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Original Article

Understanding Shoplifting of Fast-Moving Consumer Goods: An Application of the CRAVED Model

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Abstract This study examines the variation in theft of shoplifted fast-moving consumer goods. Typically, shoplifting is estimated using shrinkage—a composite of several causes of lost retail merchandise. This study, however, benefits from access to a retailer's database, in which extraordinary steps are taken to identify and record losses due to shoplifting only. This study is unique because of the more valid measure of shoplifting. A one-year cross-sectional sample of 7,468 products, sold in 204 U.S. chain supermarkets, were drawn from the retailer's specialized database. Using Clarke's (1999) CRAVED model of theft, products' theft rates were correlated to the attributes consistent with the most vulnerable targets of theft. The results show that theft rates of products were significantly correlated to the measures for CRAVED. Regression analysis indicated that the measures for CRAVED were significant predictors of theft. Specifically, products were stolen more often when they were more *Concealable*, less *Available*, more *Valuable*, *Enjoyable*, and more *Disposable*. The most-frequently stolen types of products were several types of cosmetics—primarily small but expensive products (e.g., eye, nail, lip products). Additionally, electronics, toys, and games had high theft rates. Implications for retailers, manufacturers, and governments are discussed. Suggestions for further research are also considered.

Keywords: shoplifting; shop theft; CRAVED; hot products; fast-moving consumer goods; loss prevention

Introduction

Shoplifting is often perceived to be a relatively minor crime when compared to other forms of theft (e.g., burglary). Individual incidents may result in lower losses, but shoplifting occurs with much greater frequency than most property crimes. Around one in 11 people shoplift regularly (Blanco *et al*, 2008), but only one in 150 incidents results in a shoplifter's apprehension and police involvement (Farrington, 1999). A recent study by the British Retail Consortium (2014) estimated the average loss per incident of shoplifting was £241, or roughly $370 USD. Consequently, shoplifting is a relatively low-risk/high-reward endeavor.

Because it occurs so frequently, the aggregate losses from shoplifting are staggering. exceeding $100 billion in stolen merchandise are incurred by retailers worldwide (NASP, 2006). The US alone accounts for an estimated $15 billion in losses due to shoplifting (NASP, 2006). These losses suffered by retailers are only the most visible. Consumers ultimately pay more for products when stores must raise prices of items to offset losses (Hollinger and Adams, 2010). Shoplifting inflates the price of consumer products by approximately 10 to 15 percent (Langton and Hollinger, 2005). This figure may be higher if retailers also pass along to consumers their increased or sustained investments in loss prevention measures.

Despite increased security and precautions taken by retailers, retail theft remains a substantial problem to most retailers (Carmel-Gilfilen, 2011). However, few empirical studies on opportunity-based factors exist in the literature (Bamfield, 2012b). Even less have analyzed the attributes of theft targets common amongst hot products. One exception is Farrington's (1999) review of several studies that focused on detecting incidents of shop theft. The studies used some form of surveillance of shoppers and products in stores. However, Farrington found there to be insufficient data to make inferences regarding the choices made by thieves when selecting products. Additionally, he found that the use of security personnel to detect and apprehend suspected shoplifters had limited effectiveness, since it is very difficult to catch a shoplifter in the act. Accordingly, the products stolen by apprehended shop thieves could not be generalized to explain the theft choices of the larger population.

Fast-Moving Consumer Goods

This study examines shoplifting of fast-moving consumer goods (FMCGs), the "low-cost products that are sold quickly, replaced, or fully-used within a year, usually in a matter of days, weeks, or months" (Cushman and Wakefield, 2016). Because of constant consumer demand, FMCGs are sold more often—and shoplifted more frequently—than all other types of consumer goods. Although FMCGs are relatively inexpensive, estimates of annual losses worldwide are upwards of $56 billion each year—more than the combined losses of all other types of retail goods (Bamfield, 2012a; GRTB, 2015). In 2014, half of the top-10 most shoplifted products in the world were FMCGs (GRTB, 2015). In addition, stolen-goods markets thrive from the constant demand of FMCGs. Several studies have identified FMCGs as being regularly sold and purchased through illicit markets (Stevenson and Forsythe, 1998; Sutton *et al*, 1998; Stevenson *et al*, 2001; Schneider, 2003; Gill *et al*, 2004; Schneider, 2005; Gill and Clarke, 2012).

As stated above, academic literature on shoplifting is sparse; thus, research specific to FMCGs theft is quite limited. Beck's (2010) analysis was the first empirical study that identified the types of FMCGs responsible for the most losses. Using shrinkage data obtained from retailers, he was able to compile a list of the top-50 "hot products" in the U.K.'s FMCGs sector. However, shrinkage bundles all product losses resulting from: (1) external shop theft; (2) internal (i.e., employee) theft; (3) supplier fraud; and (4) non-crime administrative losses, including: paperwork error, and damaged or expired products (GRTB, 2015).

In the absence of qualitative data (e.g., surveying shoplifters), understanding the choices of shop thieves is challenging, but not impossible. One such possibility is the analysis of product theft data—assuming a sample of products has valid and reliable measures and a high number of cases for adequate representativeness and statistical power. Additionally, theft data—disaggregated from shrinkage figures—is necessary. The current study takes this approach in order to understand the variation in theft rates of FMCGs. Using Clarke's (1999) CRAVED model of theft, several measures of target attributes were developed to ascertain their ability to explain variations in theft for a sample of FMCGs.

The CRAVED Model

Since most incidents of crime are not evenly dispersed, environmental criminology research seeks to understand specific crimes through analysis of variations and patterns of crime incidents. When studying theft, the focus is on understanding variation and why certain items are stolen more than others. Clarke (1999) proposed that the most frequently-stolen items are "hot products," sharing specific attributes that make them more attractive to thieves. Clarke (1999) concluded that items are stolen most when possessing six elements of the CRAVED model: *Concealable*, *Removable*, *Available*, *Valuable*, *Enjoyable* and *Disposable*. With adequate data, measures of the CRAVED elements can be developed and compared by theft frequencies. There is considerable evidence that the CRAVED elements are key predictors of theft. Over the last 15 years, this methodology has served as a useful starting point for understanding variation in a wide range of theft targets, including: timber theft (Baker, 2003); domestic burglaries (Wellsmith and Burrell 2005); theft of bags in licensed premises (Smith *et al*, 2006); cell phone theft (Whitehead *et al*, 2008); theft of metals (Sidebottom *et al*, 2011); internationally trafficked goods (Natarajan, 2012), and pawn shop theft (Fass and Francis, 2004). CRAVED has also been used to explain wildlife crime including: poaching of parrots (Pires and Clarke, 2011, 2012; Pires 2014a, 2014b; Pires and Petrossian, 2016); theft of livestock (Sidebottom, 2013); and illegal fishing (Petrossian and Clarke, 2014; Petrossian *et al*, 2015).

