On the Monetary Impact of Fashion Design Piracy

Gil Appel
Marshall School of Business, University of Southern California
gappel@marshall.usc.edu

Barak Libai
Arison School of Business, Interdisciplinary Center (IDC), Herzliya
libai@idc.ac.il

Eitan Muller
Stern School of Business, New York University
Arison School of Business, Interdisciplinary Center (IDC), Herzliya
emuller@stern.nyu.edu

July 2017

The authors would like to thank Roland Rust, Senior Editor and reviewers, On Amir, Michael Haenlein, Liraz Lasry, Irit Nitzan, Raphael Thomadsen, the participants of the Marketing Science and EMAC conferences and the participants of the seminars of the business schools at University of California at Davis, the University of California at San Diego, and Stanford University for a number of helpful comments and suggestions.

On the Monetary Impact of Fashion Design Piracy

Abstract

Whether to legally protect original fashion designs against design piracy ("knockoffs") is an ongoing debate among legislators, industry groups, and legal academic circles, yet to-date this discussion has not utilized marketing knowledge and formal approaches. We combine data collected on the growth of fashion items, price markups, and industry statistics, to create a formal analysis of the essential questions in the base of the debate. We distinguish between three effects: ***Acceleration***, whereby the presence of a pirated design increases the awareness of the design, and thus might have a positive effect on the growth of the original; ***Substitution***, which represents the loss of sales due to consumers who would have purchased the original design, yet instead buy the knockoff; and the loss due to ***Overexposure*** of the design that follows the loss of uniqueness due to the design becoming too popular, causing some consumer not to adopt the design or stop using it. Using data-driven simulation analysis, we find that for the kind of fashion products analyzed, overexposure emerged as having on average a somehow stronger negative effect on the original's profitability than the positive effect of acceleration, and a considerably larger role than that of substitution. This is of particular interest given that industry groups have consistently concentrated on the damage caused by substitution. We examine the moderating role of several market factors, and demonstrate the dynamics of the three effects and discuss the profit implications of a suggested legal protection period, noting that a short legal protection period may actually hurt the original brand.

Keywords: design piracy; knockoffs; counterfeits; diffusion of innovations; uniqueness; fashion

1. Introduction

Figure 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, asserting that their fashion 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].

Figure 1: Fashion designs of Trovata (lower row) vs. Forever 21(upper row)

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 public policy makers and the source of an

[1] The EU offers protection for unregistered design that has an exclusive right 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).

on-going debate in the academic legal literature, with some calling to compare the protection in the US to that provided by the EU (Diamond 2015; Cotropia and Gibson 2010; Hemphill and Suk 2009, Tsai 2005). Yet much of this discussion has been based on conceptual arguments with no structured data based analysis of the issue. It has also drawn much attention in the global fashion market, as the use of fast fashion imitation in designs has become a flourishing industry in various countries (OECD/EUIPO report 2016). In the past few years, several separate 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, because of the large financial stakes cases regarding design copying continue to reach the courts, including the Supreme Court that, in fall of 2016, dealt with design copying of cheerleaders' uniform (Kendall 2016, Riordan 2013).

Some aspects of this debate relate to its industry-level effects, such as innovativeness and the importance of the affordable fashion to mainstream consumers (Tse 2016; Raustiala and Sprigman 2006). 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 highlight the role of ***acceleration***, which might benefit the original, and whereby the presence of a pirated design increases the awareness of the design, and thus can have a positive effect on the growth of the original (Qian 2014; Raustiala and Sprigman 2012; Givon, Mahajan, and Muller 1995). Stakeholders in favor of knockoff restrictions cite the damage to original designs caused by ***substitution***, which represents the loss of sales due to consumers who would have purchased the original design, yet instead buy the knockoff (Lamb 2010).

A third factor that should be considered relates to 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 very well cause a loss to the feeling of uniqueness of their users, triggering fewer adopters and potential adopters. This stems from the fact that we use fashion to signal to others, as well as to ourselves, our social status and distinctiveness from others. Recent 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 and Locken 2016; Chan, Berger, and van Boven 2012), and in turn in aggregate market demand (Berger and Le Mens 2009; Joshi, Reibstein, and Zhang 2009). Overexposure has received less attention in the knockoff debate, and we will show here that that it plays a critical role that must not be neglected when considering the knockoff effect on an original item.

While much of the knockoff debate had been conducted qualitatively in the legal literature and in practice, the questions raised – of profitability in the interdependent growth of brands – are first and foremost a marketing issues. The tools and approaches that stem from the stream of research that deals with new product growth and profitability can certainly aid in this discussion. Thus, our aim here is to build a framework that will enable us to investigate the effect of a fashion knockoff on the original item and in particular the following two questions:

- What can we expect the overall effect of a knockoff on the sales of the original design to be, and what is the relative role of acceleration, substitution and overexposure in this process?
- To what extent could a legal protection period, that is, delaying the launch of a knockoff by a certain amount of time, as proposed by several US lawmakers and academics (Schutte 2011, Tsai 2005), alleviate the 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 types of social influence involved. An adoption or disadoption of the premium brand can effect 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 been proven useful in helping managers and policy makers predict outcomes of actions and policies in marketing related 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 other disciplines, researchers are increasingly using simulations to understand the effects of different firm actions (Gielens, Gijsbrechts and Dekimpe 2014), examine structural modeling of markets (Bronnenberg, Rossi and Vilcassim 2005) and to study via agent based models how individual level behavior aggregates to marker phenomena (Rand and Rust 2011). Simulations are in in particular relevant to issues of the diffusion of innovations because of the complexity, multi agent interactions and the nonlinear effects that characterize such phenomena (Franses 2006; Rand and Rust 2011).

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

- **The overall knockoff effect**: We find an overall negative effect of a knockoff entry on the revenues of an original item. We also find that where the price difference between the original and knockoffs is large (handbag category) the effect is stronger compared to where the price difference is smaller (apparel items).
- **Relative role of acceleration, substitution and overexposure**: Among the boundaries we examined, overexposure has a slightly stronger negative effect on the original's NPV than the positive effect of acceleration. However, the negative effect of overexposure is considerably larger than that of substitution. This is of particular interest given that industry groups have consistently concentrated on the damage caused by substitution.

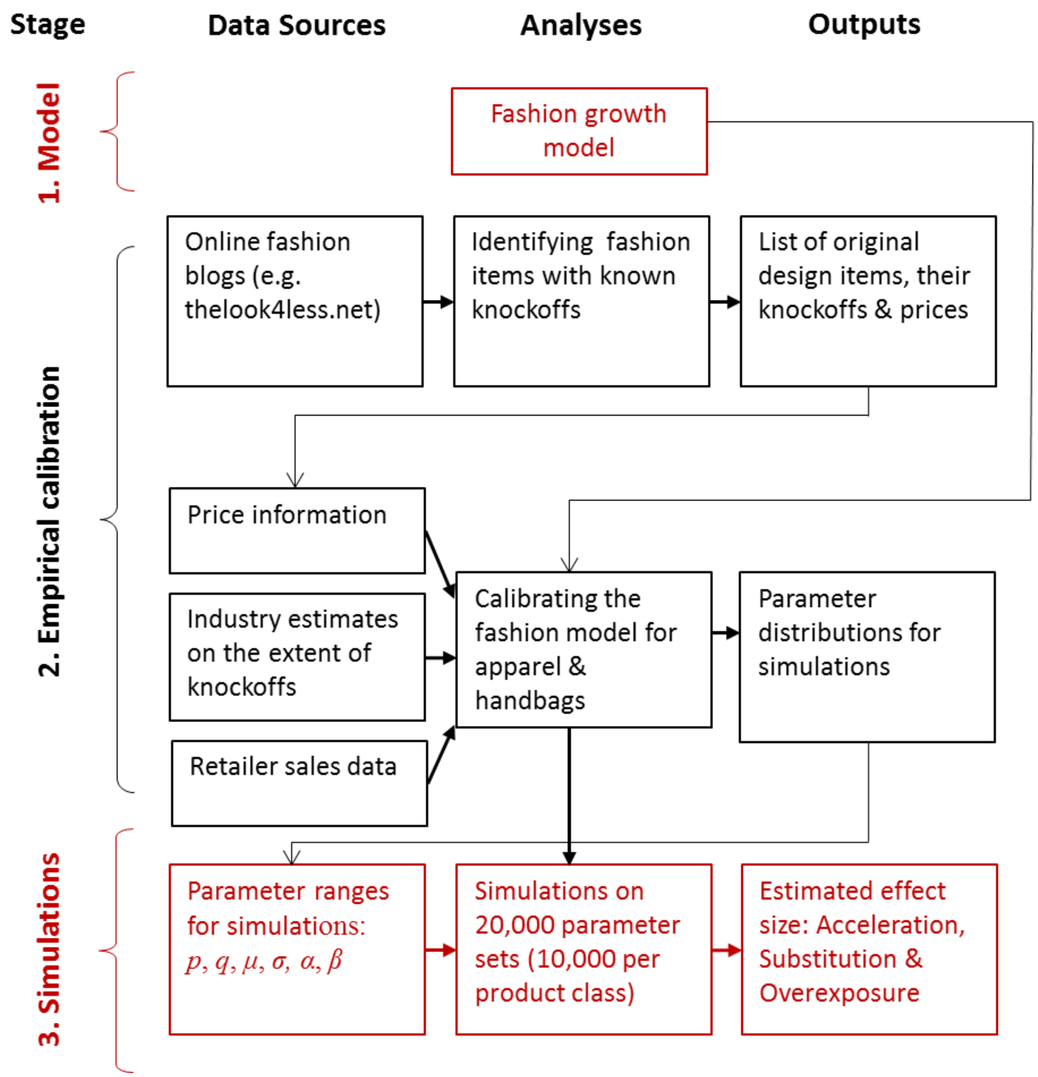
- **Dynamic effects**: Initially, the original item may benefit from the existence of a knockoff. Yet later on, as the number of adopters continues to rise, overexposure becomes the strongest effect overall, leading to a total negative impact on the NPV.
- **The role of legal protection period**: Given the calls to protect US fashion items via a legal protection period, similar to the EU, we find that a short protection period might harm the original, due to the dynamics of the opposing forces of overexposure and acceleration. For longer protection periods, a positive effect is observed.

