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A Good Signal: How Firms Can Utilize Country of Origin as a Strategic Analytical Tool

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A Good Signal: How Firms Can Utilize Country of Origin as a Strategic

Analytical Tool

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A Good Signal: How Firms Can Utilize Country of Origin as a Strategic Analytical Tool

Abstract

Abundant consumer data has made decision making more complicated rather than simple for marketers. The abundance of consumer data raises an important question about which variables in the data contain reliable information for retailers to predict future consumer purchase value (CPV) to guide strategic decisions. The authors address this question by exploring the variables “distinctive choice of brand country of origin” (DBCOO) and “country of origin diversity” (COO diversity) as analytical tools to extract insights from consumer purchase data. Building on signaling theory, the authors theorize and empirically test that DBCOO and COO diversity in a consumer’s purchase history can signal, and therefore help predict CPV. Moreover, we explore high-involvement product categories and purchase frequency as boundary conditions to develop a comprehensive framework of COO signals as strategic analytical tools. We find that DBCOO in a consumer’s purchase history indeed increases CPV and that this relationship is enhanced for high-involvement product categories but moderated curvilinearly by purchase frequency. Moreover, we find that the COO diversity – CPV link is positive but depicts a negative interaction with both moderators. This allows retailers to successfully distinguish high- from low-CPV consumers and thus enables them to manage marketing mix and resources more effectively.

Keywords: country of origin, consumer analytics, consumer purchase value, COO diversity, consumer-based strategy, high-involvement product

Analytics applied to consumer data has emerged as the prime focus of multinational companies to generate revenue and drive growth (Chen, Chiang, and Storey 2012; Grewal and Roggeveen 2020). However, anecdotal evidence suggests that despite an abundance of consumer data, managers are often unaware of where to look in the data to extract meaningful insights (Bradlow et al. 2017). This lack of knowledge about relevant metrics prevents firms from using consumer data effectively to tailor their marketing mix according to high- versus low-spending consumers, thus inhibiting firm growth potential (Saxena and Lamest 2018).

Influential studies suggest that a brand's COO affects consumer attitudes and influences 75% of consumers' purchase decisions (Kock, Josiassen, and Assaf 2019; Verlegh and Steenkamp 1999; Nielsen 2016). This influence can happen consciously or subconsciously (Herz and Diamantopoulous 2017). Moreover, consumers vary in their knowledge about which countries are the home to outstanding products and brands (Samiee and Chabowski 2021). Despite the focus on variance in consumers' COO knowledge, evaluations, and usage (Balabanis and Diamantopoulos 2008; Batra et al. 2000; Samiee, Shimp, and Sharma 2005), researchers have largely ignored how COO choice variance in consumers' purchase histories can be a vital metric and analytical tool for firms.

This study focuses on one such strategic analytical tool: The distinctive choice of brand country of origin (DBCOO). In this paper, we argue that DBCOO can reveal consumers with superior knowledge, which in turn indicates high-spending consumers. We define DBCOO as a country of origin which is associated with a superior value proposition, yet is non-dominant (Balabanis and Diamantopoulos 2008; Payne, Frow, and Eggert 2017). These two pillars, superior value proposition and non-dominance are rooted in the COO literature and signalling theory respectively. COO literature suggests that the image of a certain country is linked to consumer associations that promise products of superior value to consumers (Agrawal and Kamakura 1999; Payne, Frow, and Eggert 2017). The superior value proposition ensures that

consumers rely on the COO cue in their purchase decision and thus constitutes the first pillar of the DBCOO construct. In order for COO to work as an effective signal for companies, it additionally needs to satisfy the condition to differentiate high-quality from low-quality customers (Connelly et al. 2011; Spence 2002). Therefore, COO non-dominance is the second pillar of the DBCOO construct. COO non-dominance refers to a COO, which is not readily and frequently evoked in a product category (Balabanis and Diamantopoulos 2008). It therefore allows to distinguish between high-quality (i.e. highly knowledgeable and well-informed) from average and low-quality customers, who are more likely to opt for common and dominant COOs (Balabanis and Diamantopoulos 2008; Pecotich and Ward 2017). The non-dominant nature of DBCOO decreases signalling noise and is therefore a condition for an effective signal (Connelly et al. 2011).

As an illustration, due to the dominance of French beauty products, the average consumer may opt for French skincare brands. In contrast, high-knowledgeable consumers who are aware of natural ingredients and recent research-and-development (R&D) investments of Korean brands may opt for Korean skincare brands considering the superior value (e.g., Estée Lauder admires the R&D of Korean beauty brands; Chitrakorn, 2021). Considering France's ubiquity and dominance, French skincare brands are a common choice, while Korean skincare purchases may reflect a consumer's DBCOO.

While the COO literature mostly views COO as a cue from firms to consumers (see Table 1), we posit that COO can also be employed in the opposite direction (i.e., from consumers to firms). Specifically, consumers leave unintentional COO signals in their purchase history, which firms can extract and use as strategic analytical tools. The unintentional signaling inherent in DBCOO provides actionable insights in three ways. First, DBCOO assists firms in developing predictions about future purchases. Second, DBCOO can help firms distinguish consumers based on Consumer Purchase Value (CPV), which refers to

the monetary value of a consumer's total purchases (e.g., US\$500, US\$2000) in a given period. Such a segmentation enables firms to manage marketing mix and resources more effectively. For example, firms can apply better-targeted advertising, promotions, and preferential handling of orders for consumers with a high CPV. Such managerial actions can maximize the lifetime value of consumers with a high CPV, thus decreasing spending on low CPV consumers (Venkatesan and Kumar 2004). Third, DBCOO can be an effective tool for firms in emerging market, where aligning resources to reach consumers with a high CPV is vital for the firm's survival and growth (Cavusgil et al. 2018; Kravets and Sandikci 2014).