Some recent studies have modified CRAVED to more precisely capture attributes unique to specific theft types. For example, Whitehead *et al* (2008) developed a model of anti-theft attributes specifically-designed for cellular phones known as IN SAFE HANDS. More recently, Pires and Clarke (2011, 2012) have used a modified "CRAAVED," which unpacks *Available* into two mutually exclusive elements—*Abundant* and *Accessible*. In their research on poaching of parrots, Pires and Clarke (2011, 2012), found that certain parrots may be abundant in the wild, but their respective habitats may be inaccessible to poachers. In most cases, modified measures of CRAVED are beneficial for developing bespoke measures for specific types theft.

Attributes of Frequently-Stolen FMCGs

While the literature on the theft of FMCGs is rather limited, FMCGs are a good example of hot products (Gill *et al*, 2004; Gill and Clarke 2012; Bamfield, 2012a; Beck, 2010; Smith, 2013; Smith and Clarke, 2015). Building on prior work (Gill *et al*, 2004), Gill and Clarke (2012) argued that a large amount of FMCGs are stolen for trade or sale at illicit markets. They proposed that the first three elements of CRAVED explain the "stealability" of an item, while the latter relate to an item's "worth," or rewards. Further, they argued that these last three elements of CRAVED, notably *Disposable*, were likely the most important predictors of shop theft for FMCGs. Using CRAVED as a starting point, they developed a model of 11 *Disposability* attributes—all unpacked from the "D" (*Disposable*) element of CRAVED. Known by the acronym AT CUT PRICES, the model's attributes represent characteristics of products that are preferable to thieves who choose products to steal with the intent of selling or trading the product afterward. The model explains that FMCGs are stolen more frequently when they are *Affordable, Transportable, Concealable, Untraceable, Tradeable, Profitable, Reputable, Imperishable, Consumable, Evaluable, and Shiftable* (Gill *et al*, 2004, Gill and Clarke, 2012).

Method

Background

In its early stages, this study intended to test the AT CUT PRICES model, using a sample of stolen supermarket FMCGs. It was logical to use this model, since it specifically explains the theft of FMCGs. However, this approach was abandoned for several reasons: (1) The available data were inadequate to measure six attributes. *Transportable*, *Tradeable, Consumable* and

Shiftable would require perceptions of thieves at the time of their decision-making. *Affordable* and *Evaluable* would require the perceptions of buyers when deciding to purchase products at illicit markets; (2) Three attributes (*Untraceable, Imperishable* and *Reputable)* could be measured, but the sample's requirements left these attributes with little or no variation; and (3) *Concealable* serves as an important measure in the current study, but is already an element of the CRAVED model. Consequently, of the 11 AT CUT PRICES attributes, only one (*Profitable*) could be measured and served as the measure for CRAVED's *Disposable* element. While the AT CUT PRICES model could not be tested, the data allowed for most of the CRAVED elements to be measured. Therefore, the current study is an application of the CRAVED model, with some modifications. The data and methods are described in greater detail in the following sections.

Overview of the Design

The current study sought to understand the target attributes that make FMCGs most vulnerable to shop theft. Individual products in the sample were the units of analysis. Using a sample of store product data, a rate of theft was computed and served as the dependent variable. Independent variables were also developed from product descriptive data—included in the same sample of products. These variables were measures of CRAVED and were specially developed for this study. Theft rates and measures of CRAVED attributes were analyzed to: (1) identify variations and patterns among shoplifted FMCGs; (2) identify the CRAVED attributes which had significant effects on theft; and (3) determine the relative importance of the attributes to understand why some products are stolen at higher rates than others.

Data

The current study required unprecedented access to retail product data. This is because access to highly sensitive business practices and product data is something not normally granted to third parties. Further, the proposed research required a sample of data with a great number of cases (i.e., products), with a cross-section large enough to account for seasonal and holiday variations. Fortunately, access to data was provided by a Fortune-500 retail corporation that operates one of the largest supermarket chains in the U.S. The dataset of products provided suitable measures for a large sample of FMCGs, over the course of a year. It is worth noting that this access was highly unusual and the current study would not have been possible without the significant assistance from the retailer. Pursuant to a confidentiality agreement, the retailer's name and store locations are not disclosed herein.

The "Likely Theft" Database

The retailer provided access to their "likely theft" database. This dataset is the result of the retailer taking extraordinary steps to measure external shop theft separately from shrinkage. Measuring shop theft is notoriously difficult, largely because incidents are not readily apparent and because causes of retail losses are difficult to disaggregate. As described earlier, most retailers rely on shrinkage rates to make estimates of each category of shrinkage. Further, stores often do not investigate further as if their shrinkage rate is below an acceptable figure covered by insurance or tax write-off (Clarke and Petrossian, 2012).

In the "likely theft" database, several steps are taken to identify product loss due to shop theft. First, only products on the sales floor appear in the database. Since a large amount of losses occur in the supply chain and off the sales floor, it was assumed that supplier fraud and non-crime administrative losses should not greatly impact products known to be displayed for sale.

The “likely theft” data are uploaded by the employees that stock products on the sales floor. Their primary responsibility is to make sure enough products are always available in their respective displays. Although this is a rather simple job, it is one of the most important tasks in retail practice. If employees are not cognizant of product movement, shelves will go empty, customers will not purchase products, and the store loses profits.

Employees are assigned to certain aisles or areas of the store, where they are responsible for monitoring and replenishing products. They are aided by handheld computer units that scan the Universal Product Codes (UPC) and return real-time product movement (e.g., amount of backroom inventory stock; counts of products scanned at registers and sold). Further, when adding stock to the sales floor, the employees can input and upload those numbers. When the employees notice that a product is unaccounted for, there are several steps taken before they classify it as a “likely-theft.” The most frequent cause of a missing product is when customer has selected a product and is still in the store shopping. Typically, the product is scanned at the register when purchased, which is reflected in the database. Other products may be damaged, defective or have reached their expiration date. These products are removed from the displays and accounted for. Some missing products are accounted for when they are selected by a customer, who continues shopping, but then decides to not purchase the product. They often do not return it to its original display, but put it aside at the register, or discard it somewhere else in the store. Once the product is located, it is returned to its proper display and its status updated in the database.