Figure 2 specifies 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 brand and a knockoff, and where the joint effects of acceleration, substitution and overexposure can take followed. The goal of this model is to help us examine is the effect of the knockoff on the NPV of the original product growth.

In the second part, our aim is calibrate the model parameter drawing on information from fashion markets. We combine industry statistics, information collected from popular online fashion blogs on price difference among knockoff items and originals, and data collection from 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 the price ratio of the original to the knockoff item.

The third part of the paper is a large-scale simulation study that uses the model and the parameter values to asses the monetary effect of the knockoff on the original item NPV, and in particular the effect size of the three forces: acceleration, substitution and overexposure. Note that we use the case of 20 original items to create the range of parameters for this simulation, yet the actual number of scenarios we cover within this range is much larger. The simulation results help us assess not only the forces that drive the knockoff effect, but also the dynamics over time, which help to realize the outcome of a legal protection period.

Figure 2: Flowchart of the analysis process



One should note the distinction that we follow here, between counterfeits, which impersonate a brand including the brand's logo, and knockoffs, which copy its design and appearance (e.g., Rosenbaum, Cheng and 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 covers an exclusive right on the outward appearance of the designed product 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 (Tse 2016, Diamond 2015).

The size of the markets for apparel counterfeits and knockoffs is considerable. Using estimates of the Council of Fashion Designers of America (CFDA), 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 does: It relies on customs seizures, and then correlates it to the overall imports into the EU. This seems to be an underestimate of the true value, since it relies on customs seizures that almost exclusively targets trademark infringements rather than copyright, patents and design infringements[2]. In addition, the methodology disregards the local design piracy in the EU that despite its legal protection is likely to happen (Hemphill and 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 previously depicted in Figure 2, could be applied to counterfeits as well, and thus one can think of what we offer here as a framework to estimate the effects of knockoffs and counterfeits. In this work, we take the framework to data that we obtained on knockoffs, yet given appropriate data, one can apply the framework to counterfeits as well.

[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.

2. Acceleration, Substitution and Overexposure

In order 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, as many other such sites, depicts a collection of high-priced apparel and accessories, often with a celebrity wearing the fashion item, matched together with a low-priced knockoff, pointing to the website at which the latter is available. Figure 3a shows the actress and singer Hayden Panettiere wearing a Primp's Anchor Hoodie, together with the matching knockoff by Forever 21.

Figure 3a: Primp Anchor Hoodie and Forever 21 knockoff

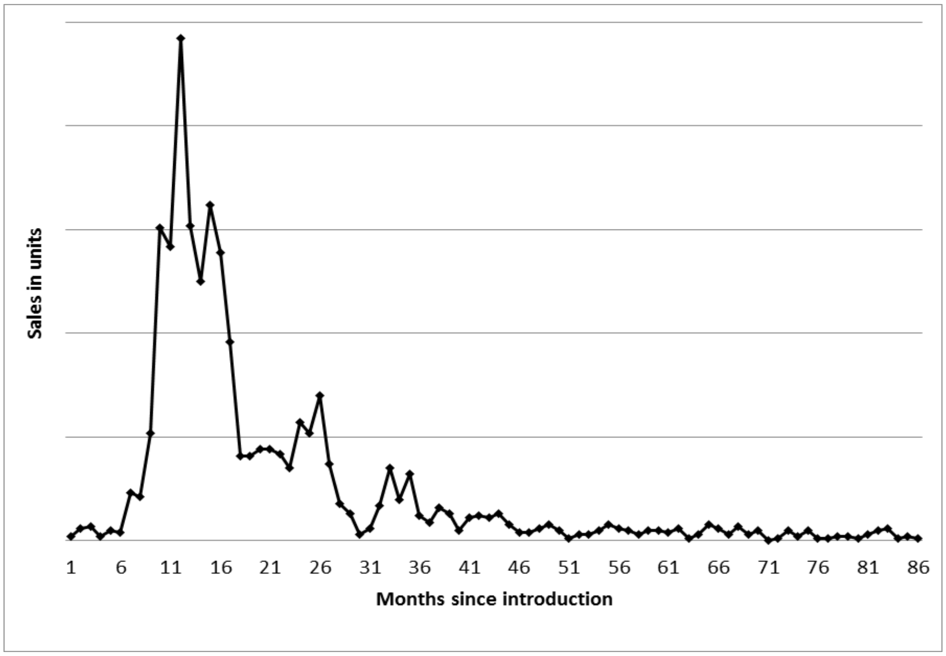
Original fashion item: Primp Anchor Hoodie, $132	Knockoff: Forever 21, $17.80
	

Figure 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 item. Though it was still selling well after four or more years, about 75% of the ultimate sales were done in the first two years[3]. We next use this example in order to facilitate the discussion on the

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

three effects of knockoff on the original fashion design: Acceleration, substitution and overexposure.

Figure 3b: Primp Anchor Hoodie unit sales



2.1 Acceleration[4]

If one thinks about the growth of 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 substitute to the original Primp design, adoption of Forever 21 knockoff will accelerate the diffusion of the original design (Van den Bulte and Stremersch 2004).

Thus ***if a knockoff is a close substitute 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 exact replicas. The acceleration effect will simply be larger the more similar are

[4] While it might seem 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.

the two products. It does require, however, that adopters are influenced by the ubiquity of knockoffs, even if they can tell, by observing the knockoff, or else the adopter of the knockoff, that it is not an original[5].

Indeed, opponents of legal intervention argue that original design owners can actually benefit from design piracy because of the contagion process described above (Raustiala and Sprigman 2012). It has further been argued that these effects should be especially crucial in fashion items, where the collective character of fashion is important for the creation of a trend or "flocking" toward particular fashion (Cotropia and Gibson 2010, Hemphill and 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.net 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 Forever 21 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 knockoff.*** As in the previous effect, we cannot simply count the number of such individuals because of their complex effect on the diffusion of Primp Anchor hoodie via word-of-mouth communications, imitation and other contagion effects.

[5] An interesting complexity can be added if there is a group of users (called "patricians" by Han, Nunes, and Drèze, 2010), defined as consumers who buy the original items, 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).

While fashion designers see this issue as a real threat to their sales, the magnitude of this effect can be debated, as many knockoffs are sold for a much lower price, and thus target a market that would not have purchased the original (Raustiala and Sprigman 2006). This may depend on the manufacturers' abilities to create knockoffs that are similar in terms of look and quality. Recent reports suggest that knockoffs are becoming considerably similar to original items, 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 see what extent the Anchor Hoodie contributes to the feeling of uniqueness of its user[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 feeling of uniqueness, and therefore would likely to cause some potential adopters to cancel their plan to adopt the anchor design and some adopters to stop wearing the hoodie.

Consumers' *need for uniqueness,* manifests in the drive to differentiate oneself from others through the acquisition of consumer goods, which serve to develop and enhance one's 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 (Smaldino et. al 2017; Morvinski, Amir and Muller 2017, Chan, Berger, and Van Boven 2012; Timmor and Katz-Navon 2008; Berger and Heath 2007). Recent studies have further investigated the role of uniqueness in increasing the desirability of certain goods (Berger and Shiv 2011), moderating consumers' word-of-mouth

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

levels in publicly consumed goods (Cheema and Kaikati 2010), and affecting consumers' preferences on brand visibility (Han, Nunes, and Drèze 2010).

Thus, ***overexposure to fashion items that become too popular might very well cause a loss to the feeling of uniqueness of their users, triggering fewer adopters and potential adopters*** (Berger and Le Mens 2009). Indeed, it has been recognized by some legal researchers that the ubiquity of knockoffs can damage sales of the original item, due to the loss of use of the original design by some consumers (Raustiala and Sprigman 2012; Hemphill and Suk 2009). Yoganarasimhan (2012) demonstrated how these dynamics drive some fashion firms to restrict information on the ubiquity of the brand, while other firms make it highly available. Yet there is no evidence on the magnitude of the effect. Note that while overexposure is also driven by the increased existence of the original in the market (internal overexposure), here when we consider overexposure we examine the effects of external overexposure, where an increased amount of users from a knockoff, affect the adoption of the original.

It should be noted that the presence of need for uniqueness is not prevent at the same time the drive of consumer to be part of the group of brand adopters, and indeed the *need for belongingness* is well recognized as a driver of human behavior in general, and brand consumption in particular (Baumeister and Leary 1995; Stokburger-Sauer, Ratneshwar and Sen 2012). Consumers that adopt a fashion brand will do so because they be part of the group associated with the brand even if small (Han, Nunes, and Drèze, 2010), and this effect will be captured in the word of mouth and imitation force that is associated with the number of previous adopters. Yet at the same time for many fashion brand, consumers are expected to desire uniqueness as well, so the number of other users cannot be too large. Any formal exploration of fashion markets should take the tension between these two forces into account.

2.4 Combined effects of acceleration, substitution and overexposure

Overall, the current findings are ambiguous with respect to the overall effect of a knockoff: On 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 take away demand from the original design. In one of the few structured approach to 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 take care of endogeneity issues, Qian found an overall positive effect of piracy on sales of high-end products and negative on low-end ones, and attributed the difference to differing size effect of acceleration and substitution. However, her work did not measure each effect separately as we do here, and did not consider the effect of overexposure.

