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What Motivates Selling and Buying in Online Gray Market? The Case of Luxury Handbags

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What Motivates Selling and Buying in Online Gray Market? The Case of Luxury Handbags

Abstract:

Gray market is a worldwide phenomenon thriving in a variety of product categories. It is critical for brand owners to understand both gray market sellers’ and consumers’ behaviors in order to better manage them. However, due to the sensitive nature of the subject, there is no prior comprehensive empirical research using actual data of gray market activities to study such an important phenomenon. To fill the gap, we tracked gray market listings and transactions on the largest Internet retail website in China for a 34-week period and examined the impact of market-level and product-level factors on market dynamics. Analysis shows that base prices, product popularity, and channel controls jointly affect the degree of gray market activities. Contrary to conventional wisdom, more expensive products are less attractive to sellers, since higher entry barrier and risks may overshadow potential arbitrage opportunities. We also reveal brand specific effects in online gray market. Furthermore, while gray market sellers and buyers observe and react to the other side’s market behaviors, information asymmetry still exists between these two sides.

Key words: online gray market, unauthorized sellers, transaction quantity, luxury handbags
Introduction

When iPad 2 was initially released in 2011, a consumer needed to pay around $1,000 to buy a 16GB Wi-Fi model in Hong Kong, which was about twice the price in U.S. As a consequence, a large amount of iPads were shipped into Hong Kong via gray market (Chang 2011). CNN Money reported that half of the iPads sold through the Apple’s Fifth Avenue store on a busy March Friday in 2011 were purchased for re-sale overseas (Elmer-DeWitt 2011). Apple is not the only company that faces challenges from gray market distributions. Luxury goods retailers, such as Saks Fifth Avenue and Neiman Marcus, restrict purchases of designer handbags due to popular demand as well as the fear that some foreign buyers may resell those bags in Europe or Asia (Wilson 2008). It was also reported that gray marketers sold some life-saving drugs, which were in critical short supply in U.S., at 650% markup (Kateyian 2011).

Gray market refers to “the sale of genuine trademarked products through distribution channels unauthorized by the manufacturer or brand owner” (Antia et al. 2006, pp. 92). It is also known as parallel importation (Ahmadi and Yang 2000). Such phenomenon thrives in a wide variety of product categories, ranging from lumber, electronic components, broadcast signals, IPOs, automobiles, heavy construction equipment, watches, cosmetics, bags, health, beauty aids to prescription drugs (Antia et al. 2004). Worldwide gray market was estimated to run over $40 billion in revenue each year (Kotler and Keller 2009).

The primary driver behind gray market incidents is the price gap between different countries, as the Apple iPad 2 case illustrated (Chang 2011). There are many factors contributing to the price gap, such as uneven purchasing power, tariff charges, changes in exchange rates, and heterogeneous market environment, that are beyond brand owners’ control (Ahmadi and Yang
Profit-seeking individuals and enterprises, i.e., gray marketer, can arbitrage by buying products in a lower-priced country and selling them in a higher-priced country.

Electronic commerce alters the landscape of unauthorized product flows (Bandyopadhyay 2010). Electronic exchanges break the geographical barrier and extend the scope of gray market. Individuals or small businesses can easily establish online unauthorized distribution channels, and reach out to a wide range of consumers at very low costs. The buyers can also easily access to multiple gray market sellers and compare the products and prices.

Brand owners need to closely monitor and manage gray market incidents, as gray market becomes another distribution channel for their branded goods in the global supply chains. In the higher-priced country, gray market products compete directly with products sourced via the authorized channels. Ignoring gray market activities could have a detrimental impact on the brand owners’ global pricing strategies and profits. In addition, gray market activities may damage the brand’s reputation and undermine the brand owner’s relationship with its legitimate distributors.

Due to its practical importance, several analytical studies have examined the impact of gray market on the brand owners’ profits (Ahmadi and Yang 2000; Ahmadi et al. 2010; Autrey and Bova 2012). The findings are mixed — the brand owner’s profits are shown to be positively or negatively influenced by gray market incidents. Prior analytical research also found that several factors, such as the number of parallel importers (Ahmadi and Yang 2000), transaction costs (Xiao et al. 2011), managerial leverages (Ahmadi et al. 2010), the nature of market competition (Autrey and Bova 2012), and consumer price elasticity (Iravani et al. 2011), affect profit allocation between the brand owner and unauthorized distributors. In addition to analytical work,
survey studies have also been employed to investigate gray market incidents (Antia et al. 2004; Myers 1999). These studies identify factors, such as product standardization and free-riding potential, that help deter or induce gray market activities (Antia et al. 2004; Myers 1999). Strategies, such as combining multiple facets of enforcement and channel integration, have been suggested based on questionnaire data collected from U.S. exporters.

Prior literature largely focuses on the brand owners’ perspective (Ahmadi and Yang 2000; Ahmadi et al. 2010; Antia et al. 2004; Autrey and Bova 2012; Iravani et al. 2011; Myers 1999; Xiao et al. 2011). Gray market sellers’ strategic behaviors have not been closely examined. For example, price gap is considered the only primary driver behind the existence of gray market sellers (Onkvisit and Shaw 1989). As a result, in the prior analytical modeling studies, the unauthorized sellers’ objectives were simply modeled as maximizing profits given the prices set by brand owners for different geographical markets (Ahmadi and Yang, 2000). This study examines other market-level drivers to the gray market sellers’ activities in addition to price gap. Our empirical analysis provides a counterintuitive finding: products with a higher price gap may not attract more gray market sellers.