When the product remains missing for a specified amount of time, employees will attempt to ascertain if it was stolen. One indicator of theft is the discovery of a product’s empty packaging or defeated security features[1] somewhere in the store. In some cases, the store’s CCTV recordings may show a person shoplifting the product. Occasionally, loss prevention officers will apprehend a shoplifter and recover the stolen products. If a product is still missing after more time passes, it is entered as a “likely theft”. The sample provided each product’s sum of “known thefts,” for all stores for one year to help calculate theft rates.

Sample

From this database, a sample of more than 8,000 products was initially drawn. The products were offered for sale during the 2011 calendar year, in 204 chain supermarkets, in various locations in the U.S. All products were non-food products that are sold by most supermarket stores.[2] 474 products were deleted from the sample because they did not meet one or more requirements of the sample. These products included: (1) food products inadvertently remaining in the data; (2) products that did not appear to be FMCGs[3]; (3) Products with missing data; and (4) Products that were not directly accessible to shoppers.[4] After listwise deletion of these products, 7,468 products remained and comprised the final sample. The products were classified into one of four main categories of products: (1) OTC Drugs; (2) Personal Care; (3) Beauty and Cosmetics; and (4) General Merchandise. They were further divided into over 600 subcategories, but a smaller, more manageable number of products was needed to understand which categories of products were stolen most. A coding sheet (see Appendix A) was used to classify products into 40 categories, or groups, of alike products.

Study Variables

Theft Rate (Dependent Variable)

The data provide products' annual sum of theft counts. Using theft counts as the dependent variable, however, was problematic because the quantities of individual products on the sales floor varied greatly. This variation was due to stocking higher numbers for products that were frequently-sold. Based on elaborate floor plans and trends in sales, stores routinely changed the quantities of products to be on the sales floor so their respective displays do not go empty. To account for this, the number of sales per product were provided and used to calculate a *Theft Rate* for each product. Specifically, by dividing a product's sum of theft counts by its sum of sales counts, the resulting quotient was its *Theft Rate*. For this analysis, *Theft Rate* was a more valid dependent variable than theft counts because: (1) rates allowed for comparison of thefts among products; (2) rates take into account a product's availability in the store; (3) rates account for the different seasons of the year when certain products are more or less popular, this making them stolen more or less; and (4) If some products were discontinued or introduced for sale during the year, rates could still provide a valid measure of theft.

CRAVED Measures (Independent Variables)

The sample provided adequate data to measure five target attributes. These variables were used as measures, or proxy measures, for five of the six CRAVED attributes: (1) *Concealable*; (2) *Available*; (3) *Valuable*; (4) *Enjoyable*; and (5) *Disposable*. Descriptions of how each attribute was operationalized are described below.

Concealable

Regardless of their method, shoplifters must inconspicuously remove products from stores. In general, thieves prefer smaller, more easily hidden products. Therefore, the sizes of products were measured. The sum of a product's dimensions (length + width + height), in inches, served as the measure for *Concealable*. Products having lower scores were expected to have higher theft rates.

Available

As stated previously, other CRAVED analyses have unpacked this element into two mutually exclusive attributes—Accessible and Abundant. The sample required all products to be accessible to shoppers. This ruled out the use of Accessible as a measure. While some products of the same type offered many choices of products, others offered far fewer. This varying degree of abundance—how common or rare products were on the sales floor—served as a proxy measure of *Available*. This was measured by calculating the number of product lines offered per product type.[5] As an example, two similar vitamin products are compared to demonstrate their abundance and rarity, (i.e., high and low scores on the *Available* measure, respectively). Vitamin C (an immune system supplement) is very abundant, with a wide selection available in most supermarkets. It is sold under many different brand names, in varying strengths (e.g., 500 mg., 1000 mg.) and formulations (e.g., tablet, capsule, chewable). In contrast, while most supermarkets carry Lecithin (a supplement for liver function), it is typically offered by only one or two brands of 1200mg caplets. Therefore, Lecithin is an example of a product with a very low *Available* score. It was expected that more *Available* products—those more abundant and plentiful in stores—would be stolen at higher rates.

Valuable

Value was defined as the monetary worth (USD) of a product. The measure used was the regular retail price of products. For reliability, the prices did not include special, or lower "on sale" prices for any products. More *Valuable* products, sold at higher prices, were expected to have higher theft rates.

Enjoyable

Choosing a valid and reliable measure for *Enjoyable* was the most challenging of all the CRAVED elements. The main reason lies in the subjective views of thieves. The literature on "hot products" identifies some products with purposes only for enjoyment (e.g., tobacco, alcohol, DVDs). Thieves often target enjoyable products for their own use "[and] this may reflect the pleasure-loving lifestyle of many thieves and the people who buy from them" (Clarke, 1999, p. 24). Clarke (1999) also notes that Walsh (1974) characterized enjoyable goods as luxury items. This approach was applied here and products' luxuriousness served as the measure for *Enjoyable*. It was easier to identify luxury products instead of "enjoyable" products because the latter would require qualitative data from thieves on their perceptions of which products they subjectively viewed as enjoyable. Therefore, *Enjoyable* is a binary measure (no=0; yes=1) with "yes" meaning the product is a luxury item. This simplified coding since it was easier to identify most products as being luxuries or not. Most luxury items were easier to identify as not every-day, essential products and some that were newer or better versions of existing products. Examples of products that were coded as being *Enjoyable* were toys, self-tanning spray, and teeth-whitening strips. In contrast, products such as deodorants, nail clippers, insecticides and shoe polish were not considered *Enjoyable*. It was expected that more luxurious and *Enjoyable* products would be stolen at higher rates.

Disposable

When thieves trade or sell stolen goods, the relative ease or difficulty depends on the particular item's "Disposability." While there are several factors that influence how *Disposable* a product is, the demand for items at illicit markets is generally reflective of those in demand at legitimate retailers (Wellsmith and Burrell, 2005). Products in the greatest demand are preferred by thieves—thereby maximizing their chance of successful bartering or resale at stolen-goods markets (Clarke and Petrossian, 2013; Sutton 1998). Further, the most reputable, popular, and in-demand items can be shifted to different locales and still be expected to be easily to traded or sold (Gill & Clarke, 2012). One of the primary reasons that illicit markets thrive is because they can provide the opportunity for buyers to acquire highly-desired products that they might not usually buy at stores because they are set at high prices by retailers. However, when retailers decrease markups on products as time and demand lessens, the illicit demand for the products decreases since buyers can afford to purchase them from legitimate sellers (Sutton, 2008). Therefore, if stores set prices higher (i.e., mark-up) for certain items, it can be indicative of their varying degree of popularity and demand, at a specific moment in time. Consequently, products' profit margin scores served as a proxy measure for *Disposable*, on grounds that thieves selling stolen goods would preferentially select those with higher scores for their perceived popularity and demand. These data are closely-guarded by retailers and rarely released. The profit margin score was calculated by subtracting the price paid to the manufacturer by the "marked-up" retail price set by the store. To compare across products, the difference was converted to a ratio, resulting in a standardized profit margin rate. Products with higher profit margin rates were expected to be stolen at higher rates. It should be noted that, unlike the previous measures, this proxy measure is not a direct estimate of the shoplifter's perception. Put another way, shoplifters are unaware of the mark-up value; however, they are aware of the easiest products to sell or trade—those most in-demand. Therefore, is an indirect estimate of products sought by thieves intending to sell or trade their proceeds.