Note that 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-doc calibration of a Bass type of a model; substitution could be studied using simulation and preference elicitation methods such as conjoint analysis; but the impact of overexposure remains elusive, especially since customers whose choices are impacted might not be fully aware themselves of their own underlying motivations. Thus, the total effect has not been formally assessed to date, and it is not clear what may be the dominant force. 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 stages: 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 item that encounters a knockoff. Second, we gather empirical data to calibrate the model's parameter distributions. We then use these parameter distributions to run simulations that will help us to study the effect of a knockoff on an individual original item. The model is based on the following assumptions:

***Time 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 at the same time as or very shortly after original products (Tan 2010). We later examine the case of knockoffs that are introduced with a time lag.

***Perception of uniqueness*:** A fundamental issue relates to how original item buyers and potential buyers are affected by others' use. Here we assume that they are affected both by the number of original items and by the number of knockoffs that they see in the market. While the former is obvious, an explanation is on point for the latter.

Note first that the owner, who paid for the good, is likely of course to be aware of the source of that good, as they could closely inspect it, and conclude 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 another individual uses. Often the interaction between the parties is brief, and sometimes from a distance (e.g., walking down the street); and the ability to inspect the item closely, and even more so to know where it was purchased and for how much, may be low. This is especially true as pirated items become ever more similar to originals, and consumers often find it hard to distinguish between originals and knockoffs (Holmes 2011; Gentry, Putrevu, and Shultz 2006).

However, even if some original item 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 item's owner identifies the source and cares about it, it is not necessarily reasonable for him/her to assume 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.

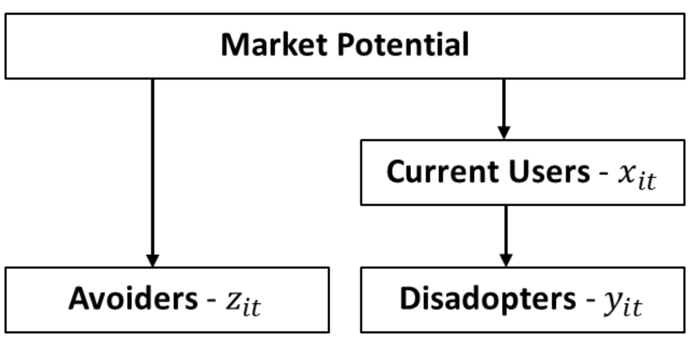
Sales of the knockoff: While our interest is the NPV of the original product, we model both the growth of the original and the knockoff while their market potentials differ (which can be attributed to a price difference, as we elaborate soon). We assume that the adopters of the original design may affect 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 users, thus accelerating adoption. On the other hand, this reciprocal effect will cause more current and potential adopters of the original product to disadopt the product due to their loss of uniqueness.

3.2 The model

Three populations to follow: Consider Figure 4 and define the following three groups 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 groups for the design broken down to the original item ($i = o$) 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

Individual threshold: The negative effect of others is modeled via a uniqueness threshold approach, where each individual has a personal threshold for the number of product users he or she is willing to tolerate before avoiding or disadopting the product. In the context of product use, threshold models have largely been used to model adoption dynamics (Goldenberg, Libai Muller 2010; Valente 1995; Granovetter 1978), but can be also used to describe attrition processes (Granovetter and Soong 1986). Thus when there is only one adopter class, 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 $M \cdot prob\,(H \leq x/M)$. When there are multiple segments, the analysis becomes more intricate as we presently show.

Figure 4: Fashion diffusion framework flow chart



It becomes clear now why disadopters are central to the process: Indeed, their ***direct*** contribution is not economically important since 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 are central to the diffusion process in two ways: First they add to the word-of-mouth activities and other contagions effect, and second, they enter the individual threshold level directly and by that influence 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 and Soong 1986). We follow this literature and assume that *H* follows a truncated normal distribution with mean μ and a standard deviation of σ, that is: $H \sim N(\mu, \sigma^2)$[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 in thresholds (Valente 1995; Macy 1991).

Disadopters and avoiders**:** Let M_{it} be the market potential for the original ($i = o$) and knockoff ($i = k$). We will deal with 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 to pass the threshold) has been passed, and subtract from this number all consumers who have already disadopted or avoided the fashion, i.e., y_{it} and z_{it} to arrive at the following equation ($i = o, k$ for the original and knockoff fashion item respectively):

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

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

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

Separating disadopters and avoiders: Equation 1 describes the change in overall rejections, but since we wish to evaluate the change in each population separately, we need to find a way to split the two. For this reason, we examine the distribution of the threshold between the current user population and the potential consumer population. Since 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:

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

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

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

Current users: The next stage needed for the model is to find the change in the number of users (x_{it}). Following the diffusion modeling paradigm, we look at adoption as a growth process with diffusion parameters *p* (representing external influence such as advertising) and *q* (internal influence such as word of mouth) and long-range market potential (Peres, Muller, and 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:

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

Hence, word-of-mouth communication is assumed to take place 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.

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 item at period t (M_{ot}) has to take into account the substitution effect. Hence, we define the percentage of the knockoff potential market that would have purchased the original if knockoffs had not been available as β. Thus, the larger β, the smaller the actual market potential 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 respectively):

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

Note that there can be a difference between the substitution factor β, and the eventual effect of substitution on NPV. The former represents the potential loss due to substitution, or the percentage of the market potential the original potentially loses to those who instead buy the knockoff. The latter is largely based on β, yet takes into account also 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 total substitution effect will not necessarily be the same.

3.3 Operationalization of the main constructs

Our interest here is not only in the total 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 consumers and potential consumers 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 value of a parameter that results in a single consumer not adopting the product, this individual now does not generate 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 social system, and therefore has implications for the information flow through the entire system. As a result of that customer'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.

Note also that this system has a nonlinear element built into it. To see it, consider a threshold normal distribution with a high mean and a low variance. An additional user or users (that might have adopted because of a small change in any of the parameter values), where this user has 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 in order to measure the effect one has to form two scenarios (with and without this change) and measure the difference between them. Therefore, we examine the following five scenarios that enable us to isolate the respective effect of each source on the NPV of the original product:

- ***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 Equations 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 the value of β (the substitution parameter) to zero.
- ***Scenario D***: Acceleration alone: In this scenario, every segment is considering only their segment 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 Equations 1-5 with one change: Each segment (original and knockoff adopters) considers only their 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 total effect ((Scenario B – Scenario A) / Scenario A) and 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%. Since it does not affect the substantive results we describe next, we highlight the results for the three main effects and the total 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. Towards 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.

We were able to follow the growth of a number of original fashion items with the help of a dataset of a major US online retailer as follows: In the first stage, we aimed to find original fashion items that face a knockoff. Online search helped us to identify fashion blogs dedicated to matching original designs and their knockoff counterparts (see Appendix A for details). We gathered the names and price levels of 300 pairs of original-knockoff design items.

In the second stage, we could look 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 could construct the growth of some of the items on our list. This demanded very large-scale data analysis efforts, 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 looked only for original items that had a minimum substantive sales data in our database (see Appendix A for details). Note that we looked for specific items, and thus getting continuous sales data over time in sufficient numbers was not straightforward. In particular, we looked for items that had at least 4 years (48 months) of continuous data points, sales having already reached a first peak, with at least 100 items sold overall.

Table 1: Estimation results for the fashion items, by class

Fashion item - Handbags	Time (months)	External effect (p)	Internal effect (q)	Threshold mean (μ)	Threshold standard deviation (σ)	RSE	MSE
Chloe Betty	83	0.0013	0.698	0.0048	0.01240	5.3	27
Chloe Paddington	95	0.0006	0.932	0.0087	0.03101	56.1	2,980
Fendi Spy	93	0.0058	0.303	0.1367	0.09570	96.3	8,768
Hermes Birkin	132	0.0009	0.058	0.1685	0.00538	19.1	349
Luella Gisele	111	0.0012	0.250	0.1854	0.04347	6.7	43
Marc Jacobs Stam	87	0.0029	0.232	0.0308	0.01046	37.8	1,348
Yves Saint Laurent Muse	87	0.0006	0.074	0.0177	0.00752	16.3	250
Average	**98**	**0.0019**	**0.364**	**0.0790**	**0.0294**	**33.9**	**1,966**

Fashion item – Apparel	Time (months)	External effect (p)	Internal effect (q)	Threshold mean (μ)	Threshold standard deviation (σ)	RSE	MSE
BCBG Cotton Poplin Dress	115	0.00002	0.116	0.1942	0.0807	23.1	511
Black Halo Ruffle Dress	63	0.00285	0.081	0.2649	0.0047	5.9	32
Christian Louboutin Decollete (shoe)	84	0.00034	0.140	0.0104	0.0204	8.5	68
Citizens of Humanity Jeans	114	0.00016	0.137	0.0009	0.0117	484.3	224,214
Current Elliot Love Jeans	50	0.00088	0.258	0.0131	0.0145	8.5	65
Dr. Martens 1460 (shoe)	132	0.00016	0.001	0.9126	0.0740	90.7	7,919
DVF Wrap Dress	132	0.00001	0.159	0.0021	0.0121	115.6	12,858
Ed Hardy Tee	93	0.00010	0.138	0.2549	0.0888	276.3	72,232
J. Crew Eliza Cami	79	0.00008	0.569	0.0047	0.0516	15.1	214
Juicy Couture Terry Hoodie	130	0.00019	0.167	0.0299	0.0372	110.4	11,715
Primp Anchor Hoodie	86	0.00016	0.957	0.0377	0.0534	14.7	204
Seven For All Mankind Dojo Denim	119	0.00006	0.117	0.00005	0.0130	162.8	25,391
So Low Foldover Pants	99	0.00278	0.028	0.2495	0.0056	9.1	78
Average	**100**	**0.00060**	**0.221**	**0.1519**	**0.0360**	**101.9**	**27,346**

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

Following this selection process, we were left with temporal 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 in Appendix B).

