only, or if the fundamental dynamics differ between the two classes. We tested the parameters' effects on acceleration and overexposure, which are the dependent variables in the linear regressions whose results are presented in Table 4. The independent variables represent three effects: the speed of diffusion (internal influence q and external influence p); the uniqueness threshold parameters (mean μ and standard deviation σ); and the parameters that represent the extent of the knockoff phenomenon (share of potential knockoff adopters α and the substitution factor β). To enable a direct comparison between the parameters, we report the standardized parameters. As the overall effect of a knockoff is the effect on the NPV of the original, a negative parameter sign indicates greater damage.

First, we see a difference in the parameters between the product classes. Using a two-sample Hotelling's t^2 test, we see that the difference between the set of parameters is significant (a t -test between each pair of parameters was also significant). Yet across the three regressions, the signs are similar between classes, as the fundamental effects appear consistent.

Second, we observe that the faster the diffusion of the item (larger p and q) the smaller the acceleration effect of the knockoff, i.e., the knockoff is less helpful to originals that diffuse rapidly on their own. This is also the direction of influence on the overall effect, so that faster-growing products with shorter life cycles are damaged more by knockoffs, i.e., they suffer from overexposure, yet do not enjoy the acceleration.

Third, a higher uniqueness threshold mean brings about lower overexposure damage, as a higher threshold implies that the average user requires a greater number of other users to adopt the same fashion item in order for him or her to disadopt. Thus, a higher threshold indicates that users care less about others' adoption, and consequently the damage from the specific knockoff is lower.

Another intriguing finding is that the effect of the standard deviation in overexposure is positive, i.e., that distributions with larger variance lead to a smaller overexposure effect. This result is driven by the nonlinearity of the exposure effect. In Fig. 5, we plot the relative change of the effects over time, and we see that the overexposure effect is very small in the early periods, when there are not a lot of adopters, but later overexposure takes off rapidly. Increasing the standard deviation means that we add to the overexposure effect at the start (where it matters less) and spread the threshold later, when the overexposure effect is more sensitive to adoption. The exact opposite dynamic holds for acceleration, as it is faster at the start and slower later on in the product lifecycle. Thus, both parameters are positive.⁸

⁸ The acceleration effect is mostly positive, thus positive parameters are associated with an increase in the effect, while the overexposure and overall effects are mostly negative, thus positive parameters are associated with a decrease in the effect.

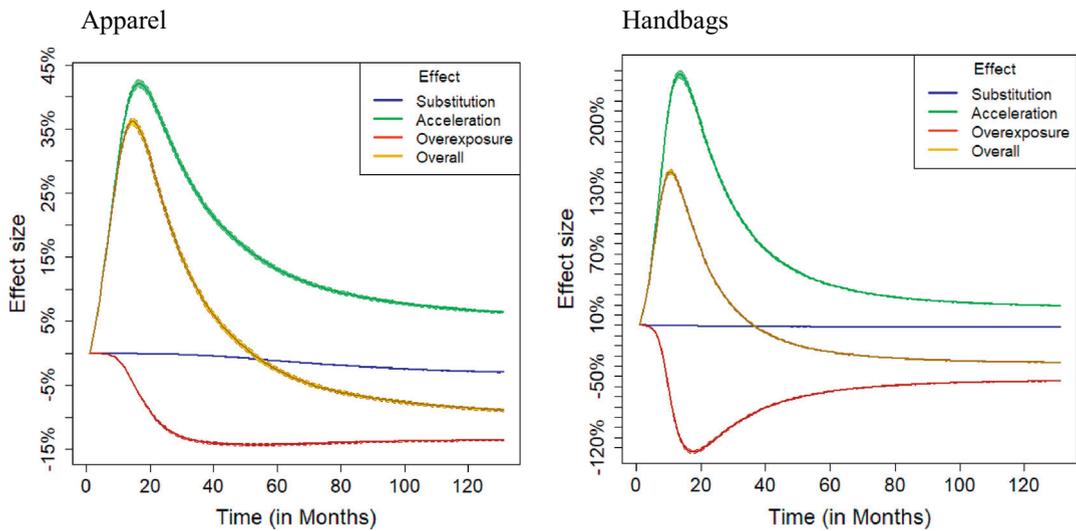


Fig. 5. Dynamics of the relative size effect.