Analyses & Results

A Kolmogorov-Smirnov test revealed that the dependent variable, *Theft Rate*, had a normal distribution. Additionally, the continuous independent variables were all normally-distributed. This allowed for the use of parametric procedures at all levels of analysis. An ANOVA was used to compare differences in the mean theft rates among all product groups. A Pearson's r analysis was conducted to identify the direction and relative importance of the CRAVED variables when correlated with *Theft Rate*. A multiple regression model assessed the combined effect of the CRAVED variables as predictors of *Theft Rate*. The results of these analyses are presented below.

Theft Rates of FMCGs: Categories and Brands of Products

On average, 4.5 (SD=3.1) products were stolen for every 100 sold. Theft rates ranged from 0.04 for a package of adult incontinence underwear to 48.2 for a mini SD 2GB memory card. While the incontinence product was almost never stolen, the memory card was stolen each time two were sold. In Table 1, mean theft rates of product groups are listed by product category, with the 3 most-stolen brands listed for each category. Products were divided into 40 categories. The mean theft rates of the product groups ranged from 0.4 (SD=0.5) for "Adult Incontinence" to 11.6 (SD=7.1) for "Nail Cosmetics." 10 of these categories had products that averaged higher mean theft rates than the sample mean (4.5). Six were beauty and cosmetic categories, while toys and games and three electronics categories made up the rest. Taken together, products belonging to these 10 product categories averaged a mean theft rate of 9.4 (SD=6.1). This represents 22% of all sampled products and is double the sample mean theft rate. In terms of the dependent variable, *Theft Rate*, the descriptives' variation is consistent with the 80-20 rule—a phenomenon in which a small proportion of something (i.e., types of products) represents a large proportion of an outcome (i.e., products' theft frequencies). An ANOVA found statistically significant differences in the mean theft rates among the product groups (F=99.48, p<.001, df=40, 7,432). Initial examination of Table 1 appears to support the CRAVED model. For example, four of the most frequently-stolen categories—Nail, Lip, Eye and Face Cosmetics—were also the most *Concealable* and were almost all coded as being *Enjoyable* products. Film and digital memory cards had the second highest mean theft rate. They also had the second highest scores on *Valuable*, were *Enjoyable*, and were the third most *Profitable*. Several of the top-stolen product categories had strong scores on CRAVED attributes—an indication that "hot products" are contained within the groups. Finally, there were 604 different brands of products in the sample. Of the sample (N=7,468), 676 products belonged to the store-brand name. These products had a mean theft rate of 1.35 (SD=2.22), which was quite low compared to the overall mean.

Applying the CRAVED Model

To determine if CRAVED could explain theft of FMCGs, bivariate and multivariate analyses were conducted to understand the relative effect of the measured attributes on products' theft rates. Descriptive statistics for the CRAVED independent variables are shown in Table 2, and the results of the bivariate analysis are presented in Table 3. The strongest correlate of *Theft*

Rate was *Concealable* (r = -.482), followed by *Disposable* (r = .276). The remaining CRAVED variables (*Valuable*, *Enjoyable*, *Available*) were all significantly-correlated with *Theft Rate* (p<.001), but had much weaker relationships. However, all coefficients were in the anticipated directions, except for *Available,* which was negatively-correlated with *Theft Rate*.

Table 4 displays the results of the multiple regression. The independent variables showed no signs of multicollinearity, and all predictors' tolerance scores and variance inflation factor (VIF) scores were within the acceptable ranges.[6] The model was statistically significant and all CRAVED variables were significant predictors (p < .001) of *Theft Rate*. In addition, their directions also remained the same from the bivariate level. Taken together, the CRAVED predictors accounted for 29.6% of the observed variance in *Theft Rate*.

Discussion

The results were consistent with previous research on the theft of FMCGs. One important example is that many of the products with the highest theft rates are also listed in annual reports as being among the top-10 most-shoplifted FMCGs. Further, these products (i.e., cosmetics, electronics, toys and games) have been consistently listed by different reports and sources for several years in a row (GRTB, 2015; Euromonitor International Ltd, 2013). While it requires careful interpretation, this initial finding suggests the study has external validity.

The results are also consistent with the expectations of the CRAVED model. All measured attributes were significant correlates and predictors of higher theft rates at the bivariate and multivariate levels, respectively. Specifically, products had higher rates of theft when they were *Concealable* (smaller-sized), less *Available* (less abundant), *Valuable* (more expensive), *Enjoyable* (more luxurious), and *Disposable* (greater profit margins). The relationships were all in the anticipated directions, except for *Available*. This finding would suggest that the rarer products were more often targeted by thieves. While many brands and forms of the same type of product may be offered, one single notable brand is perhaps the most popular, desired and targeted for theft.

Although AT CUT PRICES was not tested, one of its attributes (Profitable) was used as a proxy measure for *Disposable*—potentially the most important element of CRAVED and in the shoplifting of FMCGs (Clarke, 1999; Gill *et al,* 2004; Gill and Clarke, 2012). As anticipated, products that were more *Disposable* had higher rates of theft.

Notwithstanding the unique and valuable sample, some difficulties were encountered when considering appropriate measures for all the CRAVED elements. It is rarely the case that all CRAVED elements can serve as highly valid measures with the data available in a specific study. Even this unusually large and detailed sample could not provide appropriate measures for all CRAVED elements. This is likely because it is secondary data analysis; a primary data analysis would provide better measurements—and should be undertaken when possible (Sidebottom, 2013). Another difficulty was having to recode or compute most variables from the metrics in the retailer's data-set. For stores that sell FMCGs, data can be recorded in very different fashions—even among the same retailer's datasets (Beck, 2010).

Previous CRAVED studies have measured *Enjoyable* as a binary or ordinal variable with several levels. It was measured as a binary variable in this study, but many products were difficult to objectively code. Using a continuous variable may not be possible, but future research should develop a composite of one or more measures of *Enjoyable* to improve its reliability and show greater variation. However, it is not uncommon for other CRAVED studies to lack appropriate data to serve as measures for all six elements. In fact, Sidebottom (2013), in his analysis of livestock theft, had reported the same difficulties with the same elements described herein. This study reiterates, however, that it is important to remember that CRAVED is a useful starting point to understand the preferences and choices made by thieves, "[not] a 'theory' of target choices, capable of falsification" (Pires and Clarke, 2012, p. 139).