4.1 The magnitude of the price difference

The items we gathered represent a wide range of prices, and in particular, 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: $2,191 for handbags, and $224 for apparel. We incorporated the price markup ratio into our modeling approach by looking at the differential effects between apparel and handbags in two ways:

First, the price difference 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 price difference between the original and the knockoff, the less the cheaper knockoff can serve as a substitute for the more costly original. Based on experimental research, Staake 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 $\beta = .025$ for handbags (i.e., 2.5% of the handbag knockoff's potential buyers would have purchased the original had a knockoff not been available); and $\beta = .198$ for apparel.

Second, 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 to account 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%*price markup ratio) / (95% + 5%*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 categories: handbags and apparel.

4.2 Parameters for the fashion items

In order to develop the range for the simulated model, we estimated the value of the parameters of the fashion growth model, using Equations 1-5. We use these equations to express Equation 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 Equations 1 and 3. To estimate the value of the parameters of a design, we apply the simulated annealing method, that allows for an efficient optimization in a case where the estimated function has multiple local extrema. We applied this method using the GenSA package in R (Xiang et al. 2013; Brusco, Cradit, and Stahl 2002), selecting the parameter set that minimize the sum of square error (SSQ). For a fashion design that belongs to the apparel class, we set the value of the external parameters, $\alpha = .21$ and $\beta = .198$, and $\alpha = .68$ and $\beta = .025$ for handbag class. The estimated coefficients for each fashion item are given in Table 1.

We next ran simulations to estimate the effect of knockoffs on the NPV of the original. 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.

Table 2: Parameter value ranges for the simulation process

Fashion item - Handbags	Parameter Range
External effect (p)	0.0006 - 0.0058
Internal effect (q)	0.058 - 0.932
Threshold mean (μ)	0.0048 - 0.1854
Threshold standard deviation (σ)	0.0054 – 0.0957
Share of potential knockoff adopters (α)	0.544 - 0.816
Substitution factor (β)	0.02 - 0.03

Fashion item – Apparel	Parameter Range
External effect (p)	0.000014 - 0.0029
Internal effect (q)	0.001 - 0.957
Threshold mean (μ)	0.00005 - 0.9126
Threshold standard deviation (σ)	0.0047 – 0.0888
Share of potential knockoff adopters (α)	0.168 - 0.252
Substitution factor (β)	0.158 - 0.238

Fixed Parameters – Both segments	Parameter
Market size (M)	10,000
Time horizon (T)	132
Monthly discount rate	0.8%

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 value sets from the parameter distribution for each product group. 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 values of α and β parameters, we draw for members of each group a random value in the range of the group mean, plus or minus 20% (i.e., if handbag average α is .68, the range would be between .544 and .816). For each parameter set we estimated the NPV of the growth patters 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.

5. Simulation Results: Knockoffs' Effects on NPV

We next present the simulation results regarding the knockoff phenomena. While the strength of the simulation approach, is apparat 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 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 NPV of the original in percentage of change. We discuss here the results in terms of the mean, and provide a confidence interval for the mean. In Appendix C, we provide the full density plots of the effects (Figures C1-C4).

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 groups, the knockoff creates a 22.7% negative effect on the original's NPV. Though the results are consistent across the two groups, we do see a considerable difference in the effect size across groups. For handbags, we see that the knockoff effect is stronger, with an average total effect of -36.5%, compared to -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.

Table 3: Simulation results: The sizes of the various forces on the NPV and their importance

Overall Handbags & Apparel	**Mean**	**Mean Confidence Interval***		**ω^2 index for relative importance of the parameter**					
		lower	**upper**	***p***	***q***	***μ***	***σ***	***α***	***β***
Acceleration	12.8%	12.6%	13.0%	0.03	0.08	0.11	-	0.36	0.01
Substitution	-2.3%	-2.4%	-2.3%	0.03	0.07	0.05	-	0.05	0.13
Overexposure	-34.0%	-34.3%	-33.7%	0.24	0.03	0.19	0.02	0.46	-
Total	-22.7%	-22.9%	-22.5%	0.27	0.20	0.09	0.06	0.20	-

Handbags	**Mean**	**Mean Confidence Interval***		**ω^2 index for relative importance of the parameter**					
		lower	**upper**	***p***	***q***	***μ***	***σ***	***α***	***β***
Acceleration	19.2%	18.9%	19.5%	0.04	0.28	-	0.02	0.21	-
Substitution	-1.7%	-1.7%	-1.6%	0.01	-	0.29	0.01	0.41	0.05
Overexposure	-54.5%	-54.7%	-54.2%	0.14	0.10	0.05	0.04	0.55	-
Total	-36.5%	-36.6%	-36.3%	0.04	0.14	0.03	0.21	0.15	-

Apparel	**Mean**	**Mean Confidence Interval***		**ω^2 index for relative importance of the parameter**					
		lower	**upper**	***p***	***q***	***μ***	***σ***	***α***	***β***
Acceleration	6.4%	6.2%	6.6%	0.05	0.28	0.01	0.01	0.01	-
Substitution	-3.0%	-3.1%	-3.0%	0.01	0.44	-	-	0.04	0.02
Overexposure	-13.6%	-13.7%	-13.4%	-	-	0.25	0.02	0.06	-
Total	-8.9%	-9.1%	-8.7%	0.04	0.28	0.03	0.03	0.01	-

* Mean confidence interval is calculated by ±1.96*SE (Standard Error). N=10,000 for handbags and apparel and 20,000 for both segments together

One might wish to know 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 Equation (6):

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

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 since the effects of acceleration and overexposure work against each other (as can be seen from their counterbalancing effect values), its influence on the total effect is small. The internal and external effects (p and q, respectively) tend to be more important on the total effect, as they accelerate the overall rate of adoption.

Note that while the average total effect is negative, it is not negative in all cases, with an extent that differs across groups. A small fraction of handbags actually benefits from knockoffs according to our calculations (0.3%), and the percentage increases to 9.1% for the apparel group. 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 item. Yet the extent of this reduction can considerably vary across product groups.

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 types?

We have observed that the total effect of a knockoff differs between handbags and apparel. One might wish to know if this difference is manifested in terms of the size effect only, or if the fundamental dynamics differ between the two groups. We tested the effects of the parameters on the two main drivers of the total effect, i.e., acceleration and overexposure that act as the dependent variables in the linear regressions whose results are presented in Table 4. The independent variables represent three types of 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 allow for a direct comparison between the parameters, we report the standardized coefficients. Note that the total effect of a knockoff is the effect on the NPV of the original, and so a negative coefficient sign indicates greater damage.

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

Table 4: The effects of the parameters on acceleration and overexposure

Handbags	Total Effect	Overexposure	Acceleration
External effect (p)	-.315	.195	-.386
Internal effect (q)	-.601	.266	-.630
Threshold mean (μ)	-.084	.107	-.137
Threshold standard deviation (σ)	.733	.309	.214
Share of potential knockoff adopters (α)	-.387	-.739	.453
Substitution factor (β)	-.021 *	-.003 (NS)	- (NS)
Adjusted R^2	57%	87%	55%

Apparel	Total Effect	Overexposure	Acceleration
External effect (p)	-.189	.028 *	-.218
Internal effect (q)	-.540	.042	-.583
Threshold mean (μ)	.079	.438	-.166
Threshold standard deviation (σ)	.204	.161	.134
Share of potential knockoff adopters (α)	-.097	-.243	.091
Substitution factor (β)	-.017 (NS)	.003 (NS)	.002 (NS)
Adjusted R^2	38%	33%	36%

Coefficients are standardized, and all are significant at p-value < 0.001, except the ones marked with * (p-value < 0.01), and NS (non-significant); N=10,000.

Second, we observe that the faster the diffusion of the item (larger values of p and q) the smaller the acceleration effect of the knockoff: The knockoff is less helpful to original items that diffuse rapidly on their own. This is also the direction of influence on the total effect, and so faster-growing products with shorter life cycles are damaged more by knockoffs, i.e., they suffer from the overexposure effect, 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 very 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 Figure 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, while there are not a lot of adopters, but later the effect 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 coefficients are positive[8].

The last issue is that there is the negative effect of the Share of potential knockoff adopters (α) on the total effect in both groups. This is quite reasonable, as more people are able

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

to adopt knockoffs; the worse it is for the original firm. The substitution factor (β) is not significant since both original items and knockoffs affect the threshold. Increasing one on behalf of the other should not affect the results.