Furthermore, there is also very limited understanding of the impacts of product-level characteristics on unauthorized sellers’ behaviors. Iravani et al. (2011) differentiated fashion items from commodities. But they focused on the manufacturers’, not gray market sellers’, selling strategies for products with different features. The survey by Antia et al. (2006) considered product features such as premium positioning. However, the study relied on manufacturers’ perception to estimate gray market sellers’ potential reaction towards market environment. It is still unclear, in reality, whether and how those sellers respond to different product features.
On the demand side, consumer behavior in gray market is also not well understood in the prior literature. Studies suggest that channel authorization affects consumers’ attitude towards gray market goods (Huang et al. 2004; Lee 2006). For instance, most consumers are aware of risks associated with unauthorized channels. Therefore, interventions could be introduced to control gray market incidents from a demand perspective. However, those studies are based on the survey data, which relies on subjective measures reflecting consumers’ perceptions or intention rather than their actual purchase behaviors in gray market.

To fill those gaps, in-depth examinations of both gray market sellers’ and consumers’ behaviors are desirable. However, research is scarce because the nature of the phenomenon is sensitive and gray market data is insufficient (Antia et al. 2006). The emergence of electronic commerce offers us opportunities to observe online gray market activities and conduct related research. The ubiquitous accessibility provided by the Internet enables us to use technologies, such as web crawlers, to search billions of web pages on e-commerce websites in order to monitor, track and estimate gray market incidents.

In this study, we developed computer script files to automatically track gray market listings and transactions data on the largest Internet retail website in China for a 34-week period. Such a unique dataset enables us to perform a comprehensive empirical investigation of gray market dynamics. As an initial attempt to explore and examine online gray market activities, we focus on one product category in this paper: luxury handbags. Prior studies suggest that gray market incidents are most likely to arise under two conditions. First, the product has a prominent brand name (Bucklin 1993); and second, price gap is large across two geographic markets (Onkvisit and Shaw 1989). Luxury goods in the Chinese market satisfy both conditions.
Based on econometric analysis of our unique panel data set, we find that base prices, product popularity, channel controls jointly affect the degree of gray market activities. Contrary to conventional wisdom, more expensive products (or those with higher price gaps) are less attractive to sellers. One possible explanation is that higher entry barrier and risks of not selling may overshadow potential arbitrage opportunities. However, buyers’ reaction to base prices depends on the brand name, suggesting that brand owners should employ brand-specific strategies to control gray market activities on the demand side. We also find that while gray market sellers and buyers observe and react to each other’s behaviors, they demonstrate different preferences towards different product features. Information asymmetry between sellers and buyers still exists. Managerial implications are discussed in order to help brand owners better manage channel conflicts related to gray market.

The remaining of the paper is organized as follows. In the next section, we develop theoretical arguments for hypotheses proposed in our model based on prior literature. Section 3 describes our research context, data source, and data collection procedure, followed by our findings in section 4. Section 5 concludes with the implications of this study for theory and practice, its limitations, and avenues for future research.

**Hypotheses**

The focus of this paper is on the degree of online gray market activities on both the supply and demand sides. In the case of luxury handbags, the overwhelming majority of buyers only buy a single handbag in one transaction. Therefore, transaction quantity of a product approximately represents the number of buyers of the product in the market. On the supply side, one or multiple
gray market sellers may list a product for sales. We therefore use the number of sellers and transaction quantity of gray market goods at the product level to assess the degree of online gray market activities. By simultaneously investigating both the supply and demand of gray market goods, we can better understand market dynamics and interactions between these two important groups of players in gray market.

**Price Gap and Base Price**

As we discussed before, the major driver of gray market activities is a product’s price gap in the authorized channels between a lower-priced country and a higher-priced country (Ahmadi and Yang 2000). Therefore, the first antecedent of gray market activities considered in our model is price gap. However, instead of examining a product’s price gap, we focus on the base price, a proxy for the price gap. Base price is defined as the product’s price in the origin country. We choose to use the base price as the proxy of price gap for three reasons. First, the price gap and base price of the products in the same product category from the same brand owner are highly correlated. Or in other words, more expensive products have larger price gaps. This high correlation is due to coordination of marketing activities, which is a key dimension of global marketing strategy (Zou and Cavusgil 2002). To ensure price consistency across its products and profitability in the distribution channels, a multinational firm often jointly price and coordinate its products in different geographic markets. We found that the Pearson Correlation between a luxury handbag’s price gap between its origin country and the Chinese market and its base price is over 0.99 in our data. To avoid multicollinearity, we keep only one of those two variables. Second, while it is generally accepted that price gap motivates gray market activities, the impacts of base price are more nuanced. We later hypothesize that there are several forces at play, which could lead to mixed relationships between base prices and gray market incidents. Third, some
products are not available in the Chinese market, and hence only base prices rather than price gaps data are accessible for those products. Therefore, we focus on base prices in the analysis and discuss how they could affect gray market dynamics.

We propose that the impact of base prices on the degree of gray market activities can be ambiguous. On one hand, prior gray market literature has suggested (Ahmadi and Yang 2000; Antia et al. 2006) that more expensive products may face more gray market activities due to financial consideration. When trading more expensive goods in gray market, sellers expect to earn more and buyers expect to save more because of larger price gap. Gray market sellers, who are unauthorized distributors, obtain products in the lower-priced country and then sell them in the higher-priced country. To lure customers from authorized channels to gray market, they need to mark their prices lower than those listed by authorized distributors. Thus gray market sellers’ potential profit margin, i.e., the difference between gray market price and their own purchase price from the lower-priced country, is directly related to the price gap. Prior analytical research also confirms that gray market price is a function of prices in both the lower-priced country and the higher-priced country (Ahmadi and Yang 2000). Since a higher base price indicates a larger price gap, gray market sellers expect to gain more per unit by selling a more expensive product, and they may be more motivated to pursue the arbitrage opportunities with the high base prices.