Limitations

There were three primary limitations that should be noted before the implications are discussed. First, not all products sold in stores were included in the "known-theft" database from which the sample was drawn. The retailer stated that products were included if they received a consistent level of closer scrutiny and surveillance by employees. In general, their resources focused on the products listed in the four categories, as these were the primary objects of theft—at that specific time and the perceptions of loss prevention personnel. Consequently, some "hot products" may not have been included in the sample. A related issue is that some products may be "hot" at present--but were not included in the sample drawn in 2011. For example, detergents were not included in the database at the time. However, in 2013, Tide detergent was identified as being one of the "hottest" products—primarily because of its high value as trade currency by drug users. There are undoubtedly other such products that do not appear in the sample because of their perceived lower risk of being shoplifted in 2011. As in any cross-sectional design, the primary validity threat lies in the variations before and after the "snapshot" under examination.

The second limitation was the varying level of guardianship provided to some products. More specifically, there was an unknown level of natural surveillance provided to some products. While the products that were inaccessible to shoppers were identified, and excluded prior to the analyses, there were some products that had a higher level of surveillance than others, based on their placement in the stores. For example, some expensive and small products (e.g., batteries, USB flash drives) are typically kept close to store customer service counters. Additionally, all stores had pharmacies that usually have adjacent displays for the newest OTC drugs and products frequently-stolen to avoid embarrassment from buying them in front of others (e.g., condoms, pregnancy tests). In sum, a small number of unknown products were displayed for sale close to the employees. Whether some products were purposely placed in these locations for additional security, it seems likely they might benefit from the natural surveillance created by employees working in close proximity (e.g., pharmacy counter). The natural surveillance would also likely vary from product to product for several reasons, including distance, line of sight, and attentiveness of employees. While the number of products that could be placed near the two counters is relatively small, the findings should be carefully interpreted.

The third limitation is related to the varying quantities of each product placed on the sales floor. Retailers must estimate the supply of a product so it does not run out and goes empty before restocking. At the same time, display space is finite and stores must estimate the least space necessary for less-frequently sold products. Further, the availability of products varies over the course of a year. Seasonal items might be stocked in large numbers for a period of time, then perhaps are stocked in fewer numbers for the remainder of the year. While there is no doubt there is some unknown variance in product availability, it is important to recall that the employees in these particular stores are trained to ensure all products in their assigned areas are stocked and do not go empty. Therefore, if employees maintain a steady stock of each product—regardless of quantity, temporal, or other variations—there should be an equal level of availability for all products. In computing products' theft rates (i.e., using products' sales and theft counts), it is doubtful that an occasional variation in the quantity of a product on the sales floor would pose significant threats to the overall findings.

These limitations are unlikely to affect the confidence in the findings. The sample includes one year of theft data for over 8,000 products—each offered for sale in more than 200 chain stores across the U.S. As discussed earlier, the measure of theft is considerably more valid than if shrinkage figures were analyzed. Further, unprecedented access to sales data for all products allowed for theft rates to be computed and used as the dependent variable, instead of theft counts. Samples that are highly representative are difficult to obtain, especially in the retail sector. It would be difficult to obtain a sample that is more representative, or one having more statistical power than the sample analyzed in this study (Smith and Clarke, 2015).

Conclusions

The study's findings have implications for the study of theft, retailers, manufacturers, and government. Following a discussion of the implications, the article concludes with suggestions for further research.

Implications for Theory

This study contributes to the study of theft and is a timely addition to the environmental criminology literature. Further, the study adds to the increasing applications of the CRAVED model to provide more understanding of a specific form of theft. In this respect, the current study is the first CRAVED analysis of shoplifting; and it is also the first to examine FMCGs as theft targets.

This research would not have been possible if not for the unusually large and robust sample. The most-frequently stolen products were consistent with those identified in many security reports and surveys over several years. The standardized measures of the CRAVED attributes allowed for the relative importance of each element to be determined. Further, the measure of theft—disaggregated from shrinkage data normally analyzed in retail theft studies—provides increased confidence in the findings. This will benefit stores so they may focus responses, intended to prevent external theft, on products that are frequently shoplifted, rather than products known only to have high shrinkage rates.

As an initial study, it is evident that more information from thieves and insight to their decision-making is required for a more comprehensive understanding of shoplifting. In the case of FMCGs, it is important to understand differences in theft choices when products are shoplifted for the thief's personal use, or for disposing of via the stolen-goods market. Interviews with shoplifters, for example, can provide greater detail and insight into their perceptions, choices, motives, and their craft (Smith and Clarke, 2015). Finally, although the AT CUT PRICES model was not tested, it proved useful in conceptualizing the independent variables. A study that tests the full model is proposed for future research.

Implications for Retailers and Manufacturers

The first implication involves providing extra protection for the most frequently-stolen products in the study—small cosmetic items. The top-3 were nail, lip and eye cosmetics—all of these being among the smallest products listed in the sample. Since the strongest correlate of theft rate was *Concealable*, it is likely that effective responses to decrease the concealability of these products and others should result in significant reductions in their theft rates. Currently, making products harder to conceal is done frequently through changes in the design of the product's packaging. This is done by manufacturers, who typically will make a product's packaging several times larger than the actual product, using tamper-resistant plastic. Often electronic article surveillance (EAS) tags are added or hidden inside the packaging, to deter potential thieves from sounding alarms upon leaving the store with the product. Unfortunately, manufacturers are often reluctant to make any changes to products that have already undergone design. Any change to the product is likely to be costly, considering factories and machines that might need to be overhauled and recalibrated for the changes. Further, changes might also involve using different materials and the possibilities of changing suppliers and other difficulties to make what seems to be a simple design change. In summary, manufacturers are generally resistant to change—especially when the theft or other crime does not cause them any direct harm (Clarke and Newman 2005).

There is one possibility for bridging the gap between retailer and manufacturers. There are a few companies that specialize in antitheft equipment—from rudimentary products to the most cutting-edge theft counter-measures available. These corporations often have roles as loss prevention consultants to retailers. They obviously have an incentive to recommend their anti-theft devices to retailers; but, most importantly, have the potential to be quite persuasive to manufacturers on design changes—especially since they would benefit from supplying their own equipment for manufacturers to design-in to the newly, and hopefully, less concealable product (Smith and Clarke, 2015).