Despite the benefits of an analytical approach, prior research ignored the potential of the DBCOO signal as an accessible tool to distinguish between high- and low-CPV consumers. While recent studies have indicated the potential of brand COO for firms (Chiang and Yang 2018; Magnusson, Zdravkovic, and Westjohn 2022), they fall short of developing a comprehensive framework to provide strategic value to COO signals. We address this gap by developing a framework that depicts the use of DBCOO as a strategic analytical tool to guide marketing strategy (Marketing Science Institute 2020). In particular, we focus on three research questions: First, does a DBCOO in a consumer's purchase history allow a firm to extract information about CPV? Second, can COO diversity in the purchase basket also distinctively signal higher CPV? Finally, do variables readily observable for retailers (e.g., high-involvement product category, purchase frequency) moderate the DBCOO–CPV and COO diversity–CPV relationships?

In exploring these research questions, we make three novel contributions to marketing literature and managerial practice. First, we respond to recent calls by leading marketing scholars to develop analytical tools. For example, Bradlow et al. (2017, p. 85) state that “big data provides the opportunity for business intelligence, but the theory is needed to guide ‘where to look’ in the data and develop sharp hypotheses that can be tested against the data.”

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Drawing on signaling theory, this study shows how firms can use DBCOO as an analytical tool. Previous research has identified COO as a cue consumers can use to extract information about a brand or a firm (e.g., a cue to assess product quality or brand equity) (Table 1). In contrast, we investigate whether DBCOO can function as a signal in the opposite direction and reveal strategic information about consumers to firms. Notably, our argument builds on consumer knowledge variance revealed by DBCOO choices and we account for COO price differences that may otherwise drive the effect.

Second, diversity has been introduced as an important variable in adjacent marketing fields, such as related to the consideration set (Amaldoss and He 2019), or customer diversity (Park, Voss, and Voss 2023). Previous literature has studied diversity as an explanatory variable in hypotheses testing or as a control variable, but never as a diagnostic analytical tool. We examine COO diversity as an additional diagnostic analytical tool for separating high- and low-CPV consumers. COO diversity refers to the variety of COOs present in a consumer's purchase basket, capturing the relative competition between COOs in the purchase basket.

Third, we contribute to the literature on signaling theory. Consumers do not use DBCOO and COO diversity as signals to firms deliberately. Previous research has concentrated on intentional signals while neglecting unintentional ones despite the complexity of the latter due to its non-deliberate nature (Connelly et al. 2011, Vasudeva, Nachum, and Say 2018). Moderating conditions can introduce multiple, potentially conflicting effects; yet the literature has not examined the moderating conditions of unintentional signals (Connelly et al. 2011). We explore two moderators, readily available for retailers, on the main effects of DBCOO and COO diversity on CPV: high involvement purchase (HIP) and purchase frequency. HIP and purchase frequency relate to a signal-sender's perceived risk and signal noise in the signaling process respectively (Hoyer 1984;

Connelly et al. 2011; Smith and Bird 2005). These moderators are crucial for firms as scholars suggest tailoring strategies for HIPs and performing caution for unusually high purchase frequencies (Kukar-Kinney, Ridgway, and Monroe 2012).

(Insert Table 1 here)

Literature Review

COO-related scholarly contributions are at the heart of international marketing literature (Pappu, Quester, and Cooksey 2006; Samiee and Chabowski 2021). Recent influential works suggest that despite decades of research and debate, COO still commands high scholarly interest and practical relevance (Lu et al. 2016; Samiee and Chabowski 2021; Verlegh and Steenkamp 1999). Thus far, several streams of research have emerged in the field of COO research (Table 1), including, but not limited to, COO and consumer evaluation (Agrawal and Kamakura 1999; Verlegh, Steenkamp, and Meulenberg 2005), COO recognition accuracy (Balabanis and Diamantopoulous 2011; Samiee, Shimp, and Sharma 2005), animosity, ethnocentrism, consumer psychography, and brand origin (Batra et al. 2000; Sun et al. 2021), and COO fit (Chiang and Yang 2018; Sichtmann and Diamantopoulos 2017). For the purposes of the current study, this literature review mainly focuses on consumers' COO evaluation and COO recognition accuracy.

The COO literature has considered many derivatives of origin, such as brand origin (brand COO), country of assembly, country of manufacture, country of design, and so forth (Allman et al. 2016; Balabanis and Diamantopoulous 2008; Herz and Diamantopoulos 2017; Magnusson, Zdravkovic, and Westjohn 2022). Although scholars have found that information related to product origin and country of manufacturing (i.e., "made in") are relevant, recent COO research has identified that the most important cue is brand COO (Herz and

Diamantopoulous 2017). For example, Lindt chocolate is considered a Swiss brand regardless of the import of key ingredients such as cocoa beans and milk (Ozretic-Dosen, Skare, and Krupka 2007). Brand COO is more influential on consumer decisions than information such as country of manufacturing, as brands tend to clearly communicate their origin and brand COO is stable over time (Herz and Diamantopoulous 2017).

The influence of brand COO on consumer purchase decisions depends on consumers' knowledge and recognition accuracy of brand COO (Balabanis and Diamantopoulous 2011; Samiee, Shimp, and Sharma 2005). Consumers' experience, income, socioeconomic status, level of spending, and category expertise are positively related to brand COO knowledge and its effect on purchase decisions (Davvetas, Diamantopoulos, and Liu 2020, Herz and Diamantopoulous 2017; Samiee, Shimp, and Sharma 2005). As such, knowledgeable high-spending consumers rely more on brand COO than average consumers do (Balabanis and Diamantopoulos 2008; Bloemer, Brijis, and Kasper 2009; Pecotich and Ward 2017). Therefore, consumers' brand COO choices may contain information about consumer attributes, such as their knowledge and spending patterns. This would enable firms to rely on brand COO-related information in a consumer's purchase history as a strategic diagnostic tool to segment consumers. The finance literature has long held that banks and insurance companies can retrieve signals about customers' credit worthiness from their financial transaction histories (Broecker 1990; Linsley and Shrives 2000). Financial institutions routinely rely on signals such as credit scores and previous purchases to distinguish high from low default risk. In other words, these firms rely on signals to infer customer quality. Similarly, COO-related metrics could be viewed as a signal of customers' quality in terms of their knowledge and future purchase value.