Consumers are also willing to buy gray market goods if the price gap between gray market and the authorized channel is large enough (Xiao et al. 2011). With a large price gap buyers can obtain the product at a discounted price and potentially save more via unauthorized channels. Since larger price gaps are associated with higher base prices as a consequence of the brand owners’ coordinated pricing strategies, buyers may be motivated to enter gray market for more expensive goods.
On the other hand, risk concerns may make more expensive goods less attractive for both sellers and buyers. Gray market sellers face risks of unsold products, just as any other retailers (Padmanabhan and Png 1997). As unauthorized retailers, they do not have formal contracts with the manufacturer to share those risks. They can only return unsold products during a limited time window. The cost of returning is also elevated once the product is relocated to another country. Thus gray market sellers bear higher risks of unsold products when handling more expensive products due to higher magnitude of the potential loss (Peter and Ryan 1976). Gray market consumers also face purchasing risks associated with lack of channel authorization, such as unreliable guarantee, lack of manufacturer warranty, and unavailability of after-sales service (Huang et al. 2004; Lee 2006). Such risks increase with a product’s base price, which may cause consumers to avoid gray market products.

There are other factors that could also contribute to the negative impact of base prices on the degree of gray market activities. Higher base prices mean higher capital requirements, which could create higher market entry barriers for sellers (Porter 1980). Some sellers may be unable to afford upfront costs of obtaining the more expensive products from the lower-priced country. On the demand side, consumers may perceive less cost saving from more expensive gray market products. This is because increasing the magnitude of the original stimulus leads to less noticeable difference, as the Weber-Fecher law of psychophysics suggests (Grewal and Marmorstein 1994). Moreover, consumers who can afford more expensive products are more likely to have lower price sensitivity (Lee 2006). They tend to prefer authorized channels for more expensive products due to benefits associated with channel authorization, such as product warranties and service packages (Ahmadi and Yang 2000; Xiao et al. 2011). Therefore, more expensive products may attract fewer buyers in unauthorized channels.
Overall we propose the following hypothesis.

\textit{H1: A product’s base price is an important source of the degree of its gray market activities.}

\textbf{Product Popularity}

While price gap may lead to the potential arbitrage opportunity, gray market can exist only if there is real market demand for branded products in the export countries (Antia et al. 2006). An important reason that people waited for hours in line to buy iPads or iPhones and resold them overseas is the popularity of such consumer electronic products worldwide. Product popularity is an indicator of market awareness and interests, and tends to be self-reinforcing (Tucker and Zhang 2011). So we expect more gray market activities associated with more popular products.

Gray market sellers tend to prefer more popular products, since those products are associated with higher probability of selling to craving consumers. In addition, authorized distribution channels may be unable to meet demand for popular products in the export countries, leading to more consumers diverted to gray market channels (Anita et al. 2006).

Consumers are more likely to acquire popular products in gray market for several reasons. First, product popularity can serve as a signal of quality, which could be a cue for consumers during shopping (Szymanski et al. 1993). Second, uncertainty associated with product choice for consumers may be mitigated by product popularity (Howard and Sheth 1969). Prior study suggests that gray market consumers tend to be less familiar with the product (Lee 2006). By following others’ choices, they may feel more confident that they are buying the right products. Third, consumption of luxury goods has social implications (Wiedmann et al. 2007). Handbags can be considered conspicuous products that carry conspicuous value because the usage is publicly visible (Zhou and Wong 2008). Prior study shows that consumers may buy a luxury
handbag in order to indicate their social status or associate themselves with certain social groups (Han et al. 2010). They may want things that are widely recognized by others. This phenomenon is widely recognized for Asian consumers, who prefer popular products, as increasing market awareness propels the dream value of the product (Phau and Prendergast 2000). So we hypothesize:

**H2: Product popularity is positively associated with the degree of gray market activities.**

*Channel Controls*

Two types of controls can be used by manufacturers in channel coordination: process controls and output controls (Jaworski et al. 1993). Process control over sellers’ behaviors and output control over prices and product offerings are particularly relevant in discussing gray market imports (Myers 1999). This study examines output controls since process controls exert little product-level variance within a single product category from the same brand owner. We have hypothesized the impact of prices in the prior subsection, and here focus on the other output control, product offering.

We observe that a product available in the lower-priced country may not be available in the higher-priced country. Product differentiation is one proactive strategy used by brand owners to combat gray market goods (Berman 2004). We expect that such product differentiation strategy affects gray market activities. Unavailable products may not be appealing to gray market sellers because of the lack of brand owners’ marketing efforts (Anita et al. 2006). When a brand owner offers a product in the higher-priced country, it often invests in promoting the product via various approaches, such as TV advertising, online marketing, and in-store displays. These efforts are vulnerable to appropriation (Anderson and Weitz 1986). For instance, a product’s
market visibility and desirability will increase if the brand owner broadcasts a TV ad for it in the higher-priced country. Gray market sellers can benefit from the improved market recognition at no cost. In addition, they can also free ride on the presale and other additional services, such as product demonstration, education, and repair, provided by brand owners (Knoll 1986). The free-riding potential would be low for a product not offered in the higher-priced country (Anita et al. 2006).

Limiting product offering may also deter consumers in the lower-priced countries from entering gray market. Consumers may prefer products available via authorized channels in their own countries. First of all, they have the opportunity to closely examine those products before purchasing from online gray market. They can try them in stores, learn more about the products from marketing campaigns, and inquire the sales representatives for additional product information. Second, availability in authorized channels may help increase products’ value perceived by consumers. Financially, it is easier for gray market consumers to calculate relative cost savings by comparing prices in two countries. Socially, consumers may gain higher conspicuousness value since products offered via authorized channels have better market awareness (Wiedmann et al. 2007). Therefore, we hypothesize:

**H3: Controlling product availability is positively associated with the degree of gray market activities.**

**Interplay of Gray Market Sellers and Consumers**

By simultaneously investigating the supply and demand sides in online gray market, we are able to characterize the reaction effect of one side to the other side. Similar to any other electronic markets, information transparency is high in online gray market due to enhanced accessibility
and availability of market information (Lynch and Ariely 2000). For instance, important market information (e.g., who are offering the same product, what are their listing prices, how many transactions have been completed in the past 30 days, etc.) is publicly available. As a result, sellers and buyers can better observe and react to each other’s presence.