If all else fails, retailers have taken the most extreme step of denying access to shoppers for a select few of the highest-risk products (e.g., infant formula, Gillette razors). As described earlier, these products were not included in the sample—simply because their shoplifting is no longer an issue. Other products (e.g., cigarettes; certain OTC drugs) have also been made inaccessible to shoppers, but as result of federal regulation.

Implications for Government

Governments do not regulate consumer goods solely to prevent theft. However, on rare occasion, legislation is passed that may, as a side effect, reduce a hot product's theft. For example, broad policies to prevent underage smoking and drinking have led to regulations on how these products are handled and sold by retailers. The last notable example of federal regulation took place in 2005, and affected OTC drugs containing pseudoephedrine—the primary precursor for "cooking" methamphetamine in the U.S. Among several regulations, these products were required to be removed from the sales floor, and held behind customer service and pharmacy counters. Once these changes were implemented, the shoplifting of these drugs was no longer an issue. As discussed in the previous section, making products inaccessible to shoppers seems to eliminate external theft. In the case of government regulation, retailers must take notice of policy changes—as some may increase theft. For example, pending legislation in the U.S. Congress might actually cause a specific product to be stolen more often when federally-regulated.

At present, the "DXM Abuse Prevention Act of 2015" (H.R. 3250) has been introduced in the U.S. Congress. OTC cold and cough medicines with dextromethorphan (DXM) are often abused by young people. In this study and in Smith and Clarke's (2015) research, many of these products were stolen at high rates. The proposed legislation would ban the sale of DXM to those under 18 without a doctor's prescription. However, the bill does not require retailers to remove the products from the sales floor and place them behind the pharmacy counter, as with the pseudoephedrine law. Consequently, it is plausible that DXM products will be shoplifted in greater numbers. Underage teens will find shoplifting is the easiest and perhaps only option to obtain DXM products without having to go through another person. The chances of being caught are low and the products are generally small and easy to conceal. In order to prevent increased shoplifting of DXM products, policymakers should amend the current bill to require retailers to keep DXM products off the sales floor. Further, retailers and government regulatory entities should work to address a policy issue (e.g., reduce teen DXM abuse) in a way that is beneficial to all stakeholders.

Directions for Further Research

To conclude the article, suggestions for further research are discussed. The first suggestion is to build upon this initial study, using additional sources of data. This would help to develop and improve the measures of the CRAVED elements. Most importantly, data on the weight of individual products should be used to measure *Removable*. Additionally, other sources of data might help formulate a more objective measure of *Enjoyable*—ideally an ordinal variable to replace the binary measure. Additionally, tracking records of products would be helpful to draw a more representative sample of products. While the "known theft" database did not account for products held off the sales floor, if stores were able include their ordering and inventory records, an additional measure of loss (products ordered versus products on the sales floor) could be developed. Further, more detailed data on seasonal products would be beneficial to control for temporal variation of product theft. Perhaps stores could provide a cross-section of data which could be disaggregated from yearly to monthly product losses. This could account for seasonal variations in shoplifting, control for certain products' limited availability and potentially determine if certain seasons have more of an impact on shoplifting than others.

The second suggestion is that future research on the theft of FMCGs should test the AT CUT PRICES model. The current study set out to do this, primarily because the model was designed specifically to explain variation in the theft of FMCGs. The theoretical model has been discussed in detail, with two methods of testing the model proposed by its authors (Gill and Clarke, 2012). Unfortunately, this study did not possess appropriate data to measure the eleven disposability attributes. Appropriate qualitative data from both thieves and buyers of products could potentially test the AT CUT PRICES model. Additionally, such data could complement or improve on the CRAVED measures. Regression models could be analyzed and compared to determine which models account for more variation in theft.

The third suggestion calls for a mixed-method analysis to match the most appropriate loss prevention measures to the most targeted products. This study's findings may assist retailers in identifying the products most at risk for theft. This can help them focus their limited resources on choosing security measures to prevent the products' theft. However, thieves' perceptions of different security measures are relatively unknown. Consequently, stores may provide extra levels of security for risky products but if offenders fail to perceive higher levels of guardianship, they will not be deterred from shoplifting those products. Qualitative research is required to understand the shoplifters' perceptions of various security measures, and factors influencing their choices. A few studies have explored this area, notably Weaver and Carroll (1985), and some more recent examples (e.g., Hayes, 1999; Dabney *et al*, 2004; Carmel-Gilfilen, 2013). While most of these studies rely on interviews and self-reports, recent research by Lasky *et al* (2015) and Jacques *et al* (2015) uses a novel approach to provide an additional layer of valid data to complement interviews with shoplifters. This involves having shoplifters, engaged in simulated theft in stores, wear a device that tracks and measures their eye movement. These data would complement the current study's findings, ultimately matching appropriate anti-theft measures to the most at risk products. Consequently, a suggestion for future research is using a mixed-method approach—combining the quantitative analyses of the current study with qualitative data, including (at a minimum) interviews and surveys of shoplifters, but also the additional data from eye-tracking software or another objective physical measure. Ideally, all data would be collected at the same sites and study period, resulting in three samples of data to be analyzed and provide a more expansive understanding of choices made by shoplifters.

This study has utilized CRAVED, an empirically-tested and reliable model to understand theft preferences, in many applications. However, it must always be used first as a starting point to understand theft variation—not a theory capable of falsification. Ultimately, interviews and surveys of thieves are necessary to ensure the reliability of findings from CRAVED quantitative analyses.

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Notes

1 For example, an EAS "soft tag" that is peeled off a product's outer packaging and discarded.

2 Food items (e.g. meat and milk) were not included in the sample because (1) the retailer did not include foods in their "known theft" database; (2) most foods are not stolen for trade or illicit selling purposes; and (3) the retailer reported that foods were not given the same level of loss prevention and surveillance as other non-food products. However, these products are FMCGs and two (meats and cheeses) have been known to be frequently-stolen FMCGs (Bamfield, 2012a). The only exceptions were for vitamin and nutrition products—these are considered over-the-counter drugs and supplements.

3 There were a small group of items that could not easily be shoplifted and were questionable if they were "fast-moving" goods (e.g. lawn chairs, televisions).

4 Certain products could not be selected and stolen by shoplifters because they were inaccessible to customers. Some of these products were kept in locked cases on the sales floor—namely infant formula and certain brands of razor cartridges. Further, all tobacco products were held behind the customer service counter, while pharmacies held OTC drugs containing pseudoephedrine and others behind the counter.

5 This is different from the quantity of individual products, which was discussed earlier in the dependent variable section. As mentioned in the section on the dependent variable, some products were displayed in greater quantities than others on the sales floor. Further, the number of product lines often reflected the number of brands per product type.

