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The Short- and Long-term Impacts of Fashion Knockoffs on Original Items

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Report Summary

The question if the U.S. should legally forbid the copying of original fashion designs (often labeled *design piracy* or *knockoffs*) is an ongoing active debate among legislators and industry advocacy groups, and in the legal academic literature, with some claiming that the benefits of knockoffs may outweigh their damage to the fashion industry. It has also drawn much attention in the global fashion market, as the use of quick imitation in designs has become a flourishing industry in various countries, and could be substantially affected by changes in the legal status of design piracy. Since 2006, seven separate bills that would protect fashion items from design piracy (mainly via a legal protection period, such as that instituted in the EU) were introduced in the U.S. Congress; however, none of them has been approved.

Surprisingly, while marketing knowledge and formal approaches related to product growth and profitability are very relevant for this discussion, much of the debate has been based on anecdotes and conceptual arguments and not on empirical analysis of the financial consequences of design piracy.

In this study, authors Appel, Libai, and Muller provide the first structured analysis of this important issue. They build a fashion diffusion model and use data on 15 fashion products from Google Trends, as well as published industry statistics, to calibrate it. Using simulations they can then examine the potential financial consequences of a knockoff on the original item, focusing on three main effects: *acceleration*, whereby the presence of a pirated design increases awareness of the design, and thus can have a possible positive effect on the sales growth of the original; *substitution*, the loss of sales to people who would have purchased the original design, and buy the knockoff instead; and *uniqueness*, the loss of sales that occurs when a design becomes more ubiquitous as a result of the knockoff.

Three particularly notable findings emerge from analysis in this study:

The overall knockoff effect. Taking into account the growth patterns examined, the entry of a knockoff has an overall negative effect on the financial performance of the original. In over 97% of cases, the combined harm due to substitution and uniqueness is greater than the positive effect of acceleration, with the net present value (NPV) going down 13% on average. These results support the concerns voiced by industry groups regarding the harm done by knockoffs.

The role of need for uniqueness. Substitution is often emphasized as a means by which pirated goods cause direct harm to the profitability of originals, and acceleration has been highlighted as a potential positive effect of design piracy. Yet this study shows that both these effects may be dominated by loss of uniqueness, a factor that has been less emphasized in the context of the monetary influence of knockoffs. In the data ranges analyzed, on average, acceleration has a positive effect of about 9.5% on the profits of the original, substitution has a negative effect of 5.5%, and uniqueness has a negative effect of 18.1%. Loss of uniqueness continues to be the dominant effect even when consumers' threshold levels are much higher than the levels inferred in this analysis.

The role of time lag prior to knockoff entry. Given calls to protect original U.S. fashion articles via a legal protection period, similar to the case in the EU, the authors also examine the effect of

the duration of a protection period (i.e., a time lag between introduction of the original product and the entry of a knockoff) on the original product's NPV. They find that short protection periods have little effect due to the opposing forces of uniqueness and acceleration. However, for longer periods (one year or more, in the ranges of the data), a positive effect begins to be observed, and it grows in an almost linear pattern as the protection period becomes longer. A legal protection period of three years, as proposed for the U.S., reduces harm to the NPV by about 44% and a period of five years reduces harm by about 73%.

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Introduction

Consider Figure 1 (Figures follow References throughout), a photograph showing several apparel items manufactured by the high-end fashion firm Trovata, alongside items produced by the clothing retail chain Forever 21. It is easy to see that the items are all but identical. In fact, Trovata sued Forever 21 for copying these items (Odell 2009). However, the lawsuit, which continued for two years, was eventually settled out of court. This may not be surprising, given the failure of numerous lawsuits against Forever 21 and other US firms that have copied fashion designs (Hemphill and Suk 2009). The reason for these failures is that in the US there is no legal protection against *design piracy* of fashions: a situation in which a firm creates a copy or *knockoff* of another firm's design (not its logo or brand identity, which are legally protected).

Because of its possible impact to the US fashion industry, and due to its increasing ubiquity, design piracy has drawn much attention and lobbying effort from US fashion industry groups and has become a major issue for public policy makers (Raustiala and Sprigman 2012). It has also drawn much attention in the global fashion market, as the use of quick imitation in designs has become a flourishing industry in various countries. In particular, known actors such as Zara and H&M rely on imitations as part of their core strategy and could be substantially affected by changes in the legal status of design piracy (Weller 2007; West 2011). In the past years, seven separate bills that would protect fashion items from design piracy (mainly via a legal protection period, such as that instituted in the EU) were introduced in the US Congress; however, none of them has been approved (Ellis 2010, Riordan 2013).

Design piracy has been a subject of active debate not only among legislators but also in the business and academic literature, and in particular in the academic legal literature (Barnett 2005; Cotropia and Gibson 2010; Hemphill and Suk 2009; Raustiala and Sprigman 2006). Interestingly, scholars in this field have emphasized not only the harm but also the possible benefits of knockoffs, suggesting that, in fact, knockoffs may help the industry to flourish (Barnett 2005; Raustiala and Sprigman 2012). Looking from the point of view of the firm that introduces the original design, and of the industry in general, the question boils down to the extent to which the drawbacks of a product's design being copied outweigh any benefits it may create.

It is notable that much of the debate regarding how knockoffs may benefit or harm original designers has been based on anecdotes and conceptual arguments and not on empirical analysis of the financial consequences of design piracy. It would seem that marketing knowledge and formal approaches related to product growth and profitability are very relevant for this discussion, yet they are largely not part of it. In particular, such approaches could provide concrete insight into the effect of *uniqueness* on the dynamic demand for an original design following the entry of a knockoff, an effect that has received limited consideration thus far. Recent research strongly supports the idea that for many products, and fashions in particular, consumers' need for uniqueness plays a significant role in their adoption and attrition decisions (Berger and Heath 2007, 2008; Chan, Berger, and van Boven 2012; Cheema and Kaikati 2010) and consequently aggregate market demand (Amaldoss and Jain 2005; Bakshi, Hosanagar, and Van den Bulte 2011; Berger and Le Mens 2009; Joshi, Reibstein, and Zhang 2009). Thus, even if consumers cannot differentiate between a copy and the original design, the mere presence of more items in the market will affect the degree to which consumers perceive a design as unique and so can create monetary harm to the original product.

Our aim here is to contribute to the on-going discussion on this issue by exploring, using a formal analysis based on new product growth modeling, the monetary consequences caused by design piracy to the original items that are copied (hereafter referred to as "originals"). We consider the case of an original new fashion product that is introduced to the market, and what happens to the value of the cash stream from the growth process when a knockoff product is introduced at the same time. We look at three main factors that drive the effect of the knockoff. One is *acceleration*, whereby the presence of a pirated design increases awareness of the design, and thus can have a possible positive effect on the growth of the original. Such effects have been shown for other markets such as software (Givon, Mahajan, and Muller 1995). The second factor we incorporate is *substitution*, which represents the loss of sales due to people who would have purchased the original design, yet buy the knockoff. The third is the *uniqueness* effect, representing the loss of sales that occurs when a design becomes more ubiquitous as a result of the knockoff.

To study the effect of each factor, we build a fashion diffusion model in which customers avoid adopting a fashion or "disadopt" an adopted fashion if the number of items in the market crosses a given threshold. Gathering relevant data on growth to calibrate the model parameters is a challenge: Available fashion growth data are relatively scarce, which may also help to explain the limited quantitative academic research on the diffusion of fashions. We take advantage of the emergence of Google Trends, a tool that allows researchers to gather search pattern data for an immense set of search terms that people typed into the Google search engine. Researchers are increasingly using this tool to understand the dynamics of market phenomena (Choi and Varian 2009; Kulkarni, Kannan, and Moe 2012; Stephen and Galak 2012). We complement the Google Trends data with industry data on the extent of the knockoff phenomenon, and use these data to conduct simulations to understand the financial impact of knockoffs. Three particularly notable findings emerge from our analysis:

The overall knockoff effect. According to the growth patterns we examine, the entry of a knockoff has an overall negative effect on the financial performance of the original. In over 97% of cases, the combined harm due to substitution and uniqueness is greater than the positive effect of acceleration. Using industry data on the prevalence of design piracy, we find that on average, compared with a situation in which no knockoff is introduced, the introduction of a knockoff reduces the net present value (NPV) of the original product by more than 13%. This estimate is considerably larger than a previous assessment in the business press. These results support the concerns voiced by industry groups regarding the harm done by knockoffs.

The role of uniqueness. Substitution is often emphasized as a means by which pirated goods cause direct harm to the profitability of originals, and acceleration has been highlighted as a potential positive effect of design piracy. Yet we find that both these effects may be dominated by the effect of uniqueness, a factor that has been less emphasized in the context of the monetary influence of knockoffs. In the data ranges we analyze, we find that, on average, acceleration has a positive effect of about 9.5% on the profits of the original, substitution has a negative effect of 5.5%, and uniqueness has a negative effect of 18.1%. We also find that uniqueness continues to be the dominant effect even when consumers' threshold levels are much higher than the levels we infer. These observations suggest that the costs associated with uniqueness should receive much more emphasis in the public debate on knockoffs, and in our understanding of the profit dynamics in fashion markets.