Gray market sellers need to estimate market demand to optimize their sourcing and pricing decisions (Iravani et al. 2011). In online gray market, they can examine the transaction records and find out which products sell well and which do not. Therefore, sellers can adjust the products that they want to source accordingly in a timely manner. If a product sells well in the previous time periods, existing sellers are more likely to keep offering them and new sellers may want to enter the market to capitalize the current trend.

Gray market buyers’ decisions may be also affected by the sellers’ behaviors in several ways. A product’s market visibility may increase if there are more sellers offering it. If buyers do not know the specific product that they should buy, they may search in general, within a specific category (e.g., handbag), or within a specific brand (e.g., Coach). In this case, a product listed by 200 sellers will have a better chance to be viewed by buyers than the one listed by only two sellers. Such market visibility is likely to drive future purchase intentions. Furthermore, online sellers are heterogeneous in terms of their listing prices, reputation scores, and after-sales services. If a product is provided by more sellers, a buyer has a better chance to identify one that she would like to conduct the transaction with. Thus we propose the following hypotheses:

$H4a$: The number of sellers in gray market increases as a result of increasing transaction quantity.
**H4b**: *Transaction quantity in gray market increases as a result of the increasing number of sellers.*

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**Research Context and Data**

**Research Context**

The Asian markets come to be the centers of global luxury shopping as the western markets continue struggling with the weak economies. McKinsey & Company, the global consulting firm, reported that China accounts for about 12 percent of the global luxury-goods market and estimated that this share will grow to 22 percent by 2015 (Atsmon et al. 2011). The U.S. and Europe luxury fashion houses strive to tap into the Asian consumers with buying power and expensive tastes. For example, LVMH Moët Hennessy Louis Vuitton, the biggest luxury group in the world, continue to expand into China’s second- and third-tier cities in addition to its successful retail operations in the country’s big, thriving cities (Yousuf 2012). In 2009, Coach, the leading US retailer of luxury lifestyle handbags and accessories, acquired the Coach retail businesses in China from its former distributor, the ImagineX group, for greater control over the brand in China (Team 2010).

We focus on luxury handbags which “are the engine that drives luxury brands today” (Thomas 2007, pp. 168). The gray market incidents are likely to occur for luxury handbags because the large price disparity between the origin countries and the Chinese market and their premium positioning. For example, Louis Vuitton’s products are 45% to 47% more expensive in China than in France due to the hefty luxury tax and considerable logistics costs (Passariello 2012). To test our hypotheses, we selected both the most prestigious luxury brand, Louis Vuitton (LV), and the “affordable luxury” brand, Coach. LV is often top ranked among the most powerful luxury
brands. Millward Brown Optimor, the global brand strategy and financial consultancy, ranked it as the world’s most valuable luxury brand for seven consecutive years (Slind-Flor 2012).

Whereas Coach, renowned for introducing the “accessible luxury” to the masses (Han et al. 2010), is widely known for their high quality, but are priced lower than other designer products. However, the Coach handbags are still more expensive in China than in U.S. despite the fact that the bags are produced in China.

Both LV and Coach are popular luxury brands among Asian consumers (Han 2005; Lee et al. 2003). LVMH, followed by Chanel and Gucci, were reported as the most desired brands in China in 2011, according to research by Bain & Co (Yousuf 2012). Coach is also highly embraced by Chinese consumers. A quick search for Coach on Baidu, China’s equivalent of Google, yielded eight million hits, which is far above the Coach’s direct competitors such as Kate Spade and Michael Kors (Jannarone 2012). Including both brands in our analyses increases external validity of the results.

We collected data from Taobao Marketplace (formerly Taobao), the Chinese equivalent of eBay and Amazon. As the largest consumer-to-consumer (C2C) Internet retail and trading website in China, it provides small businesses and individuals with a platform to run online retail stores and post their products for sale. The product categories listed on Taobao Marketplace ranges from fashion, grocery, electronics, jewelry, to books. The overwhelming majority of the listings offer brand new merchandise at a fixed price; auctions only account for a very small percentage of the sales. Taobao Marketplace services more than 800 million product listings and more than 500 million registered users as of June 2012. The annual transaction volume on Taobao Marketplace reached 208 billion CNY in 2009, accounting for approximately 80% of China’s e-commerce market.¹
**Data Collection**

We test the hypotheses using data collected from both the authorized Coach and LV online distribution channels and gray market in China. In particular, we collected the Coach handbag information, such as style number, U.S. listing price, Chinese listing price, size, material (leather/no leather) and being new arrival or not, from the official Coach websites (www.coach.com and china.coach.com). The LV handbags information such as style number, France listing price, size, material and being new arrival or not were collected from the official France LV websites (www.louisvuitton.fr). Since the listing prices of LV handbags were not available on the Chinese LV website (www.louisvuitton.cn)\(^2\) during our data collection period, we acquired the Chinese selling prices from the offline distribution channel in China. The data collection was initially conducted in April 2011 and then repeated in September 2011 to incorporate new product releases for the Fall/Winter collection.

To collect gray market data, we developed a computer script, which fed the Coach and LV style numbers obtained from the official websites into Linux shell scripts to search for all matching items that were listed on Taobao.com. For each listing, we collected information such as listing prices, seller location information, times of listing page being added to wish-lists, transaction history, etc. Data collection was performed once per week automatically from May 30\(^{th}\), 2011 to January 23\(^{rd}\), 2012, about 34 weeks.

The main tools used in the information retrieval process included perl, wget, python, as well as other standard tools such as grep, sed, wc, etc. The main webpage retrieval engine was the urllib2 library for python, which was capable of loading dynamic data such as the number that a listing page was added to users’ wish-lists. It also addressed the Chinese encoding problem on the webpages that used GBK encoding.
Variables

Degree of gray market activities: We measure the degree of gray market activities for a handbag style using the number of sellers and transaction quantity, which are our dependent variables. In the prior literature, due to limited data availability, the degree of gray market activities are measured based on subjective perception, either as the likelihood that gray market occurred during the previous two years (Anita et al. 2006), or as whether it is a significant problem to the exporters (Myers 1999). Our study differs from the previous research by using objective measures based on direct observations, which enable us to more accurately examine the activities undergoing in online gray market. On Taobao Marketplace, sellers create a webpage with a unique listing ID for each single handbag style that they sell. Therefore, for each style, the number of listings approximates the number of sellers. Taobao Marketplace also posts the transaction records within 30 days for each listing page, including buyer’s nickname, transaction price, number of handbags transacted, the transaction date, and brief handbag description. The weekly transaction quantity for a handbag style is calculated by totaling the past transaction quantity of all listings for this style within a week.