The last issue is that there is the negative effect of the share of potential knockoff adopters (α) on the overall effect in both classes. This is quite reasonable, as the more consumers are able to adopt knockoffs, the worse it is for the original design. The substitution factor (β) is not significant, as both originals and knockoffs affect the threshold. Increasing one at the expense of the other should not affect the results.

5.2. The dynamics of the effects over time

In the analysis above, we find that overexposure and acceleration are important in understanding the impact of knockoffs on the NPV of the original. Both effects are substantial and drive the NPV in the opposite direction. Acceleration benefits the original design, while overexposure harms it. However, it is still not clear how these effects develop over time. To understand this, we examine how each effect's levels over time developed in our simulations across 132 periods. In Fig. 5 we plot the effects' relative sizes over time.

From Fig. 5, we can see that the effects vary dramatically across time. In the beginning, when NPV is still low, the acceleration effects represent a substantial part of the NPV, accelerating the adoption process for both the original and knockoff, but rapidly declining later. The overexposure effect takes longer, as it depends on the adoption levels passing the disadoption threshold. In the long run it is stronger than the acceleration effect, which peaks at Period 17 for apparel and Period 13 for handbags; and as overexposure already kicked in before that, the overall effect peaks after 15 periods for apparel and 11 periods for handbags (where the overexposure effect takes off faster). This means that on average, the product benefits from the existence of knockoffs in the first year, but after that, the negative impact of overexposure starts to outweigh the benefits of acceleration. We also see that substitution does not change much across the entire period. These findings are summarized as follows.

Result 3. The effects of knockoffs on the NPV of an original design change over time. Initially, the original may benefit from the existence of a knockoff due to acceleration. Later on, as the number of adopters continues to rise, overexposure becomes the strongest effect overall, leading to an overall negative impact on the NPV.

5.3. The effect of a time lag in the introduction of the knockoff

Unlike the US, the European Union has some limited legal protection for fashion designs. The European Community Design Protection Regulation (DPR), which went into effect in 2002, extends fashion designs a legal protection period of three years, which can be extended for registered designs. Fashion industry advocates in the US have lobbied for similar protection: For example, the Innovative Design Protection and Piracy Prevention Act (IDPPA), introduced to the US Senate in 2010, was intended to provide legal protection to the US fashion industry consistent with the system currently in place in the EU (Hackett, 2012; Schutte, 2011).

What would be the impact of a legal protection period on the overall monetary effect of a knockoff? To examine this issue, we re-ran the above simulations using the same ranges of parameters, this time looking at cases in which the knockoff enters the market after the original. We ran 59 sets of simulations, and for each successive set, added one month to the time lag between the introduction of the original and that of the knockoff, such that the maximum time lag was 60 months.

Looking at the percentage reduction in the original's NPV in the presence of a knockoff as a function of the protection period's duration, the following picture emerges (see also Fig. 6): A short protection period does not necessarily help the original: In the first year after launch, the protection period might even cause slight damage to the original's NPV (up to 1% on average in our

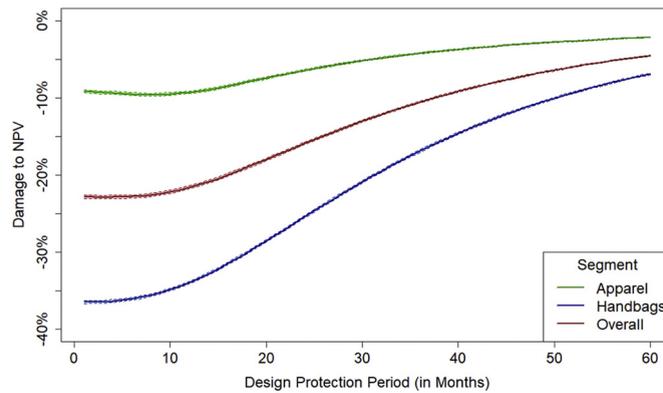


Fig. 6. Impact of protection period on NPV.

simulations), as we observe in the case of apparel. This negative short-term effect occurs because in the first year, acceleration grows faster than the negative effects of overexposure, as we observed in [Result 2](#) and [Fig. 5](#).