Theoretical Framework

Signaling Theory

We approach this study from a signaling theory perspective. Signaling theory addresses information asymmetry in a market (Akerlof 1970; Spence 1973) and has been widely applied in marketing research (e.g., Bellezza and Berger 2020; Kirmani and Rao 2000; Özsomer 2012). Information asymmetry occurs when different market entities (e.g., firms and consumers) do not have access to the same valuable information (Akerlof 1970; Stiglitz 2002). The information is not directly observable or detectable by the other entity, causing asymmetry (Connelly et al. 2011; Spence 2002). Interpreting signals transmitted by a sender (intentionally or unintentionally) is one way to decrease information asymmetry (Connelly et al. 2011). A necessary condition for successful signaling is that a signal needs to be costly to the sender; otherwise, “lemons” could simply engage in dishonest signaling (Spence 2002). If a signal involves a cost for the sender, then the receiver can elicit information about the sender, as some signalers are more willing or able to absorb the cost. For example, purchasing a specific product may reveal that a customer is knowledgeable about certain product attributes that non-buyers of the product do not appreciate (ignoring potential differences in disposable income). The purchase could therefore carry valuable information for a firm as a signal receiver.

Drawing on signaling theory, this study investigates signals related to DBCOO in customers’ prior purchases. We argue that DBCOOs are signals that allow firms to extract certain customer knowledge traits, which in turn allow firms to differentiate high-CPV from low-CPV customers (Akerlof 1970; Spence 2002). Importantly, actual purchases represent costs for consumers, which renders them credible signals (Stiglitz 1985). Therefore, our use of signaling theory differs from previous studies on the COO effect that have relied on the theory but viewed the firm’s origin as a cue for consumers (e.g., Jiménez and San Martín

2010). In the context of previous studies, a firm could disguise its origin or even hint at a false origin to consumers without higher costs than would be required to signal its true origin. For example, Chinese electronics brand Haier disguises its origin as German brand without any extra cost (Shukla 2017). Because “cost” is essential for signaling theory (Smith and Bird 2005), “cue” is a more appropriate word for the COO effect when the consumer interprets brand information that is not tied to costs for firms (see Table 1).

Consumer purchases hold unintentional signals from customers to firms. Researchers often examine intentional signals, which are easier to detect (e.g., Essman et al. 2021), but the importance of unintentional signals has been noted only recently (e.g., Friske, Hoelscher, and Nikolov 2022; Grecu et al. 2022; Horner et al. 2022). Several differences between intentional and unintentional signals have been identified. First, unintentional signals are more trustworthy (Vasudeva, Nachum, and Say 2018) because senders are less likely to send dishonest signals. Second, unintended signals are often more difficult to observe. Because signal observability is a necessary condition according to the theory (Connelly et al. 2011), we argue that “big data” opens up new opportunities for firms to observe and thus utilize unintentional signals. Nowadays, firms have access to extensive and granular consumer data that was impossible to access or process previously (Bradlow et al. 2017). We argue that with proper tools and specific theoretical guidelines, unintentional signals hidden in purchase data can reveal customer knowledge traits that differentiate high- and low-CPV consumers.

An important caveat about unintentional signals is that the receiver’s interpretation of the signal is more complex (Vasudeva, Nachum, and Say 2018). In particular, the receiver needs to observe and interpret conditions that may shift the meaning of a signal. One such condition is the sender’s perceived risk. For intentional signals, it is rational for a sender to send more precise signals under high-risk conditions, which would enhance the effect of signaling (e.g., Cui, Jo, and Na 2018; Eliashberg and Robertson 1988). High risk makes the

reduction of information asymmetry more critical; thus, senders are more precise in their signaling, which enhances the signaling impact. Unintentional signals, however, are more difficult to interpret as a sender's perceived risk may either increase a certain behavior (e.g., purchasing more of the same product) or change the behavior (e.g., purchasing a different product). We address this challenge for firms by testing HIP purchases as a boundary condition. HIP purchases are generally connected to higher risk for buyers (Hoyer 1984; Trijp, Hoyer, and Inman 1996), and thus they are a vital moderator to consider.

Similarly, signal frequency is generally understood to enhance the observability and interpretability of an intentional signal, which in turn increases the strength and effectiveness of that signal (Connelly et al. 2011). However, a more complex narrative may be connected to unintentional signals such as consumer purchases. For example, more frequent buying behavior could indicate a higher level of customer knowledge (Ofir et al. 2008), but it may also indicate changing preferences (Smith and Bird 2005), gift purchases, or group shopping (Eggert, Steinhoff, and Witte 2019). In signaling theory terms, more frequent unintentional signals cause noise, which makes the interpretability of signals more difficult (Connelly et al. 2011). To disentangle the effect, we consider purchase frequency as a potential moderating effect on COO signaling.

Hypotheses Development

Main Effects

The information consumers hold about countries and their preferences for certain countries' products differ across consumers (Bruwer and Buller 2013; Cakici and Shukla 2017). For example, socioeconomic status and gender influence COO recognition accuracy (Samiee, Shimp, and Sharma 2005). Moreover, country preferences depend on psychographic and

situational factors such as consumers' expertise (Pecotich and Ward 2017), anticipated regret, and their global category schema (Davvetas, Diamantopoulos, and Liu 2020). In other words, while consumers' brand COO choices contain informational value, interpreting it as a signal for firms about consumers' specific traits is not clear-cut due to noise in the data.