Base price: Based price is defined as a handbag style’s price in the origin country. Specifically, we use Coach’s U.S. prices and LV’s France prices as base prices.

Product popularity: Due to the lack of product-level weekly sales data from the authorized channel, we used an alternative measure for product popularity: a handbag style’s wish-list count. A registered Taobao user can add a listing to her wish-list, so that she can easily keep track of what she would like to have. We expect that more popular product styles have higher wish-list counts since they are appealing to more potential buyers. For each style, we normalize
its wish-list count by averaging the number of a handbag style being added to wish-lists per seller.

*Chanel control over product offering:* We use the product availability variable to indicate whether a handbag style was available via authorized channels in China at the time of data collection. It is a dichotomous variable where 1 represents that the handbag is available and 0 otherwise. It is worth noting that this variable only applies to the Coach handbag styles. All LV handbag styles are available in China since it offers the same products across countries.

*Interplay of Gray Market Sellers and Consumers:* Since it takes time for sellers or buyers to observe the market, process information, and adjust their behaviors accordingly, we use the lagged terms to capture the reaction effects. Using lagged variables to model reaction effects has been used in prior literature such as the arms race model (Richardson 1960). Specifically, the lagged transaction quantity is an explanatory variable to estimate the number of sellers, and the lagged number of sellers is an explanatory variable to estimate transaction quantity.

*Control variables:* To control product features, we include the variables of *size, material, new arrival* and *product age.* The handbag styles are labeled on the official websites in the size categories of small, median, large and extra-large at the time of data collection. We therefore code a nominal variable with 1 for small, 2 for median, 3 for large and 4 for extra-large. To control handbag material, we use a dichotomous variable where 1 represents leather and 0 otherwise. New arrivals may draw additional interests from consumers as well as gray market sellers but may not be readily available to the gray market sellers. Therefore, we use a dichotomous variable which equals to 1 if the handbag is newly arrived and 0 otherwise. A handbag style released earlier may accumulate a larger number of sellers and lead to higher
transaction quantity. In this study, we control a handbag style’s age by calculating the total number of weeks since the handbag style’s data was first collected. During holiday weeks such as China’s National Day (October 1), Christmas’ Day, New Year, significant sales jumps may occur as consumers may spend additional time on shopping for gifts or fun. We use a dichotomous variable to measure whether a week includes holidays, which equals 1 if includes and 0 otherwise.

**Descriptive Statistics**

The data consists of the Coach and LV handbag’s style information, gray market listings and gray market transaction records from May 30th, 2011 to January 23rd, 2012. The temporal unit in this analysis is “week”.

To control possible counterfeit products, the analysis only includes the oversea gray market sellers, who are not located in mainland China. The oversea sellers can easily obtain genuine handbags in low-priced countries. Also it would be difficult for them to obtain cheap counterfeit goods produced in China. On Taobao Marketplace, such sellers are often referred to as DaiGou—people who purchase products for other consumers who are located in a different geographic region. Table 1 provides the descriptive statistics for our data and Table 2 provides the correlation matrixes for both brands separately. We also remove the sellers whose listing prices in gray market were 30% lower than the official prices in the low-priced countries. Later we performed the robustness checks using all oversea sellers and the sellers whose listed gray market prices were not 10% lower than the official prices.

<< --- Please Insert Table 1 Here --- >>

<< --- Please Insert Table 2a Here --- >>
Analysis and Results

Model Estimation

In the analysis, we aggregate the number of sellers and transaction quantity for each handbag style at the week level. In order to test whether our findings can be generalized across brands and tease out possible brand-specific effects, we run the econometric analyses for Coach and LV separately.

The dependent variables, weekly aggregated number of sellers and transaction quantity are both count numbers (i.e., nonnegative integers). This implies that the distributions of discrete dependent variables place probability mass at nonnegative integer values only. Therefore, we use count regression models in our analysis.

Poisson regression is often used for count data analysis. However, the Poisson distribution implies the data has equal mean and variance, a property called equidispersion (Cameron and Trivedi 1999). This imposes significant restrictions on the use of Poisson regression for the count data. A quick examination of our data shows that the data has the overdispersion issue, i.e., the variances of the dependent variables are larger than the means. The Pearson goodness-of-fit result further confirms that the distribution of our data significantly differs for a Poisson distribution. Therefore, we follow the literature and estimate a negative binomial maximum-likelihood regression model (Hibe 2011; Wuyts et al. 2004):

\[ P(Seller_{it} \mid X_{it}) = \frac{\Gamma(Seller_{it} + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_{it} + 1)} \left( \frac{\alpha^{-1}}{\alpha^{-1} + \mu_{it}} \right)^{\alpha^{-1}} \left( \frac{\mu_{it}}{\alpha^{-1} + \mu_{it}} \right)^{y_{it}} \]
where

\[ \text{Seller}_{it} = \text{the number of sellers for handbag style } i \text{ in week } t; \]

\[ \Gamma(\cdot) \text{ denotes the gamma integral; } \]

\[ \alpha : \text{ the dispersion parameter; } \]

\[ X_{it}: \text{PRICE}_{it}, \text{WISHLIST}_{it}, \text{AVAILABILITY}_{it}, \text{TQ}_{it-1}, \text{NEW SIZE}_{i}, \text{MATERIAL}_{i}, \text{AGE}_{it}, \]

\[ \text{HOLIDAY}_{t} \]

\[ E[\text{Seller} \mid X, \alpha] = \mu ; \]

\[ \text{Var}[\text{Seller} \mid X, \alpha] = \mu(1 + \alpha \mu) ; \]

\[ \mu_{it} = \exp(\beta_0 + \beta_1 \text{PRICE}_{it} + \beta_2 \text{WISHLIST}_{it} + \beta_3 \text{AVAILABILITY}_{it} + \beta_4 \text{TQ}_{it-1} + \beta_5 \text{NEW}_{i} + \beta_6 \text{SIZE}_{i} + \beta_7 \text{MATERIAL}_{i} + \beta_8 \text{AGE}_{it} + \beta_9 \text{HOLIDAY}_{t} + \epsilon_{it}) . \]