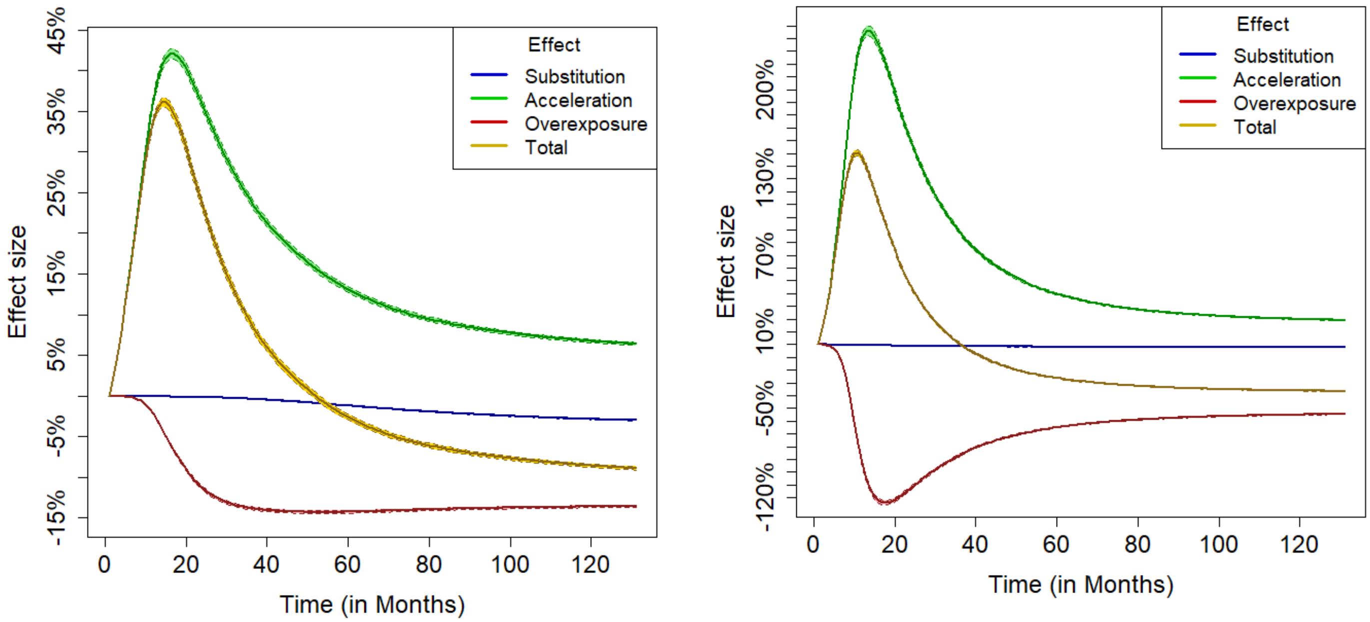
5.2 The dynamics of the effects over time

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 opposite direction. Acceleration benefits the original brand, while overexposure has a negative effect. However, it is still not clear how these effects develop over time. To understand this, we examine how the levels of each effect over time developed in our simulations across 132 periods. In Figure 5 we plot the relative size of the effects over time.

From Figure 5, we can see that the effects vary dramatically across time. In the beginning, when the NPV is still low, the acceleration effects amounts to 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 to impact, as it depends on the adoption levels passing the disadoption threshold. In the long run it is stronger than the acceleration effect, that peaks at period 17 for apparel and 13 for handbags, and since the overexposure already kicked in before that, the total effect reaches a maximum 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.

Figure 5: Dynamics of the relative size effect (with confidence intervals around the mean)

Apparel Handbags



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

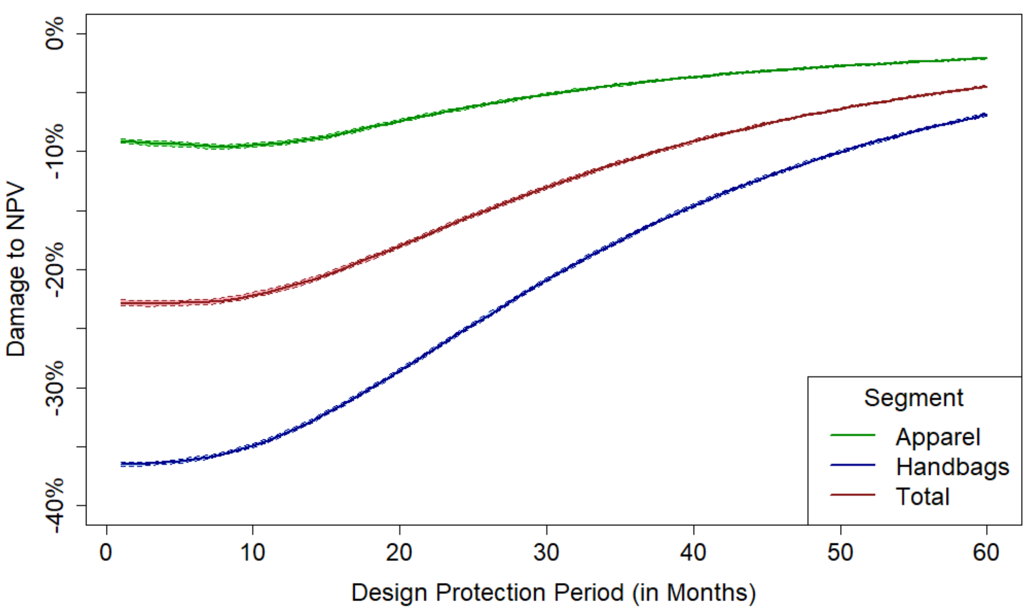
5.3 The effect of a time lag in the introduction of the knockoff

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 (IDPPPA), 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 parameter values, this time looking at cases in which the knockoff enters the market later than the original product. 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 the introduction of the knockoff, such that the maximum time lag was 60 months.

When looking at the percent reduction in the NPV of the original product in the presence of a knockoff as a function of the duration of the protection period, the following picture emerges (see also Figure 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 product's NPV (up to 1% on average in our 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 Figure 5 above.

Figure 6: Impact of protection period on NPV (with confidence intervals around the mean)



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 values of p and q), the 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 the loss of overexposure outweigh the benefits from acceleration.

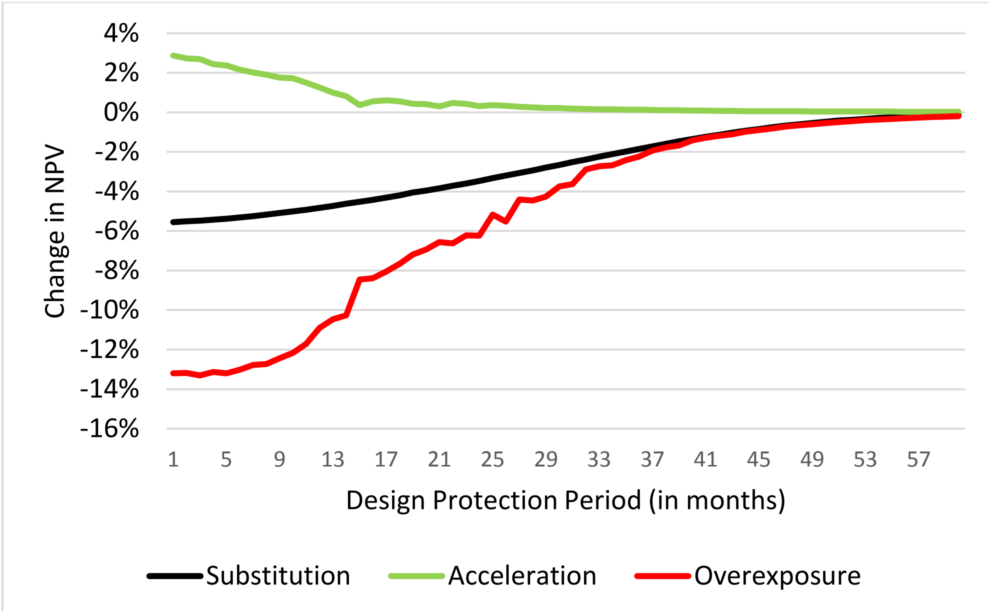
One may want to use caution in the interpretation of our simulations at this stage, as the parameter estimates we use may not be policy invariant: Changing the legal situation has the potential to change firms' strategies and market dynamics. Still, we can say based on the current situation, and using 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 NPV is certainly reduced, yet most of it still exists (see Figure 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 design, 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 that are over one-year long.

In Figure 6 we demonstrate what happens to the total effect of knockoffs if a design protection period is introduced in the market. Below we further explore this dynamics, using the parameter values of a single fashion item, the Primp Anchor Hoody. The parameters values are: $p = 0.00016$, $q = 0.957$, $\mu = 0.0377$, $\sigma = 0.0534$, $\alpha = 0.21$, $\beta = 0.198$. Figure 7 depicts the dynamics of the three effects (substitution, acceleration and overexposure), when design protection lags (from 1 month to 60 months) are being introduced in the market.

The resultant graph is somewhat noisy, as expected, but the effect remains the same – it appears that after two years, most of the damage can be alleviated and after three years it is almost gone. We can observe that the positive effects of acceleration are mostly in the first year, declining with each passing month.

Figure 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 product, and in particular the dominance of overexposure, hold when changing the basic assumptions of the model. We examine the sensitivity of the results to changes in the price markup between the original design and the knockoffs (as captured by the α and β parameters); the sensitivity of the results 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 A, the results are largely robust with respect to the changes we examined.

6. Discussion

Calibrating our model with fashion growth data and industry statistics, we formally assess the monetary effect of a knockoff on the NPV of an individual original design. Our results can contribute to the ongoing public policy discussion on the need to restrict knockoffs. We do not aspire to provide an answer as to what to do in this on-going debate: As we discuss above, there are additional industry level and legal issues, which are beyond our scope here. However, given that the central role of the damage to an original design plays in this discussion, our main findings can serve as an important input to this dialog. In particular, these include:

Fashion knockoffs have a largely negative effect. In most cases, the introduction of a knockoff damages the NPV of the individual original. Thus, the positive effect of acceleration is not enough to offset the damage created by the knockoff in other ways. This result is important in light of voices in this debate that dismiss the possible damage of a knockoff, and is consistent with the concerns in the industry regarding the damage of design piracy.