Thus, early on, the entry of a knockoff may affect the original positively (acceleration) more than negatively (overexposure). In apparel, where diffusion speed is slow to begin with (lower p and q), knockoffs' damage to acceleration is especially strong, and in fact in the first year, overwhelms that of overexposure. Yet as the lag time lengthens, the power of overexposure begins to dominate, and the damages from overexposure outweigh the benefits from acceleration.

One may want to use caution in the interpretation of our simulations at this stage, as the parameter estimates we use may not be policy invariant: Changing the legal situation has the potential to change firms' strategies and market dynamics. Still, we can say based on the current situation, and using the parameter range we examined, that for a time lag of three years – the current duration of legal protection in the EU – knockoff damage to the original's NPV is certainly reduced, yet most of it still exists (see [Fig. 6](#)).

Result 4. The effect of a time lag (legally mandated postponement) on the introduction of a knockoff is non-monotonic for short lag, and monotonic for longer lags: A short time lag may not affect the NPV of the original, and in fact may even damage it. For the ranges we analyzed, the positive effect of the protection period is observed primarily for time lags of over one year.

In [Fig. 6](#), we demonstrate what happens to the overall effect of knockoffs if a design protection period is introduced into the market. Below we further explore this dynamic using the parameters of a single fashion item, the Primp Anchor Hoodie. The parameters are: $p = .00016$, $q = 0.957$, $\mu = 0.0377$, $\sigma = 0.0534$, $\alpha = 0.21$, $\beta = 0.198$. [Fig. 7](#) depicts the dynamics of the three effects (substitution, acceleration, and overexposure) when design protection lags (from 1 month to 60 months) are introduced in the market.

While the resultant graph is somewhat noisy, as expected, the effect remains the same: It appears that after two years, most of the damage is alleviated, and after three years it is almost gone. We observe that acceleration's positive effects occur mostly in the first year, declining with each passing month.

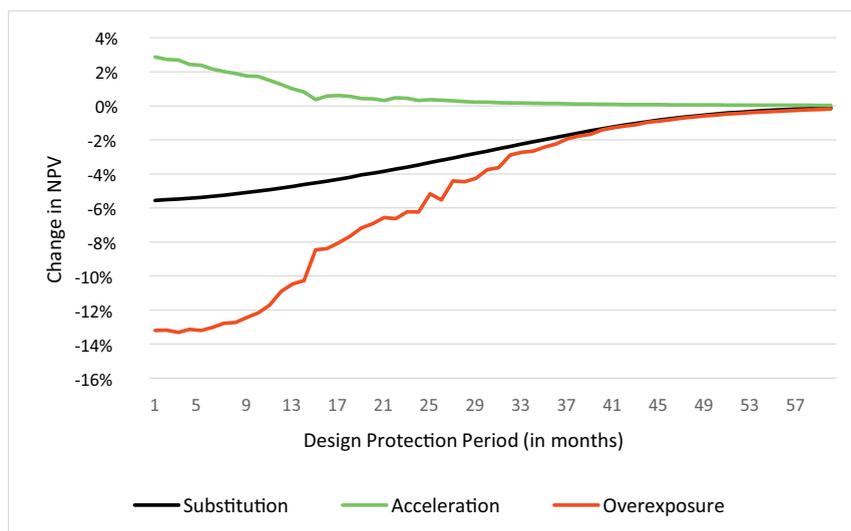


Fig. 7. Effects of a lag in knockoff introduction on NPV of Primp Anchor Hoodie.

5.4. Robustness and sensitivity tests

We conducted a number of robustness checks to further test whether the basic results for the overall influence of the three effects of knockoff on the NPV of an original design, and in particular the dominance of overexposure, hold when changing the basic assumptions of the model. We examine the results' sensitivities to changes in the price markup between the original design and the knockoffs (as captured by the α and β parameters); the results' sensitivities in a homogeneous threshold scenario (setting $\sigma = 0$); and when using a beta distribution rather than normal distribution when modeling the threshold. As can be seen in Web Appendix C, the results are largely robust with respect to the changes we examined.