6 Acceptable ranges for VIF scores = 1.04 to 1.51; Tolerance scores = 0.66 to 0.95.

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Table 1. Mean Theft Rates of Shoplifted FMCGs (*N*=7,468) by Product Category with the Top-3 Most Stolen Brands per Category.†

Product Category Brand	*N.*	Mean (*SD*)	*Product Category* Brand	*N.*	Mean (*SD*)
Nail Cosmetics	**248**	**11.6 (7.1)**	***Batteries***	**75**	**3.0 (2.8)**
Maybelline		16.5 (8.3)	Rayovac		5.5 (1.6)
Arden		15.9 (6.1)	Duracell		3.4 (3.2)
Kiss		14.2 (9.2)	Eveready		3.3 (4.4)
Film/Memory Cards	**25**	**11.5 (9.7)**	***Office & School***	**224**	**2.7 (2.8)**
Kodak		16.6 (9.9)	Pentel		6.0 (4.2)
Store-brand		9.1 (9.1)	Pilot		5.2 (2.8)
Memorex		5.4 (4.9)	Sanford		4.0 (1.8)
Cell Phone Acc.	**54**	**11.3 (7.7)**	***Sinus & Allergy***	**88**	**2.5 (2.7)**
Cellet		20.1 (5.4)	Primatene Mist*		11.4 (6.5)
Jasco		8.3 (3.4)	Vicks		4.0 (1.0)
TDK		5.8 (3.9)	Zyrtec		3.3 (1.7)
Lip Cosmetics	**499**	**10.5 (7.2)**	***Analgesics***	**230**	**2.2 (2.0)**
Loréal		11.2 (5.9)	Tylenol		3.2 (2.1)
Maybelline		10.9 (8.4)	Aleve		2.7 (1.9)
Cover Girl		10.6 (8.5)	Motrin		2.6 (1.4)
Eye Cosmetics	**660**	**9.8 (7.6)**	***Bath & Spa Acc.***	**178**	**2.0 (3.1)**
Maybelline		11.3 (8.0)	ATG		8.7 (0.7)
L'Oréal		11.2 (8.9)	Calvin Klein		7.3 (4.5)
Revlon		9.3 (6.2)	COTY		4.9 (1.4)
Face Cosmetics	**521**	**9.1 (5.9)**	***Cold & Cough***	**211**	**2.0 (1.9)**
Physician's Formula		12.4 (7.5)	Coricidin		8.0 (3.8)
Maybelline		10.7 (5.6)	Delsym		4.2 (1.7)
L'Oréal		9.4 (5.0)	NyQuil		3.3 (1.6)
Printer Ink Refills	**30**	**8.5 (7.1)**	***Antacids***	**115**	**1.9 (2.3)**
Canon		6.3 (2.9)	Zantac		6.1 (6.2)
HP		5.9 (4.1)	Zegerid		4.7 (2.8)
Jasco		5.8 (3.9)	Prilosec		3.8 (2.3)
Toys & Games	**65**	**8.2 (8.1)**	***Diet & Weight Loss***	**172**	**1.8 (3.1)**
James Toys		19.7 (0.9)	Quick Trim		17.0 (6.1)
Toy Smith		16.3 (7.3)	Alli		10.5 (9.5)
Poof-Slinky		15.8 (9.3)	Hydroxycut*		6.4 (1.8)
Cosmetic & Hair Acc.	**98**	**6.3 (5.4)**	***Shaving & Grooming***	**153**	**1.8 (1.5)**
Revlon		9.1 (7.6)	Gillette		2.1 (1.7)
Kroger		4.9 (3.2)	Just4Men		1.6 (0.9)
Conair		4.7 (3.9)	Schick		1.4 (0.8)
Household Electrical	**62**	**5.8 (5.6)**	***Deodorants***	**206**	**1.7 (2.7)**
GE		9.9 (4.2)	Dove		5.4 (6.0)
Store-brand		9.1 (9.2)	Degree		4.0 (5.2)
Sentry		3.6 (1.2)	Axe		2.9 (0.9)
Hair Coloring	**180**	**5.4 (4.3)**	***Light Bulbs***	**120**	**1.7 (1.7)**
Dr. Miracle		11.6 (5.4)	Green Lite		2.1 (1.1)
Ambi		8.6 (5.2)	GE		1.7 (1.5)
Titan		8.0 (2.5)	Store-brand		0.7 (0.4)
Hardware & Tools	**131**	**4.4 (4.7)**	***Kitchenware***	**169**	**1.7 (1.9)**
Allied		10.8 (4.7)	Wear-Ever		4.2 (1.5)
Velcro		8.6 (3.2)	OXO		2.9 (4.0)
Gorilla		6.5 (1.9)	PUR		2.8 (1.5)
Underwear & Hosiery	**114**	**4.3 (3.0)**	***Oral Hygiene***	**340**	**1.6 (2.9)**
Russell		6.3 (4.0)	Sonic Care		5.3 (4.1)
Hanes		5.7 (3.7)	Orajel		4.7 (5.3)
No Nonsense		4.7 (3.9)	Dentek		3.5 (4.5)
Clothing & Shoe Care	**55**	**4.0 (3.0)**	***Vitamins/Supplements***	**425**	**1.5 (4.6)**
Singer		4.5 (3.6)	Extenze		25.1 (9.1)
Kiwi		3.8 (2.2)	Focus Factor		14.0 (8.6)
Rit Phoenix		2.0 (0.1)	Enzyte		6.6 (7.1)
Contraceptives	**45**	**3.7 (2.8)**	***Basic Soaps***	**168**	**1.3 (7.3)**

Clear Blue		5.0 (3.0)
1stResponsePreg		4.8 (3.8)
Trojan		4.7 (2.6)
Eye & Ear	**117**	**3.5 (3.1)**
Visine		5.9 (2.9)
Clear Eyes		5.6 (2.9)
Zaditor		4.7 (1.6)
Skin Moisturizers	**344**	**3.4 (4.6)**
RoC		9.7 (2.8)
Olay		7.1 (7.3)
Garnier		6.5 (8.0)
Hair Finishing	**611**	**3.3 (6.1)**
Frederic Fekkai		19.0 (9.8)
Matrix Essence		10.7 (4.4)
Farouk		10.1 (8.9)
Automotive Acc.	**92**	**3.3 (3.3)**
Seal-It		6.0 (2.8)
Bell		5.9 (3.1)
Little Trees		4.7 (1.1)
First-Aid	**240**	**3.2 (3.0)**
First Check		10.2 (4.6)
Futuro		6.9 (3.8)
Lotrimin		5.7 (5.5)
Olay		2.2 (1.7)
Axe		2.1 (0.7)
St. Ives		1.2 (0.3)
Laxatives	**104**	**1.0 (1.0)**
Senokot		5.3 (2.5)
Colace		4.7 (2.4)
Dulcolax		4.2 (4.0)
Feminine Hygiene	**184**	**0.9 (1.4)**
Monistat		3.2 (1.4)
Summer's Eve		3.0 (2.6)
OB		1.7 (0.4)
Foot Care	**75**	**0.9 (0.3)**
Lotrimin		8.7 (9.6)
Lamisil		5.1 (1.4)
Dr. Scholl's		3.8 (3.4)
Adult Incontinence	**40**	**0.4 (0.5)**
Depends		0.5 (0.6)
Store-brand		0.4 (0.4)
Poise		0.2 (0.1)
Total	**7,468**	