Overexposure plays an important role that should be acknowledged. Industry observers often refer to substitution, rather than overexposure, when considering the monetary damage created by knockoffs (Lamb 2010), possibly, because the effect of substitution is more vivid and easier to quantify. However, our results suggest that a greater damage is caused by the effect of design ubiquity in the market. We further find that the overexposure effect exists even when a substantial percentage of the original item market is indifferent to the ubiquity of knockoffs.

The difference between product groups. We find that the knockoff damage effect can considerably differ between product groups. In particular, our analysis was based on two product groups: handbags, where the originals were high-priced and far costlier than the knockoffs; and apparel, where the difference was smaller. We saw that the basic results of the effect on the knockoff's damage were similar; yet the extent of the phenomenon differed, as the knockoff damage was considerably higher for handbags than it was for apparel.

The effects are time varying. In Figure 3b, we observed how most of the sales of the Primp Anchor Hoodie were made in the first two years, exhibiting a sharp drop after that period. This resonates well with our findings that the acceleration effect is beneficial only in the first year or so and then overexposure takes place. We know that fashion is driven by cycles, and perhaps the dynamics between acceleration and overexposure can help explain why we observe these dynamics in fashion.

The time lag effect. The public discussion on the damage of knockoffs is conducted in the presence of a heated debate on the need to restrict knockoffs by mandating a time lag during which knockoffs cannot enter the market, as is the case in the EU. There are many facets to such a law that are not considered here. For example, the ability to enforce such a law and how a knockoff will be defined in this regard. Recall that we need to be cautious given the possible policy-variant nature of some parameters.

What we see 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 create harm, as the early period is when the original enjoys the acceleration, and this is in particular important for products that otherwise diffuse slowly. However, for longer periods we see a monotonic reduction in knockoff effect. Our analysis suggests that even after a lag of three years, most of the damage to the NPV can still occur.

6.1 Relevance to the different markets

Observing the difference between the higher priced bags and lower priced apparel, we note that the analysis can be extended to other fashion products. Following the above, we can expect the role of overexposure to play a major part in the knockoff effect. For types of products where overexposure plays a smaller role, acceleration effect may dominate the overall knockoff effect, and a knockoff may not be necessarily bad news. For higher price luxury items, which cater more to the need for uniqueness, overexposure will naturally play a more dominant role. In order to understand where they stand firms will have to assess the role of overexposure in their product line. Managers, lawyers and policy makers who examine their specific case can refer to the rich literature of need for uniqueness mentioned above, and in particular, to specific scales (Tian, Bearden, and Hunter 2011) that can help to determine the relevance of the specific product type.

It should be emphasized yet that the framework presented here can is not limited to fashion products, and can be used study the competitive effects of other markets as well. In fact, at any place 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 in place. If previous research dealing with products such as software have focused on the possible positive externalities that are created by imitations (Givon, Mahajan and Muller 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 that the tradeoff between overexposure and acceleration will play an important role in our understanding of competitive market dynamics.

While our interest has focused on knockoff, it is interesting to note that our general approach can be used to study the case of counterfeits as well, as the effect of acceleration, substitution and overexposure will drive market dynamics in the case of a counterfeit that enter the market as well. Yet, in the case of counterfeits, where brand logo is copied as well, one should expect further spillover effect in the form of brand dilution that will affect sales of other products as well. Looking at spillovers is beyond our scope here and will demand more data, assumptions and analysis. Yet the framework we used here can serve as a base to start such analysis.

6.2 Limitations and extensions

Our study has a number of limitations in both its empirical and simulation parts. Like 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. In the simulations we have not taken into account the fact that the data already contain strategic decisions by the firm when it faces knockoffs in terms of price, channels of distribution, and even design. Clearly, better data will help to account for these effects.

While this endogeneity related concern is relevant for any paper that will examine empirically competitive product growth and the managerial implications of different market actions, we believe that the simulation approach we took help to mitigate some of the problem. The issue would be of more concern if we focused on the specific case of one of few brands. The fact that we use the empirical data largely to build the envelope for the simulation, and that in fact 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.

In a general sense, aiming to offer a parsimonious approach with fewer assumptions, we created a modeling framework that can clearly be extended in future research to capture more aspects of the fashion knockoff phenomenon. A few possibilities for extension include the following: First, more empirical data can be used to examine the growth of fashion products and better calibrate the parameters, possibly better distinguishing between the adoption of knockoffs and original items. The effect of knockoffs in additional categories such as electronic gadgets can be used to broaden the scope of our results. Repeat-purchase models may facilitate more in-depth analysis of the harm created when a consumer disadopts a repeat-purchase good or service.

6.3 A broader look at design piracy

The question of knockoff effect is larger than what we are able to discuss here. Other long-term and industry-level issues should be taken into account. For example, we focused on the immediate harm to the specific item, yet the negative effect of a knockoff might be even stronger if the knockoff also causes long-term harm to the brand equity of the original firm. This may occur, for example, in cases where the design is very much associated with the relevant brand, and quality issues or ownership by those not in the target market can affect brand associations. Resultant negative word-of-mouth communications could also be introduced into the framework (Mahajan, Muller and 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. From yet another angle, there are claims 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 (Qian 2014; Raustiala and Sprigman 2012; Cotropia and Gibson 2010). 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 that is lacking in previous literature, and can benefit from our approach and findings here.

References

Amaral, Nelson B. and Barbara Locken (2016), "Viewing Usage of Counterfeit Luxury Goods: Social identity and social hierarchy effects on dilution and enhancement of genuine luxury brands," *Journal of Consumer Psychology*, 26 (4), 483-495.

Baumeister Roy F and Leary Mark (1995), "The Need to Belong: Desire for Interpersonal Attachments As a Fundamental Human Motivation," *Psychological Bulletin*, 117: 497–529.

Berger, Jonah and Chip Heath (2007), "Where Consumers Diverge from Others: Identity Signaling and Product Domains," *Journal of Consumer Research*, 34 (2), 121-134.

——— and Gaël Le Mens (2009), "How Adoption Speed Affects the Abandonment of Cultural Tastes," *Proceedings of the National Academy of Sciences U S A*, 106 (20), 8146—8150.

——— and Baba Shiv (2011), "Food, Sex and the Hunger for Distinction," *Journal of Consumer Psychology*, 21 (4), 464–472.

Bronnenberg, Bart .J., Rossi, Peter .E. and Vilcassim, Naufel .J. (2005), "Structural Modeling and Policy Simulation," *Journal of Marketing Research*, 42(1), 22-26.

Brusco, Michael J., J. Dennis Cradit, and Stephanie Stahl (2002), "A simulated annealing heuristic for a bicriterion partitioning problem in market segmentation," *Journal of Marketing Research* 39 (1), 99-109.

Chan, Cindy, Jonah Berger, and Leaf Van Boven (2012), "Identifiable Yet Not Identical: Combining Social Identity and Uniqueness Motives in Choice," *Journal of Consumer Research*, 39 (3), 561-573.

Cheema, Amar and Andrew M. Kaikati (2010), "The Effect of Need for Uniqueness on Word of Mouth," *Journal of Marketing Research*, 47 (3), 553-563.

Cotropia, Christopher A. and James Gibson (2010), "The Upside of Intellectual Property's Downside," *UCLA Law Review*, 57 (4), 921-982.

Diamond, Maggie (2015), "A Defense of Industrial Design Rights in the United States," *NYU Journal Intellectual Property and Entertainment Law*, 5 (1), 1-42.

Ellis, Sara R. (2010), "Copyrighting Couture: An Examination of Fashion Design Protection and Why the DPPA and the IDPPA Are a Step Toward the Solution to Counterfeit Chic," *Tennessee Law Review*, 78 (1), 163-211.

Franses, Philip Hans (2006), "Forecasting in Marketing," In *Handbook of Economic Forecasting*, 1, 983-1012.

Gentry, James W., Sanjay Putrevu, and Clifford J. Shultz, Jr. (2006), "The Effects of Counterfeiting on Consumer Search," *Journal of Consumer Behaviour*, 5 (May-June), 245-256.

Gielens, Katrijn, Els Gijsbrechts, and Marnik G. Dekimpe (2014), "Gains and Losses of Exclusivity in Grocery Retailing." *International Journal of Research in Marketing*, 31(3), 239-252.

Givon, Moshe, Vijay Mahajan, and Eitan Muller (1995), "Software Piracy: Estimation of Lost Sales and the Impact on Software Diffusion," *Journal of Marketing*, 59 (1), 29–37.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2010), "The Chilling Effects of Network Externalities," *International Journal of Research in Marketing*, 27 (1), 5-14.

Granovetter, Mark (1978), "Threshold Models of Collective Behavior," *American Journal of Sociology*, 83 (6), 1420-1443.

——— and Roland Soong (1986), "Threshold Models of Interpersonal Effects in Consumer Demand," *Journal of Economic Behavior and Organization*, 7 (1), 83-99.

Green, Paul E. (1973), "On the Analysis of Interactions in Marketing Research Data," *Journal of Marketing Research*, 10 (4), 410-420.

Hackett, Petal Jean (2012), "Cutting Too Close? Design Protection and Innovation in Fashion Goods," CESifo Working Paper Series No. 3716.

Han, Young Jee, Joseph C. Nunes, and Xavier Drèze (2010), "Signaling Status with Luxury Goods: The Role of Brand Prominence," *Journal of Marketing*, 74 (4), 15-30.

Hemphill, C. Scott and Jeannie Suk (2009), "The Law, Culture, and Economics of Fashion," *Stanford Law Review*, 61 (5), 1147-1200.

Holmes, Elizabeth (2011), "Fashion Fakes Get More Sophisticated," *Wall Street Journal*, June 30, 2011.