The role of time lag prior to knockoff entry. Given the calls to protect original US fashion articles via a legal protection period, similar to the case in the EU, we analyze the effect of the duration of a protection period (i.e., a time lag between introduction of the original product and the entry of a knockoff) on the original product's NPV. We find that short protection periods have little effect due to the opposing forces of uniqueness and acceleration. However, for longer periods (one year or more, in the ranges of our data), a positive effect begins to be observed, and it grows in an almost linear pattern as the protection period becomes longer. A legal protection period of three years, as proposed for the US, reduces harm to the NPV by about 44%, and a period of five years reduces harm by about 73%. Clearly, various enforcement and public policy factors are important in the decision regarding the duration of the protection period, yet we supply here a first assessment of the effect of such a protection period on the profitability of an individual product.

Thus, this paper has two key contributions. First, it uses marketing knowledge and quantitative research approaches to contribute to the important public discussion on the costs and benefits of design piracy, providing fundamental insights that should be taken into account. Second, it helps to provide a general understanding of the growth of fashion products in the presence of knockoffs, taking into account the profit implications of the uniqueness effect.

The rest of this paper is organized as follows. After a background section, we develop a fashion diffusion model that will serve as the basis for our analysis. We then calibrate the model parameters using empirical data, and subsequently model the case in which a knockoff enters the market. Using simulations, we explore the effect of a knockoff's entry on the profitability of the original brand. We conclude with a discussion of the implications of our results.

Background

The question of design piracy is part of a larger issue of the extent of legal protection that should be given to original items. Interestingly, there is little empirical work that directly aims to simultaneously weight different costs and benefits of copying, which would enable researchers to assess its overall monetary impact. Most of the work in the legal literature is theoretical, supported by anecdotes, and even in the economics literature there is relatively little empirical exploration that could be applied towards a monetary assessment of the tradeoff (Grossman and Shapiro 1988; Liebowitz 2005).

One should note the distinction, which we follow here, between *counterfeits*, which impersonate a brand, and *knockoffs*, which merely copy its design and appearance (Commuri

2009). While our focus is on knockoffs, previous literature has often examined the effects of knockoffs and counterfeits together, and clearly some of the insights on the effects of counterfeits in their different forms (e.g., software piracy) apply to knockoffs and may be relevant to the current analysis.

Before presenting our approach, we next describe the common arguments on the possible costs and benefits of knockoffs.

The possible benefits of knockoffs

Acceleration. Design piracy may increase recognition and awareness of an original brand or design (see Barnett (2005) in the context of counterfeits). In addition, market availability of many non-original products can trigger contagion processes that drive adoption of a design, potentially accelerating adoption among users who choose the original product. These effects can benefit the profitability of the original product. Such effects have been noted, for example, in the context of software piracy (Conner and Rumlet 1991; Givon, Mahajan, and Muller 1995; Prasad and Mahajan 2003) but should exist for design piracy and counterfeits in general (Cotropia and Gibson 2010; Qian 2008).

Industry-level effects. In a well-known publication, Raustiala and Sprigman (2006) suggest that design piracy can actually help to promote fashion innovation. Referring to this as the *piracy paradox*, they argue that knockoffs cause product life cycles to be shorter, driving firms and designers to introduce more innovations; thus, the overall level of innovation grows. Focusing their creative energy on new designs may benefit the designers themselves, and clearly the industry as a whole.

Two issues should be noted in this regard. First, Raustiala and Sprigman (2012) acknowledge that widespread copying may still harm particular originators, yet do not quantify this damage. Second, the overall benefit to the industry is still under debate. Hemphill and Suk (2009), for example, suggest that those who survive are large firms that have means to protect their goods, while small and medium firms suffer more, and Cotropia and Gibson (2010) highlight the public policy implications of unneeded levels of innovation.

Price discrimination. Since the price level of knockoff goods can be much lower than that of originals, there are some claims that the availability of copies may cause minimal harm to the originals, because the goods are purchased by different market segments and cater to different populations (Barnett 2005). In fact, Raustiala and Sprigman (2012) note that it may be even beneficial for original designers to create knockoffs of their own products as a means of price discrimination. Yet, benefits resulting from price discrimination may apply only to cases in which people can actually distinguish between the original and the knockoff (Barnett 2005). Recent behavioral studies on counterfeits support the idea that when consumers can differentiate between the original and counterfeits, the presence of counterfeits may increase loyalty to the originals (Commuri 2009; Romani, Gistri, and Pace 2012).

The possible harms of knockoffs

Substitution. Substitution reflects the fact that some consumers who buy knockoffs (as well as counterfeits) would have purchased the original brand if a knockoff had not been available, creating a negative monetary effect on the sales of the original brand (Lamb 2010; Liebowitz 2005). It is not trivial to assess the extent of this phenomenon: On one hand, as discussed above, due to price and quality differences, substitution levels may be low. On the other hand, it is widely reported that counterfeits and knockoffs are becoming considerably similar to original items to the extent that they confuse even sophisticated shoppers (Holmes 2011). This is especially true as fashion items are increasingly purchased on the Internet, where it may be hard to distinguish a knockoff from the original (Wilson 2007).

Damage to brand equity. Damage to brand equity does not necessarily occur as a result of a specific copied item; rather, it is a more long-range effect whereby copies lead consumers to associate a brand with certain negative attributes and therefore to avoid purchasing it in the future. This can happen because the copies are of lower quality, or because they are used by people the original brand owners do not want to be associated with (Lamb 2010; Wilke and Zaichkowsky 1999).

It should be noted that while substantial claims have been made regarding the harm that copies might cause to long-term brand equity (see Staake, Thiesse, and Fleisch (2009) for a discussion in the context of counterfeits), the effect is yet to be fully explored. For example, potential loss of prestige due to counterfeits can drive original-item consumers away from a brand but also may impel some of them to make strong claims to their patronage (Commuri 2009). There are other claims that the market presence of luxury counterfeit items can in fact increase consumers' willingness to pay for well-known brands due to the pleasure of being envied (Romani, Gistri, and Pace 2012). In addition, in cases where it is difficult to differentiate between the originals and the copies, the damage to brand equity due to quality issues may be little.

We note that damage to brand equity is a more essential issue in the context of counterfeits, where brand elements are copied and consumers' perception of the overall brand can be easily affected. In cases of design piracy, where brand elements are not imitated, the effect of copies on brand equity should be considerably lower.

The effect of uniqueness. While an increased number of adopters can help to accelerate the adoption of innovations, in the case of fashions, consumers' desire to distinguish themselves (or *the need for uniqueness*) may create a negative effect on the diffusion curve, leading to shorter and faster diffusion processes (Berger and Le Mens 2009; Bourdieu 1984; Sproles 1981).

The need for uniqueness is the tendency to seek to differentiate oneself from others through the acquisition, utilization, and disposition of consumer goods, which serve to develop and enhance one's self-image and social image (Tian, Bearden, and Hunter 2001). The need for uniqueness is increasingly recognized as a major driver of consumer behavior in the context of fashions yet can be observed in various markets. Researchers have explored how consumers utilize their purchases as tools to distinguish themselves from others (Berger and Heath 2007; Chan, Berger, and Van Boven 2012, Timmor and Katz-Navon 2008). Studies have further investigated the role of uniqueness in increasing the desirability of certain goods (Berger and Shiv 2011), moderating consumers' word-of-mouth levels in publicly consumed goods (Cheema and Kaikati 2010), and affecting consumers' preferences on brand visibility (Han, Nunes, and Drèze 2010), and have shown that a loss of uniqueness can cause consumers to be upset (Arsel and Thompson 2011). Thus, the introduction of a knockoff might create harm to the original product merely by increasing the number of items in the market. Note that such harm does not necessarily depend on consumers' brand-related perceptions regarding the knockoff versus the original brand—a harmful effect may be created even if the original firm itself introduces more items into the market.

A Model for the Growth of Fashions

In this section we present a fashion diffusion approach that takes into account the effect of consumers' need for uniqueness on the growth of a product. This approach will serve as the basis for our subsequent analysis of the effect of knockoffs on the financial performance of original products. Our specific exploration focuses on apparel items, and we use fashion apparel-related empirical data to calibrate the model parameters. Yet the uniqueness effect may be relevant to other "cultural items" (Berger and Le Mens 2009) or "conspicuous consumption" products (Amaldoss and Jain 2005) that are not necessarily apparel fashions, and thus the model we present may be relevant for other markets as well.