5.5. Endogeneity issues

As in many empirical works, the data we use might have been affected by unobserved variables. These might include seasonality effects such as clothing for winter or summer; advertising campaigns, fashion shows and celebrity endorsement that might affect sales; and lifecycle and collection effects such as replacement by an updated version of the product and competition from other designs introduced by the same or other brands. Moreover, in the simulations we did not take into account the fact that the data already contain strategic decisions by the firm when it faces knockoffs in terms of price, distribution channels, and even design. In particular, we may encounter some survival bias. Some fashion brands will not make it to the market due to expected design piracy, while others will make it, yet will survive for a short time because a knockoff. Because we require a minimal stay in the market, we may miss such cases. Clearly, better and richer data that includes managerial decision making will help to account for more of these effects.

While this endogeneity-related concern is relevant for any paper that empirically examines competitive product growth and the managerial implications of different market actions, we believe that the simulation framework we formulated mitigates some of the problem. The issue would be of more concern if we focused on the specific case of one of a few brands. The fact that we use the empirical data largely to build the envelope for the simulation, and that we use a large number of scenarios within this possible range, may help to mitigate the biased effect of the specific case of one brand or another. As we later show in Table 5, looking at sub segments of the simulation we ran, we indeed see a consistency in our results across product types, including products that peak early on, where most sales happen in the first year.

6. Discussion

There are two aspects to our analysis: On the theoretical side, we highlight the need to introduce overexposure to the discussion on design piracy, and on brand competition in the presence of negative externalities, such the case of fashions. We show how to model the profits that are created in this complex growth situation, and highlight the sizeable role of overexposure and the dynamics that emerge in such situation: When a knockoff competes with an original, early on it may contribute to the original via acceleration, yet as time passes, overexposure's negative effect will begin to dominate. We further show how the fundamental results of the paper change under various market situations and segments.

Our second aim is to contribute to the ongoing debate on legal aspects of design piracy. Here we use simulations to provide insights within the range of products we have. We find that for the type of products we analyze, the introduction of fashion knockoffs has a largely negative effect on original designs: The positive effect of acceleration is not enough to offset the overexposure damage created by the knockoff. This result contradicts industry observers who often refer to substitution, rather than overexposure, when considering the monetary damage created by knockoffs. The public discussion of the damage of knockoffs is conducted facing heated debate on the need to restrict knockoffs by mandating a time lag during which knockoffs are prohibited from entering the market, as is the case in the EU. What we found is that a short period (up to about one year in our data) will not be of much help to the original, and may even harm it, as the early period is when the original enjoys the acceleration, which is particularly important for products that otherwise diffuse slowly.

Table 5

The effects of speed of diffusion, sensitivity to overexposure, and price differential on NPV.

Speed of diffusion	High				Low				Overall
	Sensitivity to overexposure		Price differential: original/knockoff		Sensitivity to overexposure		Price differential: original/knockoff		Average
Market #	High	Low	High	Low	High	Low	High	Low	Effect
	1	2	3	4	5	6	7	8	
Market potential reached at end of year one	73%	72%	46%	45%	55%	54%	2%	2%	44%
Substitution	-1%	-3%	-5%	-5%	0%	0%	-5%	-1%	-2%
Acceleration	26%	7%	12%	0%	64%	14%	83%	6%	27%
Overexposure	-55%	-15%	-37%	-10%	-68%	-18%	-47%	-9%	-32%
Overall effect	-29%	-9%	-27%	-12%	-5%	-4%	31%	-5%	-8%

6.1. Relevance to various markets

Observing the differences between the higher-priced handbags and lower-priced apparel, we note that the analysis can be extended to other fashion products. Following the above, we expect the role of overexposure to play a major part in the overall effect. For products where overexposure plays a smaller role, acceleration's effect may dominate the overall effect, and a knockoff may not be necessarily bad news. For higher-priced luxury items, which cater more to the need for uniqueness, overexposure will naturally play a more dominant role.