We argue that the signaling value of COO information from past purchases is heightened if it is possible to identify a DBCOO. DBCOO would need to be an unconventional, non-dominant COO that may be favored only if consumers have high interest in and knowledge about a certain product category. Given this, it would be possible to distinguish between ordinary consumers and those who possess high interest and knowledge. Such traits are desirable for firms because they are linked to high-purchase consumers, who spend substantially more in a product category than average consumers (Berger and Ward 2010; Wang and John 2019). For example, Ecuador is a source of cocoa beans, but not a dominant COO among chocolate brands. Accordingly, consumers choosing an Ecuadorian chocolate brand such as Pacari instead of dominant Swiss or Belgian chocolate brands are likely to have a higher interest in the product category. These consumers may know, for example, that the Pacari brand earned more than 300 international awards, beating companies from Switzerland, Belgium, and Italy (Velasco and Noboa 2017). Consumers with a high interest in and knowledge about chocolate also tend to spend more in this product category. As such, a DBCOO in the purchase basket may reveal potential high-CPV consumers (Velasco and Noboa 2017).

Conversely, average consumers may rely more on stereotypes related to a COO when forming a purchase decision (Cakici and Shukla 2017). Thus, less knowledgeable consumers might recognize and purchase only from the dominant COOs associated with a product category (e.g., Swiss and Belgian chocolate), while highly knowledgeable consumers may make more DBCOO choices (Balabanis and Diamantopoulos 2008). Similarly, previous

studies suggest that COO effects can differ between knowledgeable and less knowledgeable consumers (Josiassen, Lukas, and Whitwell 2008). The traits inherent in distinctive choices can communicate subtle signals to firms and tend to be more common among high-CPV consumers (Berger and Ward 2010). Thus, a DBCOO in previous purchases may be used to differentiate high- (vs. low-) CPV consumers.

H₁: DBCOO is positively related to CPV.

Previous studies suggest that expert high-CPV consumers use COO cues selectively and conditionally (Hong, Pecotich, and Shultz 2002; Pecotich and Ward 2017) and that the choice and combination of COOs depend on consumer knowledge and purchase extent (Ahmed and d'Astous 2008; Cakici and Shukla 2017). Therefore, high-CPV consumers' COO choices may be more complex and detailed than those of average consumers. Signaling theory indicates that more complex decision processes lead to more diverse signals (Drover, Wood, and Corbet 2018). Thus, COO diversity (i.e., the combination of COOs in the purchase basket) can be used to assess CPV variance among customers.

There are three reasons for this effect. First, COO selection among high-CPV consumers may be nuanced at the product level (Bloemer, Brijs, and Kasper 2009). In other words, high-CPV consumers may know precisely which COO is the leader in a particular product subcategory (Callaghan and Teichner 2021). Consider shoes as an example: high-CPV consumers may distinguish between brand COO in terms of which country tends to make better formal shoes (e.g., Italy) and which country makes better sports shoes (e.g., Germany, the United States). Therefore, high-CPV customers may intentionally choose different COOs for different product subcategories rather than succumb to the COO halo effect (Cakici and Shukla 2017). As such, consumers who choose distinct COOs for different product subcategories may have diverse COOs in their purchase basket. This reasoning is in line with signaling theory, which suggests that diversity is a signal for high-quality units

(Miller and Triana 2009). Thus, COO diversity does not reflect mere variety seeking; rather, it reflects a conscious and meticulous effort on behalf of knowledgeable consumers to make the best use of COO information.

Second, high-CPV consumers often engage in extensive trial and error before they come to trust a particular COO (Pecotich and Ward 2017). Consequently, such consumers may consider a pool of diverse COOs before committing to a particular one. Therefore, a diverse set of COOs in a purchase basket may indicate the more intensive selection process of high-CPVs consumers, while average consumers may simply purchase the dominant COOs associated with a product-country image.

Third, high-CPV consumers may use diverse brands to express their uniqueness (Bellezza and Berger 2020). Such consumers may select brands from a range of unusual COOs to distinguish themselves from average consumers (Velasco and Noboa 2017; Wang and John 2019). This would allow firms to use COO diversity to identify high-CPV consumers. In conclusion, COO diversity in prior purchases might suggest that consumers are more nuanced in their selection, follow a more complex selection process, and use diverse COOs to articulate their uniqueness, which in turn is linked to high-CPV.

H₂: COO diversity is positively related to CPV.

Moderation: High-Involvement Product (HIP) Category

Product involvement is a vital moderator in consumer decision making (Celsi and Olson 1988). Consumers care more about quality when purchasing HIPs (Lin, MacInnis, and Eisingerich 2020). HIP purchases often cost more than low-involvement ones (Deshpande and Hoyer 1984), and there are higher stakes connected to faulty purchase decisions (e.g., bad medicine can be life threatening) (Deshpande and Hoyer 1983; Trijp, Hoyer, and Inman 1996). Thus, HIPs are commonly linked to greater buyer risk (Hoyer 1984; Trijp, Hoyer, and Inman 1996).

According to signaling theory, higher perceived risk leads to more precise intentional signaling, as decreased information asymmetry becomes more critical (Spence 1973). While the literature has discussed unintentional signals to a lesser extent, marketing studies report findings similar to intentional signaling for riskier products. Considering the high risk associated with many HIP purchases, consumers tend to follow a more thorough and sequential assessment of these products and rely on mostly trusted sources (Menidjel et al. 2020; Nayeem and Casidy 2013; Quester et al. 2007). For skincare products, for example, “[a] consumer who feels strong hope and strong anxiety about a new skincare product might plan to read usage instructions carefully, to ask friends if they have tried it, and to look up the product’s ingredients and potential side effects” (Lin, MacInnis, and Eisingerich 2020, p. 60). Thus, due to risk and anxiety, consumers may conduct more research when considering the variance among countries in product quality and ingredient regulation (Becker 2016). This practice would, in turn, help consumers stay updated about COOs and make distinctive choices rather than going with more common decision rules (e.g., all U.S. products are good).