We examine the case of a firm that introduces a new fashion product into the market, and consider the NPV of the profits created over the diffusion period. The basic approach of the model is shown in Figure 2. Following the diffusion modeling paradigm, we look at 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 M (Muller, Peres, and Mahajan 2009).

As described above, the presence of a need for uniqueness should create attrition among users and potential users as the number of adopters increases. We therefore consider three groups of interest: ***Users*** - people who adopted the product and still use it; ***Avoiders*** - people from the market potential who have not yet adopted, and will not adopt due to the need for uniqueness; and ***Disadopters*** - people who adopted, yet stopped using the product due to the need for uniqueness.

This need for uniqueness is modeled via a uniqueness threshold model, where each individual has a personal threshold for the number of product users he or she is willing to tolerate before avoiding or disadopting ("abandoning") the product. In the context of product use, threshold models have largely been used to model adoption dynamics (Goldenberg, Libai, and Muller 2010; Granovetter 1978; Valente 1995) but can be also used to describe attrition processes (Granovetter and Soong 1986). Behavioral work has also adopted a threshold approach in looking at people's tendency to diverge given the behavior of others (Berger and Heath 2007, 2008).

At each point in time t we consider the total number of users, $x(t)$, the cumulative number of disadopters, $y(t)$, and the cumulative number of avoiders, $z(t)$. The available market potential at each point t is $N_x(t)$. This variable represents the portion of the market that has not yet adopted, disadopted or avoided the fashion:

$$N_x(t) = M - x(t) - y(t) - z(t) \tag{1}$$

Previous research dealing with attrition in diffusion processes suggests that there is a delay period between the trigger that causes attrition and the actual attrition (Libai, Muller, and Peres 2009). Correspondingly, our approach assumes that a consumer does not abandon the fashion at the immediate moment at which the number of other users crosses his or her threshold. This might be due to delayed reaction or to the fact that it takes time for consumers to become aware that their threshold has been surpassed by the current level of adoption. Brand prominence, for example, can affect this awareness, as subtle fashion designs might take longer to be noticed (Berger and Ward 2010; Han, Nunes, and Drèze 2010). According to our approach, at each time period a certain number of users (i.e., a fraction of $x(t)$) pass their uniqueness threshold levels but do not necessarily disadopt the product (e.g., because they are unaware that their uniqueness threshold has been passed). We refer to these individuals as potential disadopters, and we assume that all users who disadopt will come out of this group. We use $N_y(t)$ to denote the total number of potential disadopters, or the ***effective disadopters' potential***, at time t. Similarly, we use $N_z(t)$ to denote the ***effective avoiders' potential*** at time t, i.e., the number of consumers who have not previously adopted the product, and whose uniqueness threshold has been passed, yet have not yet decided to avoid the product.

We assume that out of the effective disadopters' potential of $N_y(t)$, a certain proportion, denoted by δ, will disadopt in the next period of time. Similarly, we assume that a proportion δ of the effective avoiders' potential, $N_z(t)$, will decide to avoid the product in the next period. We refer to δ as a conditional attrition factor. The resultant aggregate disadoption and avoidance functions, respectively, are given in Equation 2. The adoption function follows the standard diffusion pattern, adjusted for attrition, and is given in Equation 3:

$$dy/dt = \delta \cdot N_y(t) \quad and \quad dz/dt = \delta \cdot N_z(t) \tag{2}$$

$$dx/dt = \left(p + q \cdot x(t)/M\right) \cdot N_x(t) - \delta \cdot N_y(t) \tag{3}$$

Hence, word-of-mouth communication is assumed to take place between adopters (captured in $x(t)$) and consumers who have not yet adopted, disadopted or avoided the fashion ($N_x(t)$), for the calculations of the effective disadopters' potential of $N_y(t)$, and the effective avoiders' potential, $N_z(t)$, see Appendix 1.

While it is an accepted practice to model attrition using an exponentially declining function (see Libai, Muller, and Peres 2009), it is more challenging to model the effects of a threshold. The uniqueness effect implies a negative externality. Thus, if the current fraction of adopters is $x(t)/M$, and if H is the uniqueness threshold level with a given distribution in the population—then the effective market potential for disadopters at time (t) (i.e., the total number of people in the market whose threshold has been crossed) is given by $M{\cdot}prob(H \le x(t)/M)$. 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 because 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: $H \sim N(\mu, \sigma^2)$.[1]

Calibrating model parameters with fashion product data

Our next task is to calibrate the model parameters. Unlike categories such as home durables, pharmaceuticals and technological services, where product growth data have often been available to researchers, fashion growth data are not readily available. As a result, there is a dearth of quantitative academic research using fashion growth data. Here we take advantage of the emergence of Google Trends (http://www.google.com/trends/), a tool that allows researchers to gather search pattern data for search terms that people typed into the Google search engine. Research has indicated that online search data can indeed serve as a proxy for actual market behavior in various contexts, including automotive sales, home sales and travel behavior (Choi and Varian 2009); movie ticket sales (Kulkarni, Kannan, and Moe 2012); computer game sales (Goel et al. 2010); and microfinance (Stephen and Galak 2012). Although in Google Trends search results are presented in a standardized data form, if there is no need to compare the level of growth of products, the growth parameters (besides market potential) can still be assessed.

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

Using Google Trends, we considered a large number of products to incorporate into our analysis, and using a selection process described in part 1 of Appendix 2, we chose 15 different fashion products with which to calibrate our model. A general description for each of these products is presented in Table 1 (Tables follow Reference throughout), with additional details in part 2 of Appendix 2.

We then used nonlinear regression to estimate the adoption equation (Equation 3). Note that using Equations 1 through 3 and Equations A1-A3 (Appendix 1), we could express Equation 3 just as a function of x, y and z, and therefore the variables y and z were treated as latent variables whose change over time follows Equation 2. The estimated model parameters for each fashion are given in Table 2, with an average R square of .598[2]. The parameter δ, which represents the rate of conditional attrition, is greater than 0 for all products and is less than 1 in all but four products. This means that disadoption occurs, and at a fast rate, but in general it takes some time before consumers realize their individual thresholds have been surpassed. The mean threshold level μ varied between 1 and 15 percent of the market, which means that for these innovations, a rather low level of penetration is enough to ignite the need for uniqueness and cause adopters to disadopt the fashion. Lastly, we use the parameters of Table 2 to derive the parameter ranges used in simulations of the fashion diffusion models (see Table 3). We also report the average stay of a consumer, i.e., the average number of months that a consumer remains an adopter of the fashion item. This number ranges from 8 to 33 months and is highly correlated with the overall duration of the life cycle of the fashion item: On average, the consumer stays for only about a third of the overall life cycle of the fashion item.

The Knockoff Model

Basic assumptions

Given the fashion diffusion model, we next examine how the introduction of a knockoff changes the market dynamics and the profitability of the original product. We first lay out a few assumptions regarding the setting.

[2] Two fashions, Robert Geller and Thom Browne, were erratic in the monthly-level data. To ensure that the parameter values for these two items did not change the nature of our findings, we repeated the analysis without these two products and saw no substantial changes in the results.

Time of the introduction of the knockoff. We assume that the knockoff is introduced at the same time as the original brand. 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; Wilson 2007). We later examine the case of knockoffs that are introduced at a time lag.

Perception of uniqueness. For modeling purposes, we assume that buyers and potential buyers of the original product are affected both by the number of original items and by the number of knockoffs that they see in the market. One should note that the owner, who paid for the good, is likely, of course, to be aware of the source of that good. Our interest, however, is in the effect of seeing others using a similar design (such observations are often brief, and the observer has no real ability to inquire about the source), and the consequent perception created of the presence of that design in the market. We assume that knockoffs and original items will affect this perception to the same extent. In fact, recent market reports support the idea that even when purchasing an item for their own use, consumers may find it hard to assess the difference between originals and knockoffs, because the quality of knockoff products and the ability of replication are increasing greatly. Even in the case of direct counterfeits of brand identity, consumers often find it hard to distinguish between originals and knockoffs (Gentry, Putrevu, and Shultz 2006; Holmes 2011). It should also be noted that even if an original owner suspects that a certain good used by others is a knockoff of an original brand, for uniqueness purposes, it is enough for the owner to think that others will not know the difference, to create a sense of loss of uniqueness.

Sales of the knockoff. Since our focus is only on the NPV of the original product, we do not model the growth of the knockoff product. Rather, we assume that in addition to the users who adopt the original product, there is an additional portion α of users who adopt the knockoff, such that the number of consumers using either the original product or the knockoff is $(1 + \alpha)\cdot x(t)$. This will affect growth in two contrasting ways: On one hand, it will increase the number of perceived users and thus accelerate adoption (see Equation C2 in Appendix 3). On the other hand, it will cause more current and potential adopters of the original product to cross their uniqueness thresholds, thereby increasing attrition. These changes to the basic model are reflected in Equations C3 and C4 (Appendix 3) of the knockoff model.