Hereby, we offer managers a way to estimate a knockoff's expected effect in their market, depending on three characteristics of their specific market: the expected speed of diffusion, consumers' sensitivity to exposure, and the original-knockoff price differences. We present the results from simulating a two (high vs. low speed of diffusion) by two (high vs. low sensitivity to overexposure) by two (high vs. low price differential) fashion market. Specifically, we define the top seven items with a certain characteristic as having a "high" value, and the bottom seven as having a "low" value, and contrast the following:

6.1.1. Speed of diffusion

We look at the time it took each item to reach the peak of the adoption process. For example, in the adoption of the Primp Anchor Hoodie depicted in Fig. 3b, the adoption peaked at Period 12. The fast diffusions' p and q parameters are used, while low parameters are associated with a slow one (Muller & Peres, 2018).

6.1.2. Sensitivity to overexposure

We define items with low threshold means as having higher sensitivity to overexposure, and contrast the threshold mean (μ) and threshold standard deviation (σ) values of the seven most sensitive (low μ) vs. seven least sensitive (high μ) items.

6.1.3. Price differential

Low substitution factor (β) values, by definition, capture a high price m. We contrast β and share of potential knockoff adopters (α) values of the seven items with the highest price differential (low β) vs. lowest price differential (high β).

We take the parameter range of the resulting eight ($2 \times 2 \times 2$) markets, and repeat the simulation process as we did in handbags and apparel, i.e., 10,000 simulations per each of the 8 resulting contrasts, 132 periods, and use a monthly discount rate of 0.8%. In Table 5, we report the average value for each of the resulting eight markets. Furthermore, to evaluate a proxy for the actual speed of diffusion, we also report the share of consumers who remain in the market potential for the original, i.e., consumers who have not yet adopted (or avoided) the item.

The overall effect of the knockoff is negative, including when we average the results across all markets. In the case where diffusion speed and overexposure sensitivity are low and the price difference is high (Market 7), the overall effect is strong and positive at 31%. In this case, the price difference is high, meaning that the share of potential knockoff adopters (α) is also high, and in turn more consumers will adopt the knockoff than usual, causing acceleration to have a stronger effect. While ordinarily, this would lead to a stronger negative overall effect (as in Markets 1 and 3), and the low overexposure sensitivity means that the increase in similar items in the market causes less damage. Due to the interplay of these three characteristics, the overall effect is positive. Finally, we see again that substitution, which is one of the major reasons fashion designers oppose knockoffs, is still a minor effect, across all eight markets.

6.2. Relevance to fast-fashion products

A point of interest in Table 5 is the large variance in the speed of adoption. When the diffusion speed and sensitivity to overexposure are both high, more than 70% of the market potential has bought the fashion item by the end of its first year. On the other hand, when diffusion speed and sensitivity to overexposure are both low, the market potential reached by the end of the first year is about 2%. Thus, the results of Table 5 enable us to examine a wide range of fashion markets, from fast-moving fads (Markets 1 and 2) to fashions with considerably longer life cycles (Markets 7 and 8). This issue is in particular relevant given that our dataset largely consists of fashion products that survive for few years. There are many fashion items that are geared toward a season or two. While in our online dataset products do not necessarily disappear (though their demand might considerably decline), we do not have fast-fashion products in our dataset yet we do in our simulations, as shown in Table 5, and they do correspond well with our general results.

About a third of our samples are products whose peak of sales is about a year or less after launch, and about a quarter of the simulations are Table 5 fast fashion products. However, there are fashion products with even shorter cycles. A considerable amount of fashion products may enter the market only for a few months and then taken off the market. Our data and simulations do not capture the dynamics of such ultra-fast fashion products. This implies a limitation on the ability to infer from our results on this part of the fashion market.

6.3. A broader look at design piracy

Note that the framework presented here is not limited to fashion products, and can be used to study the competitive effects of other markets as well. In fact, in any case where the introduction of additional products results in the creation of negative network externalities for various reasons (including congestion, for example) this framework of analysis is useful. If previous research on

products such as software has focused on the possible positive externalities created by imitations (Givon et al., 1995), managers may want to consider the possible effect of negative externalities as well. Given the evidence that for contemporary consumers, the need for uniqueness plays an increasing role in brand selection across product categories (Yarrow, 2014), we can expect the tradeoff between overexposure and acceleration to play an important role in our understanding of competitive market dynamics.