A close examination of the data further suggests that the dependent variable, transaction quantity, has excessive zeros. In other words, many handbag styles have zero weekly transactions during the period of data collection. The process leading to no-sales could be different from the process leading to sales, thus zero-inflated negative binomial regression is chosen to deal with the excess zeros in addition to overdispersion. Specifically in our model, for each observation \( \text{TQ}_{it} \), the process that only generates zero counts is chosen with probability \( \varphi_{it} \), and the process that generate counts from a negative binomial model (\( \text{NB}(\text{TQ}_{it} \mid X_{it}) \)) is chosen with probability \( 1 - \varphi_{it} \) (Lambert 1992; Sheu et al. 2004). \( \varphi_{it} \) is the zero-inflated link function and specified as a logistic regression. To explore gray market dynamics measured by the transaction quantity, we estimated the following model:

\[ \text{TQ}_{it} = 0 \text{ with probability } \varphi_{it} \]

\[ \text{NB}(\text{TQ}_{it} \mid X_{it}) \text{ with probability } 1 - \varphi_{it} \]
where

\[ X_{it}: \text{PRICE}_{it}, \text{WISHLIST}_{it}, \text{AVAILABLE}_{it}, \text{SELLER}_{it}, \text{NEW SIZE}_{i}, \text{MATERIAL}_{i}, \]

\[ \text{AGE}_{it}, \text{HOLIDAY}_{i} \]

**Results**

In this section, we discuss our results and summarize the key findings from our estimation. Table 3 presents the estimation results.

<< --- Please Insert Table 3 Here --- >>

For both brands, the coefficients for PRICE in the equation for number of sellers are negative and statistically significant, indicating that more sellers offer luxury handbags in the online gray market for less expensive styles. This result suggests that the cost of acquiring the handbags and risk of not selling are major concerns for gray market sellers. In the equation for transaction quantity, only the coefficient for the PRICE for Coach is negative and statistically significant and that for LV is insignificant. The discrepancy between Coach and LV is statistically significant, suggesting that Coach buyers prefer handbag styles that are less expensive in online gray market but the LV buyers’ preference for a handbag is not affected by price. Therefore, H1 is only partially supported.

For both brands, the coefficients for WISHLIST are positive and statistically significant in the equations for number of sellers and transaction quantity, indicating the gray market incidents are more likely to occur for more popular handbag styles. Therefore, H2 is supported.

For Coach, the coefficient for AVAILABILITY is positive and statistically significant in the equation for the number of sellers, but is insignificant in the equation for transaction quantity. The result indicates that gray market sellers prefer to offer the Coach handbag styles which are
available in the authorized channel in China, but the buyers show no difference. So H3 is only partially supported.

We find that there is a positive and statistically significant temporal interdependence between the number of sellers and transaction quantity for both brands. An increase in demand in a previous period is associated with an increase in supply in the current period in gray market. Similarly, an increase in supply in a previous period is associated with an increase in demand in the current period. Therefore, H4a and H4b are both supported.

The results suggest that in addition to market features, product features also influence gray market dynamics. Both Coach sellers and buyers are attracted to larger handbags, however such size effect does not exist for LV. In terms of the materials, the Coach sellers tend to offer more leather handbags but the LV sellers tend to offer more non-leather (canvas) handbags. Interestingly, buyers of both brands show no material preference. For both brands, the coefficients for NEW are both negative and statistically significant in the equation for the number of sellers, indicating that fewer sellers are offering new arrival handbags in the gray market. This finding suggests that it takes time for sellers to acquire and then list new arrivals in the gray market, thus the offering of new arrivals is lagged. The LV buyers tend to purchase fewer new arrivals, where the Coach buyers show no preference. This is probably because LV has established a classic brand image and their buyers prefer classic LV handbags.

The time length that a handbag style has been introduced to gray market affects the number of its sellers and buyers. The longer a handbag had been introduced into gray market, the more sellers were offering it. This is not surprising. As time goes by, more new sellers gradually enter the market and existing sellers may not exit the market. In contrast, transaction quantity diminishes
over time. Consumers are likely to exit the market after getting the handbags that they like, and repeated purchases are rare for durable luxury goods within the limited time period of our data collection. Fewer gray market transactions happen during holidays, suggesting that online gray market may not be the place where people spend time and money during holidays.

For transaction quantities, our results also report logit coefficients for predicting excess zeros based on zero-inflated negative binomial regressions. For both brands, a handbag style is more likely to have zero sales if it is offered by fewer sellers in the previous period and less popular.

Robustness Tests

We implemented three sets of robustness tests. First, we examined an alternative explanation of why base prices affect transaction quantity differently for Coach and LV. In addition to brand-specific effect, such difference could also be caused by differences in price ranges of two brands. In our sample, the official prices for Coach handbags range from $58 to $1,400 in U.S., and the official prices for LV handbags range from $265 to $4950 in France. To rule out the alternative explanation that differences in price range lead to different consumers’ purchasing behavior for Coach and LV, we divided LV data into two sub-samples. One sub-sample is LV-low, which include all LV handbag styles whose prices are comparable to Coach (range from $265 to $1,400). The other is LV-high, which include higher-end styles, whose prices are higher than $1,400. Empirical analysis shows qualitatively similar results between two LV subsamples, and the coefficients of base prices are both insignificant. Thus, LV consumers’ purchasing behaviors in gray market are not affected by base prices, even after controlling the price range.
Second, we used an alternative measure of product popularity. Instead of using wish-list counts, we used the number of times a product listing page has been browsed by consumers to assess its popularity. All results remain the same.