In evaluating the market potential for the original product, one should distinguish between the number of adopters perceived by the consumers and that perceived by the original firm. According to our assumptions, an adopter does not distinguish between the original product and the knockoff; thus, the number of adopters he or she observes is $(1 + \alpha)\cdot x(t)$. However, when evaluating the remaining market potential $N_x(t)$, one should consider the number of adopters as $x(t)$ and not $(1 + \alpha)\cdot x(t)$, this calculation ignores the knockoff adopters who are "lost" to the firm.

The substitution effect. Another consequence of knockoffs is the substitution effect, where some people purchase the knockoff instead of the original brand. We denote the percentage of knockoff units that otherwise would have been purchased as originals as β. Thus, in the presence of a substitution effect, the market potential that the firm faces is reduced from the previous level of M to a new lower level of $\overline{M} = M/(1+\beta)$. The full formulation of the knockoff model is given in Appendix 3.

Since we could not estimate parameters α and β from the data described in the previous section, we had to rely on external estimates and then perform sensitivity analyses to check the validity of our results. Fashion knockoffs are estimated to account for 5% of monetary sales of the US fashion market (Wilson 2007). Given the difference in price markup between knockoffs and original goods for fashions, it is estimated that, on average, the unit number of fashion knockoffs is around 27% of the total unit market share (US Customs and Border Protection 2012). This means that for every 100 original fashion items sold, another 37 knockoffs are sold. Thus, we set the parameter $\alpha = 1/.73-1 = .37$. To estimate β we rely on the findings of Staake and Fleisch (2008, p. 126) who demonstrate that when the ability to purchase apparel knockoffs is eliminated, 20.8% of consumers who would otherwise have chosen to purchase knockoffs decide to purchase the genuine article. If we consider that, in the presence of a knockoff, the total number of design users (originals + knockoffs) is 37% greater than the number of users of the original product (i.e., $1.37\cdot x(t)$), but that 20.8% of knockoff adopters would have purchased an original product if the knockoff had not been introduced into the market, we can say that introducing a knockoff into the market actually decreases the starting market potential by $.37\cdot.208 \approx .077$, and thus $\beta = 7.7\%$.

Simulation of the knockoff model

To explore the monetary consequences of the introduction of a knockoff, we simulated growth patterns with and without knockoffs, using the range of parameters in Table 3, and compared the NPV created at the end of the growth horizon. We used 98 months (periods), the maximal number of periods in our dataset, as the growth horizon. We varied the parameters (*p, q,* μ, σ and δ) across five values each in a full-factorial design, to produce a total of 15^5 = 759,375 growth patterns.

To translate the temporal adoptions into NPV, we assume an annual discount rate of 10% and assume one unit of profit for each item upon adoption.

Our interest here is not only in the total effect but also in its composition into the three factors described above, i.e., acceleration, substitution, and uniqueness. Therefore, we examine additional scenarios that enable us to isolate the effect of each source on the NPV of the original product (see Appendix 4 for the process of decomposing the total effect into isolated components). The isolated effects can be summarized as follows:

Acceleration effect: The value that the presence of a knockoff contributes to the NPV of the original by accelerating adoption, in the absence of substitution and uniqueness effects. Acceleration should contribute positively to the NPV.

Uniqueness effect: The isolated effect of the fact that the knockoff increases prevalence of the design in the market, leading people to disadopt or to avoid adopting. This effect should be negative.

Substitution effect: The isolated effect of the fact that some people will buy the knockoff instead of the original. This effect should be negative.

Total effect: This is the sum of all effects—acceleration, uniqueness, substitution and their interaction—on the NPV of the original item.

We found that the interaction effect of the three main effects is relatively small with a M .9% (SD 1.7%) and does not affect the substantive results we describe in what follows. Thus, we highlight the results for the three main effects and the total effect.

Results: The Knockoff Effect on NPV

The 15 fashion products

Before we turn to the full simulation analysis it is interesting to see the four effects for the 15 fashion products we used for parameter calibration. This will reflect what would be the expected monetary effect of the introduction of a knockoff early on for each of these products. The results are presented in Table 4, and show some interesting patterns.

First, we see that for all items but one the negative effect of uniqueness is larger than the positive effect of acceleration, and is by far the strongest effect on the NPV. On the other hand, in all cases the positive effect of acceleration is larger than the negative effect of substitution. The picture of the total effect for these items is consistent: For all items the overall effect on NPV is negative.

The full simulation

Turning to the full set of model simulations, we first find that in 97.2% of cases in which a knockoff is introduced, a negative total knockoff effect is observed, i.e., the NPV of the original item is lower than that without a knockoff. On average across all simulations, the introduction of a knockoff reduced the NPV of the original by 13.1% (SD 5.4%). As with the 15 original products, the combined negative effect of uniqueness and substitution is larger than the positive effect of acceleration. We see that the scarce cases in which the NPV did go up in the presence of a knockoff are the extreme incidents where the diffusion parameters p and q are particularly low. In such cases, the jump-start that the knockoff gives to the diffusion process by helping to accelerate adoption is enough to overcome the damages of uniqueness and substitution.

Result 1. *Taking into account acceleration, substitution and uniqueness, the overall effect of the introduction of a knockoff is a reduction in the NPV of the original item.*

Looking at the isolated effects of acceleration, uniqueness and substitution, we see results that are consistent with the patterns shown in Table 4. We find that the largest effect is that of uniqueness, with an average of -18.1% (SD 3.2%), followed by acceleration, with an average of 9.5% (SD 7.3%), and finally substitution, with an average NPV impact of -5.5% (SD 2.1%).

To test whether the differences between the effects were significant, we ran a paired sample *t*-test, comparing the effects of uniqueness, acceleration and substitution over their respective growth patterns, and found the average difference to be significant, with $p < .001$.

To carry out the comparisons between the effects, we used the averages of the parameters in our range, and, in particular, we used the average mean of the uniqueness threshold level distribution (μ), which is estimated to be 7.8% in our dataset. However, when the average threshold level is higher, people will be affected less by uniqueness, and the relative contribution of substitution will go up. Therefore, we subsequently attempted to identify the upper limit of the value of the threshold mean that maintains the observed order of effect sizes (i.e., in absolute values, uniqueness > acceleration > substitution). We ran the model for every value of the threshold mean from 0% to 90%, in increments of 5%, while varying the other parameters, as before, in a full factorial design according to the values of Table 3.

The results of the simulations appear in Table 5. We see that even for large values of μ, the order of effect sizes holds. We also see that the total effect of knockoffs continues to be negative even for high threshold levels. Note that the thresholds are a function of the original market potential, and knockoffs add 37% to the current perceived adoption levels, so the effective threshold in the original market potential is somewhat lower. For an example: when knockoffs are introduced in a scenario where the mean of the threshold is 70%, the effective threshold is actually much lower and is equal to 51% (.7/1.37). Nevertheless, even when making this adjustment, uniqueness dominates even at high threshold levels.

Result 2: A*mong the three effects—acceleration, substitution and uniqueness—on average, the effect of uniqueness on the NPV of the original (a negative effect) is the strongest, followed by acceleration (a positive effect) and then substitution (a negative effect).*

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

Unlike the US, the European Union has legal protection for designs. The European Community Design Protection Regulation (DPR), which went into effect in 2002, provides fashion designs with 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 in line with the system currently in place in the EU (Hackett 2012).

What would be the impact of a legal protection period on the overall monetary effect of a knockoff? Would the effect of a two-year protection period differ from that of a four-year period, for example? To examine these questions, 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 60 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).

Figure 3 presents the percent reduction of the NPV of the original product in the presence of a knockoff, compared to a case with no knockoff, as a function of the duration of the protection period. The dynamic picture that arises from Figure 3 is interesting. A short protection period does not necessarily help the original: Protection periods of 12 months or shorter even decrease the damage to the original product's NPV by one percentage point at most (i.e., the damage is -12.1%. as opposed to -13.1% in the case of no time lag). For longer protection periods, a positive effect begins to emerge. For a time lag of 36 months, the current duration of legal protection in the EU, damage to the NPV decreases by almost half, to -7.4%. For a time lag of 60 months, the damage drops to -3.5%, which is less than a quarter of the damage without any lag.

A closer look at the influence of the individual components of the knockoff effect (acceleration, uniqueness and substitution), shown in Figure 3, enables us to understand the sources of the pattern. For shorter time lags, the total effect is largely influenced by two opposing forces: the positive effect of acceleration, which decreases as the time lag increases, and the negative effect of uniqueness, which also weakens as the time lag increases. The drop in the effect of acceleration is consistent with previous research showing that the role of a customer in accelerating the NPV from new product growth is disproportionately high in the very early period of the product life cycle (Hogan, Lemon, and Libai 2003; Libai, Muller, and Peres 2013). For shorter time lags, the effect of acceleration weakens at a slightly faster rate compared with the effect of uniqueness; however, as the time lag increases, the pattern changes, and the effect of uniqueness weakens at a faster rate compared with the effect of acceleration. Thus, beyond a certain time lag duration, the positive effect of the time lag on the original product's NPV becomes more pronounced. This effect is further supported by the fact that the substitution effect also weakens as the duration of the time lag increases.