Joshi, Yogesh V., David J. Reibstein, and Z. John Zhang (2009), "Optimal Entry Timing in Markets with Social Influence," *Management Science*, 55 (6), 926-939.

Kendall, Brent (2016), "Supreme Court Considers Fashion v. Function in Cheerleading-Uniform case," *Wall Street Journal*, (October 31, 2016).

Lamb, Rachel (2010), "Countering Counterfeits: How Luxury Brands Are Challenging the Knock-off Culture," *Luxury Daily*, July 5, 2012.

Macy, Michael W. (1991), "Chains of Cooperation: Threshold Effects in Collective Action," *American Sociological Review*, 56 (6), 730-747.

Mahajan, Vijay , Eitan Muller and Roger A. Kerin (1984), "Introduction Strategy for New Products with Positive and Negative Word of Mouth," *Management Science*, (30), pp. 1389-1404.

Morvinski, Coby , On Amir and Eitan Muller (2017), "Ten Million Readers Can't Be Wrong! Or Can They? On the Role of Information about Adoption Stock in New Product Trial," *Marketing Science*, 36 (2), 290-300.

Odell, Amy (2009), "Trovata's Suit Against Forever 21 Ultimately Has No Effect on Knockoff Regulations," *New York Magazine*, (October 13, 2009).

OECD/EUIPO (2016), *Trade in Counterfeit and Pirated Goods: Mapping the Economic Impact*, OECD Publishing, Paris.

Peres, Renana, Eitan Muller, and Vijay Mahajan (2010), "Innovation Diffusion and New Product Growth Models," *International Journal of Research in Marketing*, 27, 91-106.

Qian, Yin (2014), "Counterfeiters: foes or friends? How counterfeits affect sales by product quality tier," *Management Science*, 60 (10), 2381-2400.

Rand, William and Roland T. Rust (2011), "Agent-Based Modeling in Marketing: Guidelines for Rigor," *International Journal of Research in Marketing*, 28 (3), 181-193.

Raustiala, Kal and Christopher Sprigman (2006), "The Piracy Paradox: Innovation and Intellectual Property in Fashion Design," *Virginia Law Review*, 92 (8), 1687-1777.

——— and ——— (2012), *The Knockoff Economy: How Imitation Sparks Innovation*. New York: Oxford University Press.

Riordan, Staci (2013), "Fashion Copyright Bill Dies in Congress," Fashion Law Blog, (accessed February 17, 2013), [available at http://fashionLaw.foxRothschild.com/2013/01/articles/fashion-law/fashion-copyright-bill-dies-in-congress/].

Rosenbaum, Mark S., Mingming Cheng, and Ipkin A. Wong (2016), "Retail Knockoffs: Consumer acceptance and rejection of inauthentic retailers," *Journal of Business Research* 69 (7), 2448-2455.

Schutte, Loni (2011), "Copyright for Couture", *Duke Law & Technology Review*, 11, 1-19.

Smaldino, Paul E., Marco A. Janssen, Vicken Hillis and Jenna Bednar (2017), "Adoption as a Social Marker: Innovation diffusion with outgroup aversion," *The Journal of Mathematical Sociology*, 41 (1), 26-45.

Staake, Thorsten and Elgar Fleisch (2008), *Countering Counterfeit Trade*. Heidelberg: Springer Berlin.

Stokburger-Sauer, Nicola, S. Ratneshwar, and Sankar Sen (2012), "Drivers of Consumer–Brand Identification," *International Journal of Research In Marketing*, 29(4), 406-418.

Tan, Irene (2010), "Knock It Off, Forever 21! The Fashion Industry's Battle Against Design Piracy," *Journal of Law and Policy*, 18 (2009-2010), 893-924.

Tian, Kelly Tepper, William O. Bearden, and Gary L. Hunter (2001), "Consumers' Need for Uniqueness: Scale Development and Validation," *Journal of consumer research* 28(1), 50-66.

Timmor, Yaron, and Tal Katz-Navon (2008), "Being the Same and Different: A Model Explaining New Product Adoption," *Journal of Consumer Behaviour*, 262 (June), 249-262.

Tsai, J. P. (2005). Fashioning Protection: A Note on the Protection of Fashion Designs in the United States. *Lewis & Clark L. Rev*, 9 (2), 447-468.

Tse, Tiffany F. (2016), "Coco Way Before Chanel: Protecting Independent Fashion Designers' Intellectual Property Against Fast-Fashion Retailers," *Catholic University Journal of Law and Technology*, 24 (2), 401-431.

Valente, Thomas W. (1995), *Network Models of the Diffusion of Innovations*. Cresskill, NJ: Hampton Press.

Van den Bulte, Christophe and Stefan Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test," *Marketing Science*, 23 (4), 530-544.

Wilson, Eric (2007), "Before Models Can Turn Around, Knockoffs Fly," *New York Times*, (September 4, 2007).

Xiang, Yang, Sylvain Gubian, Brian Suomela, and Julia Hoeng (2013), "Generalized simulated annealing for global optimization: the GenSA package," *R Journal* 5 (1), 13-28.

Yarrow, Kit (2014), *Decoding the New Consumer Mind: How and Why We Shop*, Jossey-Bass

Yin, Chien-Chung (1998), "Equilibria of Collective Action in Different Distributions of Protest Thresholds," *Public Choice*, 97 (4), 535-567.

Yoganarasimhan, Hema (2012), "Cloak or Flaunt? The Fashion Dilemma," *Marketing Science*, 31(1), 74-95.

Appendix A: The selection process of the fashion items

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 300 of these original-knockoff pairs and then searched for the sales data of the original items in our database. Since we wished to use the sales data for the adoption and use of these fashion items, we applied a strict filtering process to ensure that we ended up with the best available data. Thus, a fashion growth pattern was selected if and only if it fulfilled the following criteria:

1. We used only monthly-level data, and only data for sales transacted in the US and only to US citizens, in order to minimize geographical and cultural biases.
2. We avoided data with strong seasonality effects such as boots, coats, or swimsuits.
3. The data needed to have at least 48 continuous data points in addition to sales having already reached a first peak, as estimations before the peak are relatively unstable, and estimations with less than 48 data points resulted in non-significant parameters with large standard deviations in our estimations.
4. The sales of the item must be substantial, selling more than 10 items per month on average, and 100 items total.

At the end of this process, we were left with 20 suitable fashion items, given in Table 1.

Appendix B: Three pairs from Table 2 – original fashion items and knockoffs

Original fashion item	**Knockoff**
Chloe Paddington Bag, $1,540 	Shop Sui Boutique, $48 
Marc Jacobs Quilted Stam Bag, $1,350 	Shop Sui Boutique, $48 
J Crew Eliza Cami $88 	Arden B. Cami $29.99 