The question of the effects of knockoff on the original design is larger than what we are able to discuss here. Other long-term and industry-level issues should be taken into account. While we focused on the immediate harm to the specific item, the negative effect of a knockoff might be even stronger if it causes long-term harm to the original design's brand equity. This phenomenon may occur in cases where the design is highly associated with the parent brand, and quality issues, or ownership by those not in the target market, could affect brand associations. It may also occur due to some spillover effects at the brand level: For example, if most Louis Vuitton bags are being pirated, either by knockoffs or by counterfeits, then the rest of the brand's original designs might suffer as well. The resultant negative word-of-mouth communications could also be introduced into the framework (Mahajan, Muller, & Kerin, 1984).

Neither did we consider various market-level effects. For example, one could argue that consumer welfare might go up in some cases, due to ubiquity of a design with a lower price; or that the presence of knockoffs drives firms to introduce more products into the market, which can promote innovation and thus positively affect the industry and consumers (Cotropia & Gibson, 2010; Qian, 2014; Raustiala & Sprigman, 2012). We do not address the existing controversy on this issue, as industry-level analysis is beyond the scope of this research. What we do argue is that the discussion should include an informed analysis of knockoffs' effects on individual firms – a topic lacking in previous literature – and can benefit from our framework and findings here.

Appendix A. Short-term fashion items

Our fashion item selection process started with a list of 300 products and filtered out items with high seasonality, low sales volume, or items that have not yet reached peak. We also filtered out products with less than 48 periods of sales (see Section 4.1). To see if the inclusion of items with shorter life cycles can affect our findings, we went back to our data and found four more products that were not seasonal, with substantial sales, yet lasted less than 48 months. The items and their estimated parameters are described in Table A1. Apart from the length of the time-series that is shorter than that of our original 20 items, these products are very similar to the products listed in Table 1, and of the 16 parameters estimated, 14 fall within the parameter range of Table 2. The two exceptions are highlighted in Table A1. We then reran the simulation analysis, using these items, together with the 20 from Table 1, without a substantial difference in the resulting effects compared to Table 3 in the paper – see Table A2. We also reran the rest of the analysis in the paper with those items, without much change in the results.

Table A1
Estimation results for the four short-term fashion items.^a

Fashion item	Time (months)	Time to reach sales peak (months)	External effect (p)	Internal effect (q)	Threshold mean (μ)	Threshold standard deviation (σ)	RSE
Proenza Schouler PS1 (Handbag)	46	38	.0002	0.081	0.0547	0.00541	5.4
Mulberry Alexa (Handbag)	35	30	.0007	0.205	0.0167	0.02084	3.9
Equipment Signature Silk Shirt (Apparel)	25	19	.00083	0.337	0.7537	0.02351	11.8
Isabel Marant Wedge Sneaker (Shoe)	11	9	.00022	0.665	0.0176	0.00306	4.0

^a The highlighted parameters do not fall within the parameter range we used in the paper (see Table 2).

Table A2
Simulation results for long-term vs short- and long-term items.^a

	Simulations based on 20 items as reported in Table 3 (long-term items)	New simulations based on 24 items (short- and long-term items)
Handbags		
Substitution	–1.7%	–1.6%
Acceleration	19.2%	22.1%
Overexposure	–54.5%	–56.8%
Overall effect	–36.5%	–35.9%
Apparel		
Substitution	–3.0%	–3.2%
Acceleration	6.4%	5.1%
Overexposure	–13.6%	–13.4%
Overall effect	–8.9%	–10.0%

^a N = 10,000.

Appendix B. Three pairs from Table 1

Original fashion design	Knockoff design
Chloé Paddington Bag, \$1,000 	Urban Outfitters, \$68 
Marc Jacobs Quilted Stam Bag, \$1,350 	Fred Flare, \$50 
J. Crew Eliza Cami \$88 	Arden B. Cami \$29.99 

Fig. B1. Original fashion vs. knockoffs designs.

Appendix C. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijresmar.2018.08.003>.

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