Result 3: *The effect of the duration of a legal protection period, modeled as a time lag between introduction of the original product and the introduction of a knockoff, is monotonic and nonlinear: A short time lag may not affect the NPV of the original brand. For the ranges we analyze, the positive effect of the protection period is observed primarily for time lags that are more than one year long.*

Robustness tests

Following the above, we conducted a number of robustness checks to see whether the basic results for the overall influence of a knockoff on the NPV of an original product and the relative influence of uniqueness hold when changing the basic assumptions of the model. First, we simulated an agent-based model to check whether we would obtain different results if we modeled the diffusion and uniqueness processes on an individual level rather than on an aggregate level[3]. We further examined the sensitivity of the results to the assumptions regarding the duration of the fashion and regarding the level of knockoffs and substitution in the market. These tests results are largely robust with respect to the model parameters and settings. The one exception is the case of very large substitution levels, under which substitution can dominate over uniqueness. However, even at such extremely large substitution levels, the uniqueness effects are still substantial.

Discussion

The question of whether fashion designs should be legally protected from design piracy is a pressing public policy issue that has attracted much attention and discussion. Yet, to date, there is a scarcity of formal analysis that considers the overall financial impact of knockoffs on the financial performance of original products. Here we argued that new product growth modeling can serve as a framework for a quantitative examination of the issue. We created a fashion diffusion model that takes a uniqueness effect into account, calibrated its parameters using data from Google Trends, used this model to consider the effect of a knockoff on the NPV of the

[3] For more information regarding the robustness tests and their results, contact the authors of this report

original product, and decomposed the effect into its sources. We obtained three main results that are directly relevant to the public discussion of design piracy: The overall effect, the specific effect of uniqueness, and the effect of a legal protection period.

The overall effect of a knockoff

Looking at the combined impact of acceleration, uniqueness and substitution, we see that the overall knockoff effect on the profit of the original product is negative: In over 97% of our simulations (with no time lag), the entry of a knockoff was associated with a decrease in the original product's NPV, as compared to the case in which no knockoff was introduced. The average reduction was more than 13%. Interestingly, this number is more than two times greater than previous assessments of the knockoff effect in the business literature (Wilson 2007). Our findings are thus consistent with the concerns in the industry regarding the damage of design piracy.

Of course, 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 people who are not in the target market can affect brand associations. However, since design piracy is not necessarily associated with long-term damage to brand equity, and because such damage depends on a number of specific, non-trivial market factors, we did not include this scenario in our analysis.

While our analysis indicates that the introduction of a knockoff negatively affects the NPV the original product, we did not consider market level effects. For example, one could argue that consumer welfare might go up in cases where people who cannot afford to purchase an original product are able to enjoy the design by purchasing a lower-priced knockoff. From 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 (Raustiala and Sprigman 2012). We do not get into the existing controversy on this issue (Cotropia and Gibson 2010; Hemphill and Suk 2009), 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 the effect on individual firms, a topic that is lacking in previous literature, and can benefit from our approach and findings here.

The relative strength of uniqueness

Our second key finding relates to the strength of uniqueness in determining the damage of a knockoff to the NPV of an original product. Our analysis indicates that the damage due to uniqueness is generally greater than the damage that stems from the reported substitution rates, and it is also greater in magnitude compared with the positive effect of acceleration. This observation holds even when we assume uniqueness thresholds that are considerably higher than the ones we used in the main analysis. Interestingly, industry observers often refer to substitution, more than uniqueness, when considering the monetary damage created by knockoffs (Lamb 2010), possibly because the effect of substitution is more vivid and easier to quantify. In comparison, the effect of uniqueness is more complex: To calculate it, it is necessary to quantify the dynamic effect of people who have already adopted and then disadopt, thereby slowing the diffusion process, as well as the effect of people who might have adopted, but do not because the product has become too prevalent in the market. Given the magnitude of the effect we identify, we believe that the "cost of uniqueness" should become part of the discussion on the legal aspects of knockoffs.

In a more general sense one could think of the positive and negative aspects of "social effects" that influence product diffusion. Additional users can have a positive financial impact for a firm due to both word of mouth and network externalities, which are together captured in the parameter of internal influence in the basic diffusion models (Givon, Mahajan, and Muller 1995; Van den Bulte and Stremersch 2004). However, a greater number of adopters can also have a negative impact, owing to social effects such as congestion (Chen, Gerstner, and Yang 2009) and uniqueness. Isolating the acceleration and uniqueness effects provides a rare opportunity to compare positive and negative social effects. In the case of fashion knockoffs we see that the negative effect of uniqueness is larger than the positive effect of acceleration. Thus, the overall "social effect" is negative.

The role of the legal protection period

The question of whether to implement a legal protection period for fashion designs is of much interest, given a recent proposal to adopt a three-year protection period in the US, following the EU's example (Hackett 2012). The EU currently provides three years of protection to unregistered designs, upon registration of the design the period can be extended in blocks of five years, up to 25 years (Monseau 2011). While issues relating to the actual use, enforcement and legal aspects of such a law are beyond our scope, one should clearly understand the consequences of this protection period and the influence of its length when discussing its benefits.

Our results highlight the role of the length of the protection period in its ability to prevent damage to the original product's NPV. We see that for a protection period to help the original, it should be long enough, probably longer than one year. However, it could be less than the three-year period mentioned (it does depend of course on the cycle of the specific fashion). The reason is that, while all the effects diminish over time, early on the benefits of the acceleration effect almost cancel out the negative consequences of substitution and uniqueness, such that the positive effect of protection begins to emerge only for protection periods of 12 months or longer. This issue can be of much importance, since as part of a compromise on the issue of legal protection, a protection period shorter than three years may be offered as a solution (Stevens 2012); however, such an offer might not necessarily take into account the dynamics identified here.

Overall implications of this analysis

Our overall contribution to the public discussion on legal protection for design piracy can be summarized as follows: Design piracy may harm originals more than previously assessed, in large part as a result of the uniqueness effect, for which the acceleration does not compensate. Furthermore, a short protection period may not contribute much, or even at all, towards protecting the original product, whereas a protection period of three years can substantially reduce the damage caused by introduction of a knockoff. Of course, the minimal duration of the protection period may depend on the duration of the fashion cycle. Here we used averages based on the products we analyzed. It may be faster or slower for specific products. In addition, if a knockoff creates long-term damage to brand equity, this should also be taken into account.

Further research and limitations

While our study focused on the case of design piracy in fashion, the approach presented here can be extended to more general questions that should be of interest to managers and researchers. Such examples include:

Counterfeits. The approach we presented can help in analyzing questions regarding the damage caused by counterfeiting, which often occurs in addition to design piracy (Staake, Thiesse, and Fleisch 2009). We note however, that the analysis of the effects of counterfeits may be more complex. First, the longer-term brand equity harm of counterfeits can represent a significant part of their impact, and thus must explicitly be taken into account. Second, people frequently use brand elements such as logos to create their identity, and this identity is often group based (Berger and Heath 2007). Thus, it may be beneficial to carry out the analysis using a segment-based model in which the dynamics among groups are explicitly considered, and in particular the attraction and repulsion among elite and mainstream consumers (Amaldoss and Jain 2008; Bakshi, Hosanagar, and Van den Bulte 2011), as well as differential adoption over time based on status (Hu and Van den Bulte 2012).

The effect of within-firm knockoffs. While in most cases design piracy occurs without the cooperation of the firm, in some cases firms may want to copy their own designs in order to reach lower price markets. For example, retailers such as H&M carry lines created with the cooperation of well-known designers, which are similar in design to those designers' original collections, yet are much cheaper. The approach presented here can be applied to help firms plan their actions in an informed way, e.g., to identify the optimal number of self-knockoffs in the market.

Marketing mix effects. Recent research has started to examine optimal marketing mix activities such as pricing (Amaldoss and Jain 2005) or new product seeding (Bakshi, Hosanagar, and Van den Bulte 2011) in the presence of the need for uniqueness. It may be of interest to explore the optimal marketing mix strategy for an original product in the presence of a knockoff. For example, one could modify the price to enhance acceleration or to reduce the substitution effect. However, encouraging customers to adopt early on might affect uniqueness perceptions of other consumers, which may have negative consequences for the firm. The framework used herein can help in analyzing these processes.

Need for belongingness. We have modeled the effect of uniqueness; yet customers are also affected by the need for belongingness or assimilation when making adoption and choice decisions (Chan, Berger, and Van Boven 2012). This effect is current captured in the internal effect parameter q of the diffusion model. However. in the same way that network externalities can be separated from word of mouth via a threshold model (Goldenberg, Libai, and Muller

2010), future research can consider a more comprehensive model that will also separate belongingness, and will help researchers to better understand the basic mechanism of growth in that respect.