Third, we used two different datasets to address the concerns that the existence of counterfeit products may bias our results. We relaxed the price constraint and used all oversea sellers in the first dataset and strengthen the price constraint and excluded oversea sellers whose listing prices were 10% lower than the base prices in the second dataset. We found that all results for hypotheses testing are qualitatively the same.

**Discussion and Conclusion**

Our study empirically demonstrates factors affecting selling and buying activities in online gray market. By using a large sample of field data to objectively quantify the degree of gray market activities, we offer a deeper understanding of drivers of gray market. The results have important implications for both research and practice in the area.

**Research Implications**

Our findings suggest that motivations associated with making/saving money alone cannot explain gray market dynamics. On the supply side, profit-seeking should not be the sole consideration when modeling gray market sellers’ behaviors. Negative consequences associated with big ticket items, such as large initial investments and high potential losses from unsold products, are also very important. In fact, in our case, these concerns overshadow the potential higher earning opportunities for more expensive handbags, leading to fewer gray market sellers.

In online gray market investigated in this research, the majority of sellers are individuals or small
businesses, who have limited financial resources and are not very capable to deal with unsold inventories. Future study should explore whether such a negative association between the base prices and the number of gray market sellers exists in other research contexts, where resourceful and organized enterprises are orchestrating the parallel import. Nevertheless, profits from gray market should be adjusted by related risks.

Similarly, on the demand side, cost saving from gray market goods can be canceled out by other factors. While more expensive products could potentially lead to more cost saving, they also imply higher purchase risks and more lost benefits warranted by channel authorization. In addition, high-end products are likely to face consumers with less price sensitivity. Therefore, we do not observe the positive relationship between the base prices and gray market transaction quantities.

Interestingly, we further find that consumers’ reaction to big ticket items is different between Coach and LV. The base prices do not significantly affect LV’s gray market transaction quantities, while their impacts on Coach’s transactions are significantly negative. The result is robust even after controlling the price range of LV handbags. It suggests that brand-specific effects may exist (Srinivasan 1979). Other results also indicate that consumers’ preferences are indeed different between these two brands. For instance, in terms of size, Coach buyers preferred larger handbags while LV buyers did not show such preference. Coach buyers treated new arrivals the same as existing styles, while LV buyers were less likely to embrace newly released products.

We extend prior research of product popularity to online gray market and confirm their importance (Tucker and Zhang 2011). A popularity cue may mitigate uncertainty in a channel
without brand authorization. It attracts more sellers and buyers, and reinforces the dominance of products.

Channel control via product offering is effective in deterring gray market sellers, but not buyers. The results suggest that authorized channels’ marketing efforts could be leveraged by gray marketers (Antia et al. 2006). For products available in the authorized channel, the gray marketers can free ride on the authorized distributors’ marketing effort and warranty benefits. Such free-riding potential draws more sellers to enter gray market. However, product availability does not affect buyer’s behaviors at all. One possible explanation is that regional promotion by brand owners and their distributors is not the only way consumers get to know the products.

Chinese consumers can easily find out Coach styles offered in US via the Internet. Detailed product descriptions as well as user comments are readily available through social media. In addition, word-of-mouth plays an important role in promoting the unavailable styles, since many Chinese tourists travel to U.S. to buy luxury products with their increasing purchase power (Clifford 2012). It also suggests that marketing efforts can easily spill over from one geographical region to another in the Internet era.

By simultaneously investigating both the sellers’ and buyers’ behaviors in gray market, this study reveals interesting interactions between those two groups of players. Similar to other online channels, electronic gray market offers great information transparency to participants. Thus it is possible for sellers and buyers to observe and react to each other’s behavior, and our analysis validates the temporal interdependency between them. In gray market, one side’s existence reinforces the other side’s market entry. Nevertheless, their understanding of the other side’s behaviors is not perfect. For example, while sellers tend to offer products available in the authorized channel to free ride on brand owners’ marketing expenditures; buyers actually show
no preference towards those items. Empirical results also suggest that sellers and buyers favor handbags with different product features, such as material. It implies that information asymmetry exists in electronic market. Especially, for online gray market, sellers are mostly individuals or small businesses, and the lack of business analytical tools and skills hinders sophisticated analysis of market demands and deep understanding of their customers.

**Managerial Implications**

In the global economy, firms need to proactively manage their global supply chains, including the unauthorized channels. Gray market emerges with price disparities, which occur due to many factors out of firms’ control, such as taxation, import duties, and exchange rates. Gray market incidents often have a negative impact on the brand owners’ revenues, brand images, consumer perceptions, and relationship with authorized retailers. It is important for brand owners to properly monitor and manage gray market activities.

Industry experts summarize brand protection strategies against gray market diversion as a five-step process: assess, design, protect, monitor, and enforce (Kodak 2010). Our study shows a feasible way to more accurately detect, track and quantify gray market activities. Brand owners can combine data collected from Web surveillance and their own supply chains to estimate how gray market incidents affect their revenue. Then they can decide whether to ignore, block, or allow gray market activities (Iravani et al. 2011). They can also compare purchase patterns between gray market and authorize channels to better identify what types of consumers they are likely to lose to gray market. In addition, we show that gray market dynamics can be brand specific. Brand owners could apply a data-driven approach to identify brand idiosyncratic effects and design more effective customer retention strategies.
Since sellers and buyers reinforce each other’s existence, brand owners should combat gray market from both supply and demand perspectives (Berman 2004). On the supply side, differentiating product offering in different markets can discourage gray market sellers, due to lack of free-riding benefits from brand owners’ regional marketing spending. However, designing entirely different products in different markets could be costly and potentially lead to inconsistent brand images across markets. Our results suggest that brand owners can focus on product differentiation for low-end products, since high-end products are less vulnerable to gray market threat. Another possible way to limit the number of products diverted to gray market is quantity control used by Coach, “which limits the number of identical or similar items that may be purchased by an individual” (Sherman 2011). However, enforcing such policy may cause controversy or even public relationship disaster (Sherman 2011). Our results indicate that it is feasible to apply quantity limits policy selectively. For instance, many oversea gray market sellers prefer popular low-end handbags. Brand owners, such as Coach, can limit consumers’ purchase quantity and explain that the shortage is caused by high market demand. Such strategy and explanation may be more acceptable for legit consumers.