Appendix C: Density plots of the effects on NPV

Figure C1 Density plot of the Acceleration effect over the various segments

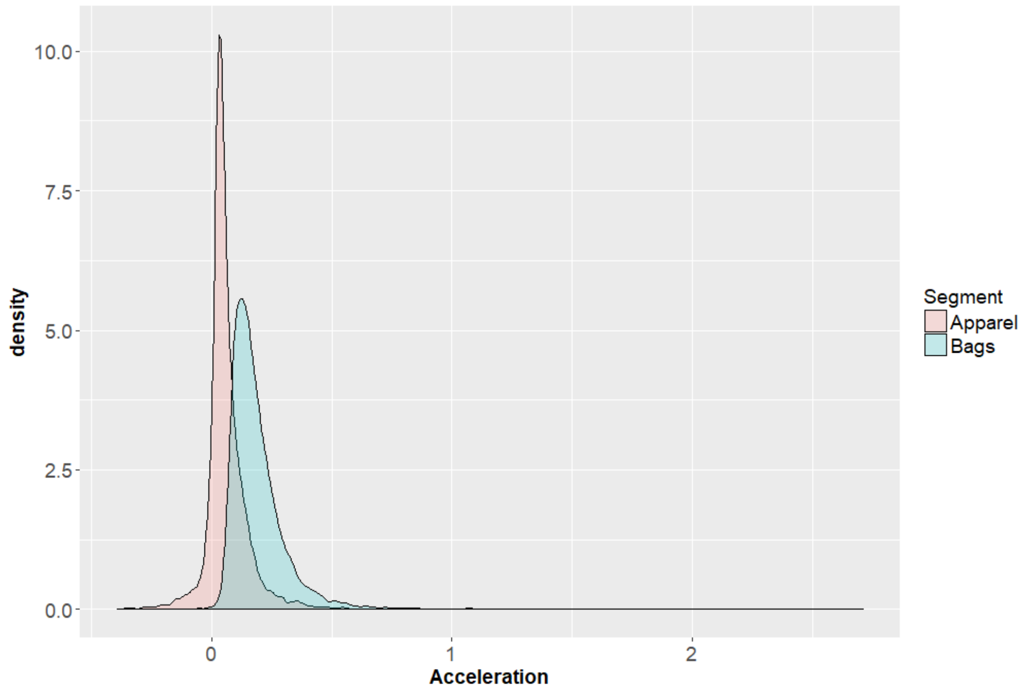


Figure C2 Density plot of the Substitution effect over the various segments

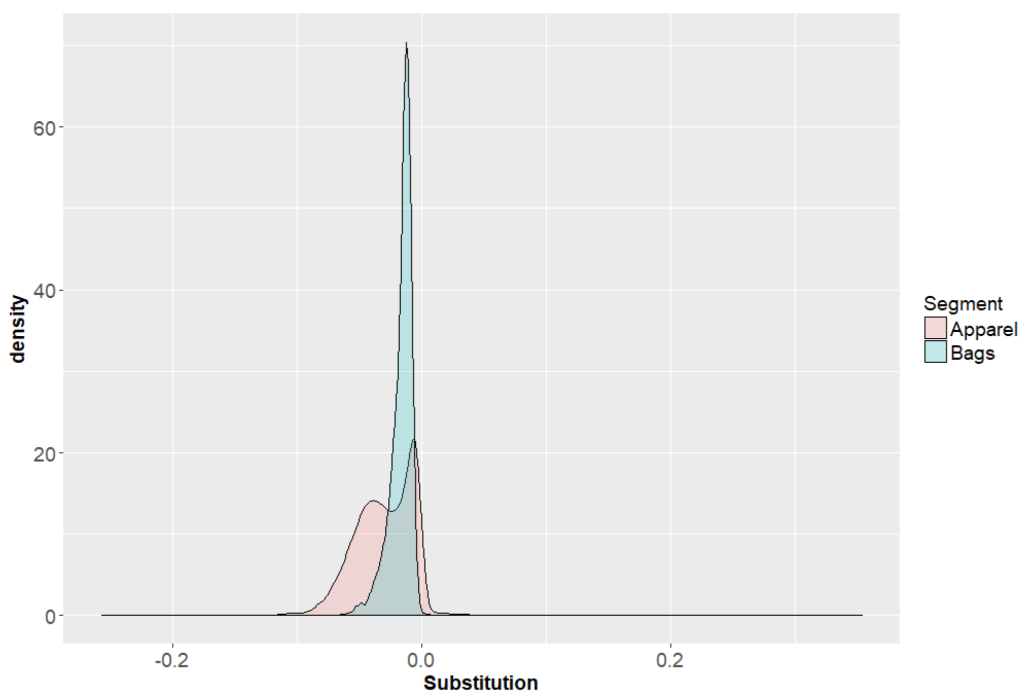


Figure C3 Density plot of the Overexposure effect over the various segments

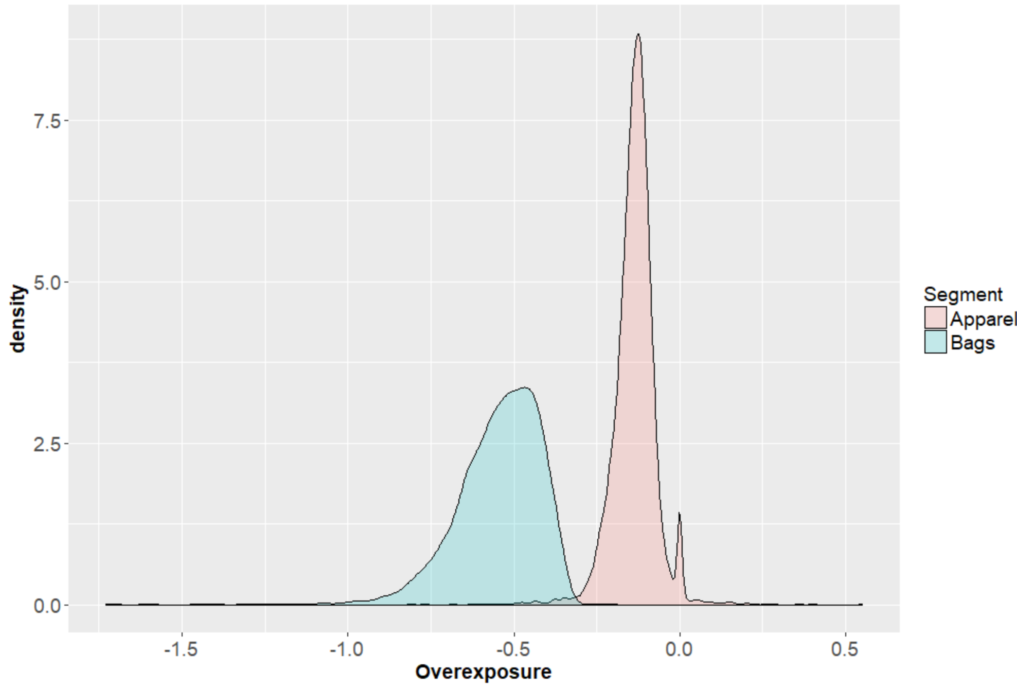
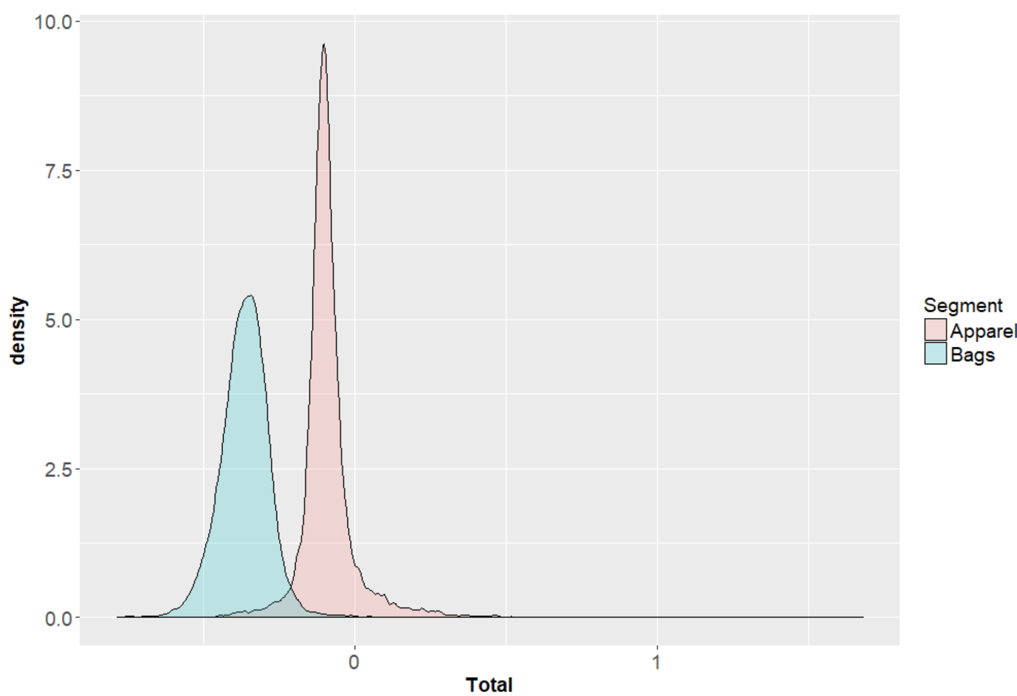


Figure C4 Density plot of the Total effect on the NPV over the various segments



Web Appendix A: Robustness Checks

In the model, we use a truncated normal distribution to model the threshold levels in the population. In this appendix, we examine what happens if we alter this distribution, and if our findings are robust to these alterations.

The effects of threshold heterogeneity

In the model, we assume heterogeneity in the threshold level between consumers. If we remove this assumption, and assume that all of the consumers have the same threshold level, would our results be similar? We re-ran the simulations with the same parameters for each class, this time with zero variance. In such a scenario, the total effect is much larger at -34.7% (-56.1% for handbags, and -13.3% for apparel); this is mostly driven by a substantial drop in the effect of acceleration (See Table WA1 for the effect comparison).

The reason for this jump in the loss to the NPV, is that in a world with no variance in the uniqueness threshold, the acceleration effect would halt immediately as soon as it reached the threshold, and the overexposure effect would be larger, as the introduction of knockoffs would rapidly reach threshold and to the stop point much faster.

The effects in a beta distribution threshold

Another assumption regarding the threshold's distribution is that it is normally distributed. How would the results change if the threshold's distribution was beta distributed rather than normal? We re-estimated the model with a beta rather than a normal distribution (using *a* and *b* as shape parameters in place of mean and standard deviation[9]) and re-ran the simulations with a beta distributed threshold. In the both scenarios, there was almost no change in the average results. (see Table WA2 for the effect comparison).

[9] To avoid biases from extreme values, we limited the shape parameters *a* and *b* to be less than 100

Table WA1 Simulation results for the heterogeneous vs non-heterogeneous model

Overall	**Heterogeneous Average**	**Non - Heterogeneous Average (Zero Variance)**
Acceleration	12.8%	7.1%
Substitution	-2.3%	-0.8%
Overexposure	-34.0%	-41.1%
Total	-22.7%	-34.7%

Handbags	**Heterogeneous Average**	**Non - Heterogeneous Average (Zero Variance)**
Acceleration	19.2%	10.9%
Substitution	-1.7%	-0.2%
Overexposure	-54.5%	-66.7%
Total	-36.5%	-56.1%

Apparel	**Heterogeneous Average**	**Non - Heterogeneous Average (Zero Variance)**
Acceleration	6.4%	3.3%
Substitution	-3.0%	-1.3%
Overexposure	-13.6%	-16.1%
Total	-8.9%	-13.3%

N=10,000 for Handbags and Apparel and 20,000 for Both segments together

Table WA2 Simulation results for normal and beta distributions of the threshold

Overall	**Normal Distribution Average**	**Beta Distribution Average**
Acceleration	12.8%	12.8%
Substitution	-2.3%	-2.2%
Overexposure	-34.0%	-36.9%
Total	-22.7%	-25.3%

Handbags	**Normal Distribution Average**	**Beta Distribution Average**
Acceleration	19.2%	21.4%
Substitution	-1.7%	-1.1%
Overexposure	-54.5%	-58.3%
Total	-36.5%	-37.9%

Apparel	**Normal Distribution Average**	**Beta Distribution Average**
Acceleration	6.4%	4.2%
Substitution	-3.0%	-3.4%
Overexposure	-13.6%	-15.6%
Total	-8.9%	-12.8%

N=10,000 for Handbags and Apparel and 20,000 for Both segments together