Other markets. While this analysis was applied to fashion apparel markets, the need for uniqueness plays a role in many consumer markets. Raustiala and Sprigman (2012) point to several other markets where design piracy may exist in a similar manner to that of apparel including restaurant cuisine, stand-up comedies and financial investments. Design piracy is also an issue in more technological markets: smartphones, sophisticated laptops and numerous electronic gadgets are constantly improved and new versions with original designs are introduced into the market to enable their owners to feel unique. Similar to the case of apparel, the design of such products is often copied by other firms that aim to introduce to the market cheaper versions.

Future research will thus want to examine how the framework presented here for fashion apparel can be applied to other markets. It should be recalled that we calibrated our model using data on fashion apparels, so category specific information should be used for other cases. One should also consider that in other categories additional features in addition to design that create uniqueness are not necessarily copied (e.g., technological features in some products). Caution should be thus taken when assessing the specific effect of design piracy in these markets .

Other limitations. In a general sense, aiming to offer a parsimonious approach with fewer assumptions, we created a modeling approach 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 distinguishing between different types of fashion goods. Advanced agent-based models that are based on diverse network structures can help to examine the effect of network structure on the results we present. The effect of knockoffs in additional categories such as music 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 person disadopts a repeat-purchase good or service.

Conclusion

In their influential work on design piracy, Raustiala and Sprigman (2006) argue that since high-intellectual property (IP) protection has never existed in the US fashion industry, "it is difficult to say with any certainty whether raising IP protections would raise consumer or producer welfare". While achieving certainty on this issue is certainly unrealistic, given its importance to public policy, we believe that it is possible to come much closer. A formal analysis that aims to isolate the effect of each component of the knockoff effect and to provide insight into understand the total effect is appropriate means towards achieving this end. We hope that this study is just one step in that direction.

Appendix 1

Calculating the Effective Avoiders and Disadopters Potential

To calculate the effective avoiders' potential, $N_z(t)$, we need to take all consumers who passed their uniqueness threshold (M multiplied by the probability to pass the threshold) and subtract from this number all consumers who have already disadopted or avoided the fashion, i.e., $y(t)$ and $z(t)$, and the effective disadopters' potential $N_y(t)$, to arrive at the following equation:

$$N_z(t) = Max\left(0, M \cdot prob(H \le x(t)/M) - y(t) - z(t) - N_y(t)\right) \quad \text{(A1)}$$

The reason the max function is used in Equation A1 (and in Equation A3) is as follows: When $x(t)$ increases, the fraction of users increases, which means that more consumers are likely to perceive the product as "insufficiently unique" (i.e., pass their uniqueness thresholds) and to abandon it. Yet when a sufficient number of consumers disadopt the product, the value of $x(t)$ decreases, and the fraction of users may once again dip below the uniqueness thresholds of consumers who already abandoned the product. These consumers are not added back into the market potential, however (we consider abandonment as final in the model). This means that at a given point in time, the total number of avoiders and disadopters might be larger than the number of consumers in the market potential who are currently past their uniqueness thresholds. Thus, we set the lower limit of both $N_y(t)$ and $N_z(t)$ to zero.

Since the probability to adopt is independent of the uniqueness threshold level, as we can see in Equation 3 and in Figure 1, the adoption process acts like a process of sampling from a population with a conditional uniqueness threshold distribution. And because a single conditional attrition factor (δ) is used to model both disadoption (i.e., the reduction in $x(t)$) and avoidance (i.e., the reduction in $N_x(t)$), the distribution is not affected by attrition. Thus, the proportion of individuals in $x(t)$ who have passed their uniqueness threshold and the proportion of individuals in $N_x(t)$ who have passed their uniqueness threshold will converge to the same mean, with standard deviations depending on the sizes of the two populations.

This means that the expected ratio of individuals who have passed their uniqueness thresholds is equal in both the adopter population and the available market potential, such that:

$$E(ratio(t)) = \frac{N_y(t)}{x(t)} = \frac{N_z(t)}{N_x(t)} \tag{A2}$$

Substituting from Equation A1, the effective disadopters' potential, $N_y(t)$, is given by the following:

$$N_y(t) = Max\left(0, \frac{M \cdot prob(H \le x(t)/M) - y(t) - z(t)}{M - y(t) - z(t)} \cdot x(t)\right) \tag{A3}$$

Note that when δ = 0, or when μ = 1 and σ = 0, no one abandons the fashion, and the model reduces to the classic Bass diffusion model.

Appendix 2

The 15 Fashion Items In This Research

Part 1: the process of selecting the fashion items analyzed

In order to avoid bias originating from our perceptions of fashions, we turned to the following sources for names and types of recent fashions and fashion designs:

- Council of Fashion Designers of America (CFDA) award winners (2004-2011)
- TIME Magazine's fashion top 10 lists:
    - Fashion moments 2008-2009
    - Fashion must-haves 2007
    - Fashion statements 2010
    - Fashion trends 2006-2007
- Thefullwiki.org - a website that indexes Wikipedia searches by topic:
    - Top 2000s fads and trends
    - Top 2000s & 2010s fashion
    - Top high fashion brands
- Style.com item of the week
- Shefinds.com: Ten 2010 Trends We Couldn't Live Without

Since Forever 21 was noted as the one of the leading knockoff manufacturers (Hemphill and Suk 2009), we also added to this list 18 fashion firms that sued Forever 21 over intellectual property infringements (gathered on January 2012 from Justia.com).

We gathered 532 fashions and collected web-search data regarding each one using Google Trends (http://www.google.com/trends/). This service is a free online tool that allows researchers to examine the aggregate search patterns for any web search made through the Google search engine. It offers updated and normalized web-search data starting from January 2004 that can be filtered by search type, geographical area, time frame and search category. Since most of the Internet searches in the US (83%) are performed through Google (Purcell, Brenner, and Rainie 2012), this tool may give us representative data regarding the global Internet search patterns of fashions.

Since we wished to use the search data gathered from Google Trends for the adoption and use of these fashions, 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. The fashion should have started after January 2004, since Google Trends did not collect data prior to this date.
2. We used only monthly or weekly level data, and only data for searches made in the US, in order to minimize geographical and cultural biases.
3. The data needed to have at least 18 continuous data points in addition to sales having already reached a first peak, as estimations before the peak are relatively unstable.
4. In the rare case that several fashion cycles were witnessed (such as high-waist jeans, which peaked in 2007 and came back in 2011), only the first cycle was used.
5. We avoided data with strong seasonality effects such as boots, coats, or swimsuits.
6. The search term share in the selected category should be more than 25%, as Google's tool warns that the results will be less specific for said category with less that 25%.
7. We also avoided search terms whose growth was less than the category's growth, as this means that the search terms are less attractive than the average product in the category.

After applying this filtering algorithm, we ran another test for each search term to determine whether there was any external reason for declines in the popularity of the search-term (e.g., the product was discontinued, or it was involved in a media controversy). At the end of this process, we were left with 15 suitable clothing and accessory fashions, given in Table 1. The only exception to the selection criteria is the Crocs fashion trend, as Crocs went on sale in 2002. However, Crocs began expanding in the US only after June 2004, when the company purchased the patent for the foam of the shoe.

Part 2: description of the 15 fashion items[4]

A Bathing Ape (www.bape.com): A Japanese clothing firm founded by Nigo (Tomaki Nagao) in 1993. Based in Japan, it opened its first U.S. store in 2005. A Bathing Ape is known

[4] Celebrity spotting for the celebrities using the fashions in this appendix was done through www.coolspotters.com website, a social website focused on discovering the brands celebrities are wearing.

for its one-of-a-kind footwear and is a popular brand among celebrities, with many international celebrities appearing in magazines and catalogs wearing the firm's clothing.

Band of Outsiders (www.bandofoutsiders.com): Launched in 2004 by Scott Sternberg, Band of Outsiders focuses on vintage inspired fashion. Band of Outsiders has won two CFDA awards and caters to celebrities such as Kirsten Dunst, Kanye West and Michelle Williams.

Boyfriend Jeans: Voted as one of TIME magazine's top 10 Fashion moments 2008, these jeans are looser and modified from jeans for men. Katie Holmes was one of the first supporters of this trend, when she was spotted in August of 2008 wearing Tom Cruise's old jeans, and the trend was subsequently adopted by Reese Witherspoon, Sarah Jessica Parker and many other celebrities.

Coach Bonnie Collection (www.coach.com): In 2009, luxury leather goods firm, Coach, released a handbag collection inspired by the firm's first high end designer Bonnie Cashin, one of the leading designers of ready-to-wear fashion of the 1960s. The collection was featured as item of the week on www.style.com and in many other fashion blogs and is worn by celebrities such as Eva Longoria, Eva Mendes, Lindsay Price and more.