We argue that more careful consideration leads high-CPV consumers to access more information (Leung et al. 2022) and to consult their trusted network more to identify DBCOOs that promise the best quality (Bloemer, Brijs, and Kasper 2009; Lin, MacInnis, and Eisingerich 2020). This practice may lead consumers to choose a DBCOO rather than exhibit the dominant COO halo effect for HIPs.

H₃: HIPs enhance the positive relationship between DBCOOs and CPV.

While the more deliberate consideration associated with HIPs leads to an enhanced signaling effect for a DBCOO, we argue that it attenuates the signaling effect in the case of COO diversity. The higher risk associated with HIPs decreases consumers’ experimentation and variety seeking (Trijp, Hoyer, and Inman 1996). Instead of experimenting to test different COOs, consumers may rely more on published information and word of mouth from trusted

peers to identify the best COO. For example, consumers experience more pleasure when searching for information for HIPs (vs. low-involvement products) (Mathwick and Rigdon 2004). In addition, variety seeking is more risky for HIPs, and consumers may be better off selecting a brand from a trusted COO (Trijp, Hoyer, and Inman 1996).

Furthermore, different countries have distinctive product standards and guidelines (Lalor and Wall 2011). Thus, regulation and product information vary from country to country, which poses a higher risk for consumers to experiment. This point is especially relevant for emerging-market consumers who cannot always rely on stringent product safety regulations in their home country. For example, the European Union has banned 1,300 chemical ingredients in personal care products, while the United States has banned only 11 chemical ingredients (Becker 2016). Therefore, for HIP (i.e., high-risk) categories, the COO diversity signal is expected to decrease in strength because consumers choose trusted, more strongly regulated COOs rather than experimenting with diverse COOs.

H₄: HIPs attenuate the positive relationship between COO diversity and CPV.

Moderation: Purchase Frequency

Signaling theory suggests that increasing the frequency of intentional signals enhances the observability and credibility of the signal (Connelly et al. 2011; Janney and Folta 2003) and thus strengthens its accuracy (Filatotchev and Bishop 2002). A similar argument may apply to unintentional signals. Studies suggest that consumers who shop frequently make informed decisions and retain brand information better than those who shop less often (Ofir et al. 2008). Customers who are more interested and knowledgeable may choose a DBCOO more deliberately, which would enhance the accuracy of the signal and thus strengthen the ability of a DBCOO to indicate CPV.

However, the logic behind unintentional signals is more complex, as more frequent unintentional signals may also cause noise, which makes the signal more difficult to interpret

and decreases its strength (Connelly et al. 2011). Noise may be introduced for several reasons. First, a higher shopping frequency may reflect a customer's rapidly changing brand preferences (Smith and Bird 2005). In this case, higher shopping frequency may indicate less- (vs. more-) informed consumers. In addition, the purchase basket of frequent shoppers may reflect group shopping (Eggert, Steinhoff, and Witte 2019). In such a case, signals from multiple consumers would be mixed, which introduces noise into the signaling process and curtails the explanatory power of the DBCOO signal. Frequent shoppers may purchase products as gifts along with products for personal use (Eggert, Steinhoff, and Witte 2019). In this case, noise is introduced by mixing the preferences of different consumers, and noise in the signaling process reduces the DBCOO signal's strength to indicate high-CPV consumers.

In summary, purchase frequency can introduce opposing effects into the signaling process. On the one hand, signaling may become more accurate when purchase frequency indicates that customers are more informed and consider their decisions more deliberately. On the other hand, the signaling effect may become weaker if purchase frequency introduces noise into the signaling process (Connelly et al. 2011). We argue that for low levels of purchase frequency, both effects are low so there is little moderation of the main effect of DBCOO on CPV. For medium levels of purchase frequency, the signal would mainly indicate that customers are more informed and knowledgeable with little noise that would disturb this effect. As such, the main effect of DBCOO on CPV would be enhanced relative to low levels of purchase frequency. At high levels of purchase frequency, however, the effect of signaling noise - caused for example by group or gift shopping - would dominate, and DBCOO's ability to signal CPV would be suppressed. Therefore, moderation of the main effect describes a curvilinear relationship.

H₅: Purchase frequency has an inverted U-shaped effect on the relationship between DBCOO and CPV.

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While we anticipate that a DBCOO's signal of CPV is quadratic due to the opposite effects of purchase frequency, we expect a linear negative effect for purchase frequency's moderation of the COO diversity–CPV link (see Figure 1). Both effects related to purchase frequency (i.e., knowledgeable consumers and signaling noise) point in the same direction for the COO diversity signal. In other words, we expect that the positive effect of COO diversity on CPV will be attenuated for highly frequent customers.

Empirical research indicates that consumer product knowledge increases with shopping frequency (Mägi and Julander 2005). Consumers who shop often make decisions that are more informed and retain brand information better than those who shop less frequently (Ofir et al. 2008). More informed decisions reduce experimentation with different COOs among high-CPV consumers, thus leading to more stable choices and decreasing the effect of COO diversity on CPV. For example, retail research suggests that frequent consumers tend to repurchase the same products (Macdonald and Sharp 2000). As such, the signaling effect related to knowledgeable consumers suggests a negative moderating influence of purchase frequency on the COO diversity–CPV link. In addition, the effect of noise for high-frequency shoppers would decrease the signaling strength (Connelly et al. 2011). Specifically, high-frequency shoppers' purchase baskets may make their diverse COO preferences a less trustworthy signal because high frequency may be the result of shopping for others (e.g., gifts, community shopping) (Eggert, Steinhoff, and Witte 2019). Such behavior may reflect the COO preferences of multiple consumers rather than the focal customer. Therefore, purchase frequency can create unwanted noise in the COO diversity signal that may be difficult to declutter (Kukar-Kinney, Ridgway, and Monroe 2012). In conclusion, effects related to knowledgeable consumers and signaling noise both suggest a decrease in the explanatory power of the COO diversity signal for increasing levels of purchase frequency.