On the demand side, we confirm prior literature that channel authorization matters to consumers, which could cancel out or even dominate saving associated with high-end products. Therefore, brand owners should emphasize risk awareness of gray market shopping. They can educate consumers (Berman 2004) and explicitly list authorized distribution channels. They can also use technologies to limit valuable pre- and post-sales services to products obtained from authorized channels. For instance, it is easy to identify and track individual handbags by using technologies such as RFID. As a result, brand owners could restrict value-added services, such as cleaning and repair, to consumers who originally purchase the products or obtain them as gifts with validated
gift receipts. In this way, the brand owner can direct more consumers to the authorized channels. For instance, Mercedes-Benz rejected warranty claims of gray market cars in Thailand (TEBA 2011).

**Future Research**

There are some limitations of our study, which could be the basis of future research. First, as the first step to empirically investigate gray market dynamics, we only focus on a single product category: luxury handbags. Because of the time-consuming and computational-expensive nature of data collection, we only analyzed two brands. In the future, we can examine more variations of products to test the generalizability of our findings. Second, our analyses were based on product-level aggregation. Future research can explore gray market activities at individual levels and examine how seller-level characteristics affect the likelihood of gray market transactions. Third, while we accurately measured the extent of gray market activities using objective measures, our data did not capture psychological or social aspects of consumers engaged in gray market transactions. Future research may investigate the gray market players’ behaviors using both the subjective measures and objectives measures to gain insights into the interaction between gray market sellers and buyers.
References


http://online.wsj.com/article/SB10001424052970203750404577173371712048172.html


http://online.wsj.com/article/SB10001424052702303513404577351331720729676.html


Footnotes


2.  During our data collection period, the China LV website (http://www.louisvuitton.cn) served as an information distribution channel only. It did not provide e-commerce transaction functions.

3.  Our exploratory data screening showed that sellers were not shy about selling counterfeit products. Sellers often explicitly indicated that the products they were offering were counterfeit and listed such products at much lower prices than the authentic ones.

4.  A handbag style has multiple observations of official prices in the low-priced country due to the price increase and the fluctuation of exchange rates.

5.  The variables Official Price in China, Product Availability, Size, Material and New Arrival are product-level variables. The number of observations for the variable, Official Price in China, is less than other product-level variables because not all Coach handbags were available in China during the time period of data collection.
### Tables

#### Table 1: Summary Statistics

<table>
<thead>
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#### Table 2a: Correlation Matrix for Coach

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<td>5. Product Availability (AVAILABILIT)</td>
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1. No of Seller (SELLER) & 1 & & & & & & & \\
2. Transaction Quantity (TQ) & 0.51 & 1 & & & & & & \\
3. Base Price (PRICE) & -0.41 & -0.15 & 1 & & & & & \\
4. Average Wishlist (WISHLIST) & 0.34 & 0.34 & -0.13 & 1 & & & & \\
5. Size & -0.04 & -0.02* & 0.12 & 0.06 & 1 & & & & \\
6. Material & -0.47 & -0.16 & 0.44 & -0.07 & 0.01* & 1 & & & \\
7. New Arrival (NEW) & -0.28 & -0.10 & -0.28 & -0.01* & -0.08 & 0.32 & 1 & & \\
8. Product Age (AGE) & 0.24 & -0.02 & -0.14 & -0.02 & 0.04 & -0.16 & -0.28 & 1 & \\
9. Holiday & 0.06 & -0.04 & -0.03 & -0.01* & -0.00* & 0.01* & 0.04 & 0.30 & 1 \\

* Denotes insignificance. The rest coefficients are significant at the 0.05 level.
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<td>Age</td>
<td>0.00457</td>
<td>0.02071***</td>
</tr>
<tr>
<td></td>
<td>(0.00354)</td>
<td>(0.00188)</td>
</tr>
<tr>
<td>Holiday</td>
<td>-0.02975*</td>
<td>0.08959***</td>
</tr>
<tr>
<td></td>
<td>(0.01255)</td>
<td>(0.01216)</td>
</tr>
<tr>
<td>Cons</td>
<td>2.96789***</td>
<td>3.596***</td>
</tr>
<tr>
<td></td>
<td>(0.12919)</td>
<td>(0.14705)</td>
</tr>
<tr>
<td>Inflated_Price</td>
<td>0.00003</td>
<td>-0.00002</td>
</tr>
<tr>
<td></td>
<td>(0.00014)</td>
<td>(0.00002)</td>
</tr>
<tr>
<td>Inflated_Wishlist</td>
<td>-</td>
<td>0.22007***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0305)</td>
</tr>
<tr>
<td>Inflated_Availability</td>
<td>0.11825</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(0.31391)</td>
<td></td>
</tr>
<tr>
<td>Inflated_Lagged</td>
<td>-</td>
<td>0.08706***</td>
</tr>
<tr>
<td>Sellers</td>
<td></td>
<td>(0.01068)</td>
</tr>
<tr>
<td>Inflated_cons</td>
<td>3.25293***</td>
<td>4.25671***</td>
</tr>
<tr>
<td></td>
<td>(0.37218)</td>
<td>(0.35426)</td>
</tr>
<tr>
<td>N</td>
<td>6397</td>
<td>7365</td>
</tr>
<tr>
<td>---------------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Maximum Likelihood $R^2$</td>
<td>0.399</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Note:

1. Robust standard errors are listed in parentheses.
2. ***, **, and * denote significance at 0.001, 0.01, and 0.05, respectively.