Crocs (www.crocs.com): The Crocs fashion, or rather anti-fashion, spurred a lot of controversy and polarized opinions regarding the design of the shoes. The shoes feature regularly in "top worst" lists (e.g. TIME magazine's "The 50 Worst Inventions"). However, their unique design has also drawn some famous supporters, and celebrities such as Brooke Shields, Steven Tyler, Morgan Freeman and even George W. Bush and Michelle Obama have been spotted wearing crocs shoes.

Harajuku Lovers (www.harajuku-lovers.com): Launched in 2005 by American singer and fashion designer Gwen Stefani, this apparel, accessories and stationery brand revolves around the "Kawaii" culture of the Tokyo Harajuku region. Apart from Gwen Stefani, musicians such as Madonna, Avril Lavigne and Mika have been spotted wearing Harajuku Lovers' goods.

High-Waist Jeans: Also called high-rise jeans, these jeans were dominantly in fashion in the 1970's. Recently, these more "conservative" and comfortable jeans have trended back into fashion, featuring in TIME's top 10 fashion must-haves for 2007. Many celebrities, such as Jennifer Lopez, Scarlett Johansson and others, have been spotted sporting a pair of high-waist jeans.

Norma Kamali for Walmart (www.normakamalicollection.com): In 2008, fashion superstar designer and three-times Coty award winner Norma Kamali joined forces with retail giant Walmart to produce a joint fashion line bringing haute couture to the masses.

Phillip Lim 3.1 (www.31philliplim.com): Phillip Lim launched his fashion label 3.1 Phillip Lim in 2005. Two years later he was awarded the 2007 CFDA emerging talent award for his designs, which combine the dressy with the casual. Phillip Lim's "effortlessly chic" elegance is favored by celebrities such as Jennifer Lopez, Rachel Bilson and Lindsay Lohan.

Robert Geller (www.robertgeller-ny.com): After working for luxury fashion firm Marc Jacobs, Robert Geller went on to open his own fashion firms, the first with a partner under the brand Cloak, and the second under his own name in 2007, winning both CFDA and GQ awards for new designers in 2009. Robert Geller's customer list includes True Blood's Alexander Skarsgård and Garrett Hedlund.

Skinny Cargo Pants: In 2010, New York-based trend site shefinds.com mentioned this fashion in its *Ten Trends We Couldn't Live Without* list. While this fashion trend seems to have been short lived, it was favored by celebrities such as Rihanna, Kim Kardashian and Gwen Stefani (Ingersoll Schwartz 2010).

Skinny Jeans: Slim fitting apparel has been around since the 19^{th} century. However, in 2005 this style swept the nation, in a comeback driven by supermodel Kate Moss and other celebrities such as Angelina Jolie and Sienna Miller. Skinny jeans were also featured as one of TIME magazine's top 10 fashion trends for 2006 (Maxwell 2006).

Thom Browne (www.thombrowne.com): Thom Browne is an award winning American fashion designer (CFDA in 2006 and GQ in 2008 among many others). After working for Ralph Lauren and Club Monaco, Thom Browne started his own label in 2001. His big break came when he announced his partnership with Brooks Brothers to design their top of the line Black Fleece collection. Thom Browne dresses celebrities such as Usher, Ryan Gosling and Shia LaBeouf and even *Gossip Girl* starlet Leighton Meester wore a Thom Browne men's suit for the 2010 Gotham Independent Film Awards

Tokidoki (www.tokidoki.it): In 2005, Italian artist Simone Legno founded this Japanese-inspired brand, which is known for its cute and bright designs, in Los Angeles, California. Tokidoki focuses on collaborating with many other brands (e.g., Hello Kitty, Levi's, Marvel Comics, Barbie and many more) and creating Japanese-inspired versions of those brands.

Tokidoki is worn by hot young celebrities such as Cobie Smulders, Ariel Winter, and Elle Fanning**.**

Trovata (www.trovata.com): This California-based fashion brand, which focuses on casual contemporary apparel, was founded in 2002 by three college friends (currently only one remains from the original group). Trovata has won many awards for its designs and is known for its seasonal collections, in which each season's collection is based on a different fictional story, and as you purchase more apparel, the story is revealed. Celebrities such as Jessica Simpson, Hilarie Burton and Caroline Winberg were spotted wearing Trovata's designs, and the brand is also favored by fictional character Gregory House in the *House* TV show.

Appendix 3

Formulation of The Knockoff Model

Given the assumptions above, we formulate a model for the scenario in which a knockoff is introduced into the market. The model is based on the basic fashion diffusion model (Equations 1–3 and A1-A3), where Equations 2 and A2 remain the same, and Equations 1, 3, A1 and A3 are replaced with Equations C1-C4, respectively, where $\overline{M} = M/(1+\beta)$:

$$N_x(t) = \overline{M} - x(t) - y(t) - z(t) \tag{C1}$$

$$dx/dt = \left(p + q \cdot (1+\alpha) \cdot x(t)/M\right) \cdot N_x(t) - \delta \cdot N_y(t) \tag{C2}$$

$$N_z(t) = Max\left(0, \overline{M} \cdot prob\left(H \le (1+\alpha) \cdot x(t)/M\right) - y(t) - z(t) - N_y(t)\right) \tag{C3}$$

$$(N_y(t) = Max\left(0, \frac{\overline{M} \cdot prob\left(H \le (1+\alpha) \cdot x(t)/M\right) - y(t) - z(t)}{\overline{M} - y(t) - z(t)} \cdot x(t)\right) \tag{C4}$$

Appendix 4

Decomposing the Total Effect

To decompose the different effects, we consider the NPV created in a number of scenarios:

Scenario A. Basic model: The fashion model with no knockoff (Equations 1-3,A1–A3).

Scenario B. Full model: All effects described in Equations C1-C4 above. The case of a knockoff where acceleration, substitution and uniqueness occur.

Scenario C. Uniqueness + Acceleration: In this model we remove the substitution effect by setting β (the substitution parameter) at zero. This will affect the market potential in Equations C1, C3 and C4.

Scenario D. Acceleration alone: Similar to scenario A, but Equation 3 is replaced by Equation C2 since the knockoff positively affects acceleration.

Scenario E. Substitution alone: In this scenario we set α to be zero, and β is not zero. We use this scenario because estimating the substitution effect from the full model (scenario B) might ignore the interaction when the three effects are combined.

Hence the different effects (and the level of interaction):

The Acceleration effect is calculated as:

$$Acc.effect = (ScenarioD - ScenarioA) / ScenarioA$$

Uniqueness is calculated as: $Uniq.effect = (ScenarioC - ScenarioD) / ScenarioA$

Substitution is calculated as: $Sub.effect = (ScenarioE - ScenarioA) / ScenarioA$

The total is calculated as: $Total.effect = (ScenarioB - ScenarioA) / ScenarioA$

And the interaction is: $interaction = Total.effect - Acc.effect - Uniq.effect - Sub.effect$

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Tables and Figures

Table 1: summary description of dataset of clothing and fashion items

Fashion item	Main product line	Designer/ celebrity promoter	Country	Main target market
Bathing Ape (BAPE)	Lifestyle and street-wear	Nigo (Tomoaki Nagao)	Japan	Men, women, kids
Band of Outsiders	Preppy menswear	Scott Sternberg	USA	Mostly men, recently women
Boyfriend Jeans	Oversized denim jeans	Katie Holmes	USA	Young women
Coach Bonnie Collection	Bags and accessories	Bonnie Cashin	USA	Women
Crocs	Footwear & accessories	Brooke Shields	Canada/USA	Kids, women, men
Harajuku Lovers	Accessories, beauty products	Gwen Stefani	USA/Japan	Young women
High-Waist Jeans	High-waist denim jeans	Jennifer Lopez	World-wide	Young women
Norma Kamali for Walmart	Haute couture for the masses	Norma Kamali	USA	Women
Phillip Lim 3.1 line	High-end womenswear	Phillip Lim	USA	Women
Robert Geller	High-end menswear	Robert Geller	USA	Men
Skinny Cargo Pants	Bulky-pockets slim pants	Kardashians/ Rihanna	USA	Youth market
Skinny Jeans	Slim-fit pants and jeans	Kate Moss	World-wide	Youth market
Thom Browne	High-end Menswear	Thom Browne	USA	Men
Tokidoki	Cute, bright fashion & toys	Simone Legno	USA/Japan	Youth market
Trovata	Casual, preppy fashion	John Whitledge	USA	Men & women