H₆: Purchase frequency decreases the positive effect of COO diversity on CPV.

(Insert Figure 1 about here)

Method

Empirical Context

Country selection. To test our theoretical model, we selected Bangladesh for two reasons. First, Bangladesh is an emerging market of growing importance where consumers rely heavily on COO in their purchasing decisions due to weak regulations in local product quality (Boston Consultancy Group 2022; Kaynak, Kucukemiroglu, and Hyder 2000). 80% of Bangladeshi consumers consider brand origin when assessing product quality (Munir, Muehlstein, and Naubhar 2015). Second, the estimated 3.5 million medium-income and affluent Bangladeshi consumers by 2025 represents a substantial base of high-CPV consumers (Boston Consultancy Group 2022). Bangladeshi consumers earn more than those in their neighboring countries (e.g., India, Pakistan) and are willing to spend more for quality products (International Monetary Fund 2022; Munir, Muehlstein, and Naubhar 2015). These indicators make Bangladesh a promising context for testing COO-related signal effectiveness. Yet Bangladesh has been largely ignored by marketing researchers (see Table 1). The context–theory match and lack of research on Bangladeshi consumers justify our choice of Bangladesh as an empirical setting.

Category selection. We selected beauty products as an appropriate category for the following reasons. First, recent studies suggest that beauty ideals and purchase choices are strongly interlinked with consumer aspirations (Madan et al. 2018; Mady et al. 2023). Furthermore, such aspirations attached to beauty products are connected to COO. Research suggests that consumers from certain countries aspire to a bright and fair look (Kim and Hong 2017). For

example, Indian subcontinent consumers who want fair-looking skin are particularly fond of products from countries that follow a similar ideal (Moniea and Roy 2022). This strong connection between aspirational purchases and COO in the beauty product category may be less vital in other categories (e.g., soft drinks, cars) (Aichner 2014; Melnyk, Klein, and Völckner 2012).

Second, beauty products have a lot of variety in terms of ingredients, suitability, and product styles (Madan et al. 2018). This makes consumer knowledge a key attribute that influences purchases. Moreover, beauty product regulation differs considerably among countries, which drives consumers to focus more on COO to attenuate risk factors inherent in using ingredients not suitable for their skin (Becker 2016). Thus, the beauty product category is ideal for COO signaling research based on consumers' knowledge variance.

DBCOO selection. We choose Korea as the focal DBCOO for several reasons. Korea has positioned itself as a strong COO in the beauty industry. In 2005, the Korean government initiated the “Hallyu! The Korean Wave” project, which helped Korea connect its media, culture, and representations of beauty to the broader world (Li, Min, and Lee 2021). The Korean Wave hit the Bangladeshi upper-income segment consumers and shaped their beauty purchase behavior (Moniea and Roy 2022; Shaan 2022). One reason for this is that Korean beauty products focus on fair-complexion “glass skin” (glass skin refers to a flawless, glowing lighter skin ideal), which resonates with the aspirations of many Bangladeshi consumers to have a lighter skin tone (Deshpande and Chaturvedi 2016; Karnani 2007; Kim and Hong 2017). Second, although Korea has made commendable advancements in beauty product R&D, it is still considered a COO for “people in the know,” which helps ensure that Korean beauty products command exclusivity among consumers (Kim and Hong 2017; Li, Min, and Lee 2021). Exclusive stores and expert consumer segments are more inclined toward Korean beauty products than is represented in the mass-merchandise beauty product

market (Caldwell 2016; Morosini 2019). Therefore, the affection for Korean beauty products is associated with a distinguished segment of consumers, not the mass market. Thus, Korea represents a DBCOO for beauty products in Bangladesh.

In contrast, French and other European country beauty brands are popular among mass-market segments. These more dominant beauty brands rely on strong advertising spending and may be present among high- and low-CPV consumers. Thus, while expensive, such a brand COO may not effectively indicate high CPV. Therefore, we view Korea as a viable DBCOO that differentiates consumers with expertise (and potentially high CPV) from others.

Qualitative Research

Qualitative studies are recommended for exploratory field research to identify potential variables, validate information, and prepare for quantitative research (Guo, Heinberg, and Zou 2019; Hennink 2014). We conducted three online qualitative focus group discussions in preparation for the quantitative study. We wanted to precisely understand Bangladeshi consumers' take on Korean brands as a DBCOO choice. Moreover, we focused on exploring how skincare and makeup products are distinct in consumers' perceptions and COO choice. Thus, this qualitative study was essential to improve the rigor of our study.

Methodology. Each discussion consisted of four to six participants and lasted approximately 60–75 minutes (Hennink 2014). Participants were from diverse occupational background that includes but is not limited to managers, entrepreneurs, homemakers, students, lawyers and academics. We were careful to get participants' consent and ensure their comfort during the focus group discussions.

As a screening process, first, the participants' recognition of brand COO and product categories was assessed. Participants were shown 10 logos from brands represented in the Bangladeshi market. Brands were from a diverse range of countries and prices. On average,

participants identified three out of four brand origins correctly. Moreover, we showed pictures of 10 different beauty categories (including skincare, haircare, and makeup) to participants. All participants accurately identified the beauty categories such as skincare and make-up for the products. Following the screening process, we started the discussion session. To facilitate the discussion, we have focused on topics that include but are not limited to consumers' reliance on COO, perception regarding different COOs and distinctions, product category importance, purchase frequency and COO exposure etc. Please refer to Web Appendix A for detailed topics and questions. Next, we summarize key findings of the focus group discussion.