†Products were sold under 605 brands, including the confidential "Store-brand." The brands displayed under each product category are the three with the highest mean theft rates, among those offered, within the respective category. Rows are sorted by Category Mean Theft Rates (in bold) in descending order (highest to lowest) from the top of the left column and continuing to the right column. "Acc." stands for accessories.
*These products have been discontinued after the sample was selected.

Table 2. Descriptive statistics for CRAVED Variables (*N*=7,468)

Variable	Measure	%	Mean	(*SD*)	Min.	Max.
Theft Rate (DV)	(*N.* Stolen ÷ *N.* Sold) • 100		4.5	(3.1)	0.04	48.20
Concealable	Dimensions (in.)		11.2	(3.6)	1.30	51.20
Available	*N.* Lines per Type		21.6	(13.4)	3.00	50.00
Valuable	Sales Price (USD)		6.8	(4.1)	0.29	47.99
Enjoyable	Luxurious (1=yes)	24.7				
Disposable	Profit Margin Rate		4.5	(0.1)	0.18	2.47

Table 3. Bivariate correlations between CRAVED elements and *Theft Rate*.

Variable	Pearson's r
Concealable	-.482
Available	-.188
Valuable	.147
Enjoyable	.122
Disposable	.276

Note: All coefficients were significant at the $p < .001$ level (two-tailed).

Table 4. OLS regression predicting *Theft Rate* of FMCGs (*N*=7,468), 204 stores, 2011 calendar year.

CRAVED Variable	Coef.	*SE*	Sig.
Concealable	-.239	.012	.000
Abundant	-.130	.004	.000
Valuable	.073	.020	.000
Enjoyable	3.310	.131	.000
Profitable	.475	.060	.000
Constant	9.935	.172	.000
Adj. R^2 =.296			
F=629.401, df=5, 7,462, p<.001			

Note: Unstandardized coefficients are reported.

Appendix A. Product categories with examples of products†

***Adult Incontinence*: Male & Female absorbing underwear, pads, diapers

Analgesics: Aspirin, acetaminophen, ibuprofen, naproxen

Antacids: Tums, Alka-Seltzer, Pepto-Bismol, Prevacid, Prilosec, Zantac

Automotive Accessories: Maintenance fluids, air fresheners, interior & exterior clean/shine sprays

Basic Soaps: Bath/Shower bar soaps, hand soap, body wash, antibacterial soaps (all are for basic cleanliness purposes (e.g., Dial, Zest, Ivory)

Bath Accessories: Specialty soaps, bath trays, soap dishes, dispensers, toothbrush holders, tub baskets

Batteries: Alkaline, 9V, AAA, AA, C, D, assorted watch/smaller sized; Lithium AA, AAA

Cell Phone Accessories: Holsters, chargers, cables, cases, screen protectors

Clothing & Shoe Care: shoe cleaning, polish, clothing patches, sewing products, dry cleaning

Cold & Cough: Tablets, liquids, nasal sprays, containing cough expectorants, suppressants, etc. (Includes products containing DXM)

Contraceptives: Condoms, pregnancy tests, personal lubrication, spermicides

Cosmetic & Hair Accessories: nail clippers, tweezers, makeup brush,

Deodorants: Male/Female/Clinical Strength, anti-perspirants, anti-odor, bars, sticks, sprays, gels

Diet & Weight Loss: Weight loss pills, energy drinks, nutrition supplement drinks, caffeine pills

Eye & Ear: All eye drops & ear drops; topical ear treatments

Eye Cosmetics: Eyeshadow, Eyelash/Mascara, Eyebrow color, Eyeliner

Face Cosmetics: Foundation, Blush, Makeup remover, Concealer

Feminine Hygiene: Tampons, Maxi Pads, Anti-infective washes, sprays, creams, gels

Film & Memory Cards: Camera film, SD memory cards, USB flash drives

First-Aid: Band-Aids, bandages, braces, slings, antiseptics, anti-infectives, dressing, topical remedies

Foot Care: Topical applications for blisters, corns, etc., shoe inserts,

Hair Coloring: Hair dye, highlights, color shampoos/conditioners, beard coloring, cut/nick remedies

Hair Finishing: Treatments, gels, sprays, mousse,

Hardware & Tools: Basic tools—hammers, screwdrivers, screws, cleaners/polishes for wood, stone, metals, extension cords, door knobs/locks, lubricants, adjustable wrenches, pliers, utility tools and knives, rope.

Household Electrical: Phone, TV, speaker accessories; wiring, adapters, plugs, recordable CD, DVD, VHS

Kitchenware: Cooking trays, pots, pans, cutlery, silverware, can openers, spatulas, measuring cups, peelers

Laxatives: Fiber drinks, tablets, suppositories

Light Bulbs: Assorted sizes, colors, brightness for common house lights

Lip Cosmetics: Lipstick, lip gloss, lip treatments,

Skin Moisturizers: Facial therapy lotions, masks, anti-acne creams, pore cleansers, treatments

Nail Cosmetics: Nail polish, lacquer, enamel, remover

Office & School: paper (computer/notebooks, pads etc.) writing (pens, pencils), color (markers, crayons, permanent), office supplies (tape, paper clips, post-its),

Oral Hygiene: Toothpaste, non-powered toothbrushes, floss, mouthwash, treatments for gums/teeth

Printer Ink Refills: Inkjet printer replacement cartridges (for most common household printers)

Shaving & Grooming: Razors, razor cartridges/refills, shaving creams, aftershave & pre-shave lotions,

Sinus & Allergy: Antihistamines, decongestants (all but those containing pseudoephedrine)

Toys & Games: All toys, any games (cards, board)

Underwear & Hosiery: Men’s, women’s underwear, socks. Pantyhose.

Vitamins & Supplements: All non-FDA approved—vitamins, supplements. Includes sexual enhancement drugs.

†Examples listed are not exhaustive of category