Table 2: estimation results for 15 clothing and accessory fashion products

Fashion item	Time (months)	p	q	δ	μ	σ	Average Stay [a] (months)	MSE	Adjusted R^2 (%)
Bathing Ape	98	.00023	.143	.414	.147	.008	27	19.81	95.3
Band of Outsiders	73	.0003	.079	1	.02	.025	24	108.93	70.2
Boyfriend Jeans	44	.00104	.091	.697	.034	.011	15	124.78	43.3
Coach Bonnie Collection	39	.00117	.382	.369	.023	.009	11	60.74	88.8
Crocs	98	.00039	.065	.763	.087	.012	29	119.78	69.9
Harajuku Lovers	80	.00216	.091	1	.147	.175	30	147.4	59.3
High-Waist Jeans	35	.00154	.174	.986	.105	.028	11	25.79	89.4
Norma Kamali for Walmart	41	.00156	.132	1	.031	.021	14	276.42	24.5
Phillip Lim	79	.00025	.138	.896	.011	.015	24	146.57	57.0
Robert Geller	49	.003	.032	.999	.106	.024	20	174.14	5.4
Skinny Cargo Pants	24	.00332	.266	.967	.044	.024	8	153.16	33.3
Skinny Jeans	80	.00021	.06	.402	.058	.024	23	118.38	79.8
Thom Browne	78	.0004	.096	.985	.009	.011	26	181.23	10.6
Tokidoki	77	.00028	.162	1	.016	.014	23	60.55	84.1
Trovata	93	.00117	.232	.994	.038	.063	33	71.72	86.3

[a]: *"Average Stay" is the average number of months a consumer remains an adopter of the fashion item*

Table 3: parameter ranges for the simulations

Parameter names in the simulation	Parameter ranges
p - external influence parameter	.00021 - .00332
q - internal influence parameter	.032 - .382
μ - mean of the uniqueness threshold distribution	.009 - .147
σ - standard deviation of the uniqueness threshold distribution	.008 - .175
δ - conditional attrition factor	.369 - 1

Table 4: Uniqueness and substitution effects for the different products

Fashion	Substitution Effect (%)	Acceleration Effect (%)	Uniqueness Effect (%)	Total Effect [a] (%)
Bathing Ape	-5.24%	10.18%	-23.37%	-18.26%
Band of Outsiders	-7.48%	24.02%	-25.76%	-7.98%
Boyfriend Jeans	-3.93%	10.24%	-24.74%	-17.36%
Coach Bonnie Collection	-3.20%	8.35%	-24.43%	-18.86%
Crocs	-5.85%	17.64%	-25.85%	-12.49%
Harajuku Lovers	-6.90%	12.60%	-16.36%	-9.50%
High-Waist Jeans	-3.99%	6.02%	-22.30%	-18.64%
Norma Kamali for Wal-Mart	-4.03%	9.97%	-23.70%	-16.95%
Phillip Lim	-5.96%	19.72%	-27.23%	-12.24%
Robert Geller	-4.46%	7.16%	-19.61%	-16.12%
Skinny Cargo Pants	-3.56%	4.62%	-21.97%	-19.38%
Skinny Jeans	-8.36%	27.09%	-26.81%	-6.33%
Thom Browne	-5.40%	15.91%	-25.22%	-13.59%
Tokidoki	-5.08%	16.15%	-26.97%	-14.78%
Trovata	-5.08%	9.17%	-19.69%	-14.51%
Average	**-5.23%**	**13.26%**	**-23.60%**	**-14.47%**

[a]*: Note that due to interaction, the sum of the three effect columns does not equal the total effect*

Table 5: Uniqueness and substitution effects as functions of threshold mean

Mean of the Threshold Distribution (%)	Substitution Effect (%)	Acceleration Effect (%)	Uniqueness Effect (%)	Total Effect [a] (%)
0%	-6.35%	12.55%	-17.66%	-10.60%
5%	-5.60%	10.14%	-18.28%	-12.81%
10%	-5.30%	8.72%	-18.04%	-13.67%
15%	-5.20%	7.94%	-17.67%	-13.95%
20%	-5.21%	7.42%	-17.22%	-13.97%
25%	-5.27%	7.14%	-16.75%	-13.82%
30%	-5.39%	6.97%	-16.24%	-13.57%
35%	-5.55%	6.84%	-15.69%	-13.22%
40%	-5.75%	6.89%	-15.24%	-12.84%
45%	-5.84%	6.92%	-14.62%	-12.39%
50%	-6.12%	7.00%	-14.18%	-11.91%
55%	-6.34%	7.03%	-13.48%	-11.46%
60%	-6.50%	7.21%	-13.03%	-10.94%
65%	-6.69%	7.34%	-12.41%	-10.30%
70%	-6.98%	7.45%	-11.68%	-9.81%
75%	-7.21%	7.67%	-11.18%	-9.19%
80%	-7.49%	7.77%	-10.44%	-8.47%
85%	-7.77%	7.94%	-9.65%	-7.86%
90%	-8.09%	8.05%	-8.84%	-7.09%
Average	**-6.24%**	**7.84%**	**-14.33%**	**-11.47%**

[a]*: Note that due to interaction, the sum of the three effect columns does not exactly equal the total effect*

Figure 1: Forever 21 fashion designs (above) vs. Trovata's (below)

Figure 2: Fashion diffusion model flow chart

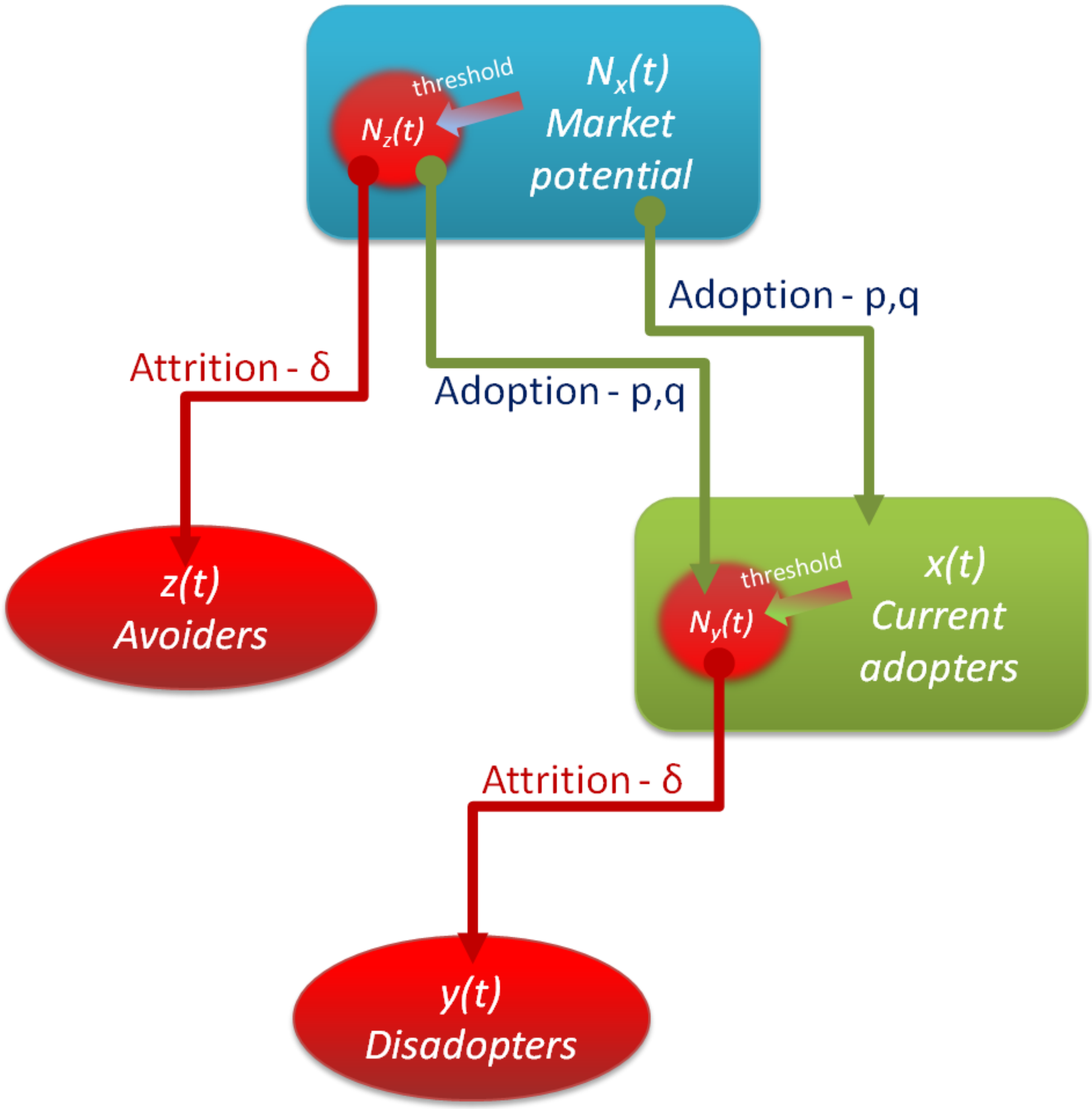

Figure 3: The impact of knockoff introduction lag on the profitability of the original