Korea as DBCOO. Korea's country image was described as "science and R&D [focused]" as well as "nature and wellness friendly", which is a match for attributes respondents valued in beauty products. This suggests that Korea fulfills the requirement according to the first pillar of our DBCOO definition, supervisor value proposition linked to the country image. Most participants revealed that they had been exposed to Korean beauty products through sources in their network (e.g., beauty consultants, friends, colleagues) and reviews. Korean products are not advertised or communicated as broadly as Western beauty products in Bangladesh, making it difficult for most to access this information. This suggests that Korea fulfills the requirement according to the second pillar of our DBCOO definition (non-dominant COO). Moreover, it became apparent in the focus group that knowledge of Korean beauty products translated into purchases. For example, participants stated that they repeatedly use Korean products because of the scientifically selected natural ingredients, which lead to lower perceived risk when applied to the skin and promise superior results. These qualitative findings support our choice of Korea as a DBCOO for beauty products in Bangladesh.

COO diversity as a signal of high CPV. There was some evidence that those different preferences are more common among high-spending participants. For example, one high-

spending participant mentioned, *“Well one country makes one product well another country another. For example, I really like makeup from the U.S.A. and UK because of more options. I opt for Bangladeshi natural remedies for haircare. For skincare, I rely on Korean products and homemade natural remedies”*. Compared to this, one low-middle-spending consumer stated, *“Well, I generally don’t care much. However, products from wealthy countries such as the US and UK are usually good. I don’t care much about Indian or Bangladeshi products though, I generally avoid them.”* This suggests that COO diversity is not mere variety seeking, but a conscious effort to use COO cues meticulously, especially for high-spending consumers. Compared to this, the COO halo effect was more prevalent for low-middle spending consumers. Hence, we see support for the notion that COO diversity may signal consumer purchase value.

Skincare as a HIP category. Participants suggested that they were more concerned about the ingredients, COO, brand reputation, and reviews for skincare products than for makeup or haircare products. Furthermore, participants generally expressed that skincare is the most important category to them, which translates into more knowledge-seeking for this subcategory. As one participant stated, *“I take extra caution when choosing skincare because I think of it as a long-term investment, if a skincare product goes wrong it can harm my skin and health tremendously.”* This finding complements our desk research and indicates that skincare has a higher degree of involvement than other beauty products (e.g., makeup, haircare) and is thus a HIP. For a detailed discussion, see Web Appendix A.

Quantitative Research

Data and sample. We test our hypotheses using consumer purchase history data from one of Bangladesh’s largest online beauty product retail platform. We observed more than a million transactions (1,044,079) from 327,863 consumers across 12 months (2021–2022). The data contain purchase histories of beauty products from 613 brands and 26 COOs. Beauty

products were mainly from skincare, haircare, and makeup categories, with few products coded as “other.”

Data preparation and operationalization. We first explored initial insights and salient subsets in the data (Chiang and Yang 2018) and then coded each product according to its category (i.e., skincare, makeup, haircare, other). Subsequently, we coded brands according to their COO (e.g., Korea, the United States, Bangladesh etc.). Considering multiple transactions per consumer across the observation period of one year, we set up the data as a monthly panel in which each consumer is observed over 12 monthly time windows. The monthly panel suits a common purchase interval for beauty products (Kantar 2022; Statista 2023). In the observation period, the top 10% most frequent consumers made 15 or more purchases, consumers ranking 11%–25% in terms of frequency made 7–14 purchases, those ranking 26%–50% in terms of frequency made 4–6 purchases, and consumers ranking in the bottom 25% in terms of frequency made 1 purchase.

Variable Operationalization and Measurement

Dependent variable. Our dependent variable, CPV, refers to a consumer’s total monetary value of purchases in a given period (in Bangladeshi Taka [BDT]). We applied a logarithmic transformation to CPV to reduce the influence of extreme cases (Hendry and Ericsson 1991). Because the value of zero is not permitted in logarithmic transformations, we add a negligible value of 1 BDT (equivalent to .001 USD) to all calculated CPVs before the transformation (see Table 2).

DBCOO. We refer to DBCOO as the share of a non-dominant yet superior value-proposing COO in the consumer’s purchase history. We chose Korea as the DBCOO following our desk and qualitative research. DBCOO is the ratio of the number of Korean products in a customer’s purchase history to the sum of products from other COOs in the purchase history (see Table 2).

COO diversity (COOdiv). COO diversity reflects the variety of COOs in a consumer's purchase basket, thus capturing the relative competition among COOs in the consumer's purchase basket. To measure COO diversity, we use the Herfindahl–Hirschman index (Churchill and Smyth 2017; Vassalo et al. 2019). First, we square the share of each COO in the purchase basket and then sum the resulting numbers as follows:

$$\text{COO diversity}_j = 1 - \sum_{e=1}^N S_{ej}^2,$$

where S_{ej} is the share of COOs in the consumer's purchase basket j and N is the number of COOs in the purchase history (Churchill and Smyth 2017; Schaeffer 2013). The variable is coded so that a high value indicates high diversity, whereas a low value indicates low diversity.

HIP category. Based on our qualitative research, skincare products entail a higher level of involvement than other beauty products and thus represent a HIP category. The literature supports this; consumers exhibit high anxiety and caution when purchasing skincare products which is evident through their intensive recommendation-seeking and knowledge-acquisition activities (Lin, MacInnis, and Eisingerich 2020). Due to high health risks and long-term effects, consumers are concerned about ingredients and safety when purchasing skincare products (Euromonitor 2022). These attributes constitute a HIP, as consumers engage in more information processing and are cautious when purchasing skincare products (Leung et al. 2022; Reardon, Vianelli, and Miller 2017). While makeup products promise instant results, consumers need longer-term usage of skincare products to achieve the desired results. Such attributes closely match HIP attributes in the literature (Reardon, Vianelli, and Miller 2017). Furthermore, previous literature has considered skincare a HIP (e.g., Cho 2010). We measure HIP by assessing the presence of skincare products in the consumer purchase basket, such that $\text{HIP} = 1$ (otherwise 0).

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Purchase frequency (Pfreq). Purchase frequency refers to the number of specific times a particular consumer makes a purchase throughout the observation period (Connelly et al. 2011; Smith and Bird 2005).

Western developed-country brands share (WDB share). WDB refers to brands from Western developed countries such as the United States, the United Kingdom, Germany, France, Italy, Switzerland, Sweden, Denmark, and Spain. We calculate WDB as a ratio of the number of WDB products to the sum of products from other COOs in the consumer's purchase basket.

Local brand share. Local brand share refers to brands from Bangladesh, which is the local brand in the context of this study. We measure local brand share as the ratio of the number of Bangladeshi products in the consumer's purchase basket to the sum of products from other COOs in the consumer's purchase basket.

Indian brand share. We measure Indian brand share as the ratio of the number of Indian products in the consumer's purchase basket to the sum of products from other COOs in the consumer's purchase basket.

Average price of COOs. We control for the average price of COOs to ensure that our findings are robust across price effects. We do this to rule out the possibility that a higher CPV is simply driven by a higher price of products from some countries. We control for the average price of Korean (avK), WDB (avWDB), local brand share (avLocal), and Indian products (avInd) in a consumer's purchase history.

Product Categories (haircare and makeup). We control for the presence of haircare and makeup products in the consumer purchase basket.

Basket size: Basket size refers to the average number of products a consumer purchased per shopping trip (Sorensen et al. 2017). We operationalize basket size by dividing the total unit of products a consumer purchased over the observation period by that consumer's purchase frequency.

(Insert Table 2 here)

Model and Estimation

To test our hypotheses, we run a monthly panel regression analysis on the following model:

$$\begin{aligned} \text{CPV}_{it} = & \beta_0 + \beta_1 \text{DBCOO}_{it-1} + \beta_2 \text{COOdiv}_{it-1} + \beta_3 \text{DBCOO}_{it-1} \times \text{HIP}_{it-1} + \beta_4 \text{COOdiv}_{it-1} \times \text{HIP}_{it-1} \\ & + \beta_5 \text{DBCOO}_{it-1} \times \text{Pfreq}_{it-1} + \beta_6 \text{DBCOO}_{it-1} \times \text{Pfreq}_{it-1}^2 + \beta_7 \text{COOdiv}_{it-1} \times \text{Pfreq}_{it-1} + \beta_8 \text{WDB} \\ & \text{Share}_{it-1} + \beta_9 \text{Local Brand Share}_{it-1} + \beta_{10} \text{Indian Brand Share}_{it-1} + \beta_{11} \text{avK}_{it-1} + \beta_{12} \text{avWDB}_{it-1} + \\ & \beta_{13} \text{avLocal}_{it-1} + \beta_{14} \text{avInd}_{it-1} + \beta_{15} \text{Pfreq}_{it-1} + \beta_{16} \text{Pfreq}_{it-1}^2 + \beta_{17} \text{HIP}_{it-1} + \beta_{18} \text{Makeup}_{it-1} + \beta_{19} \\ & \text{Haircare}_{it-1} + \beta_{20} \text{Basketsize}_{it-1} + \varepsilon_{it} + \gamma_i \dots (1) \end{aligned}$$

In this model, CPV is the dependent variable, DBCOO and COO diversity are independent variables, and HIP and purchase frequency (Pfreq) are moderators. Subscript *i* denotes an individual consumer's purchase basket, and subscript *t* represents the month. The dependent variable (CPV) is measured at time *t*, while independent variables are measured at time *t* – 1.

Analysis and Results

Before testing the hypotheses, we assessed multicollinearity. We estimated the variance inflation index; the mean variance inflation factor (VIF) (3.54) and individual VIFs are below the threshold of 10 (Hair et al. 2010; Kock and Lynn 2012). Thus, we do not find evidence of multicollinearity. Descriptive statistics and correlations appear in Table 3.

(Insert Table 3 here)

Hypotheses testing. H_1 suggests that DBCOO is positively related to CPV. In support of H_1 , the coefficient of DBCOO is positive and significant ($\beta = .13, p < .01$) (Table 4, Column 4). This result implies that the presence of Korean brands in the purchase basket is an essential indicator of a high-CPV consumer. We also controlled for brands from other nondistinctive COO's: WDB share ($\beta = .05, p < .01$), local brand share ($\beta = -.05, p < .01$), and Indian brand share ($\beta = -.21, p < .01$). Following a reviewer's suggestion, we assessed if other countries (e.g., France) could substitute for Korea as a DBCOO. According to our argument and

additional test, France would be a common and dominant COO and thus would not help identify knowledgeable consumers. Our results confirm this: while the DBCOO strongly signals high CPV, nondistinctive COOs such as France do not (see Web Appendix B).

H₂ suggests that COO diversity is positively related to CPV. The results show that the coefficient of COO diversity (COOdiv) is positive and significant ($\beta = .35, p < .01$), in support of H₂ (Table 4, Column 4). This finding suggests that greater COO diversity increases CPV in the consumer's purchase basket. H₃ suggests that HIPs enhance the positive relationship between DBCOO and CPV. The results support this positive moderation ($\beta = .14, p < .01$, 95% CI [.120, .249]) (Table 4, Column 4). H₄ suggests that HIPs attenuate the positive relationship between COO diversity and CPV. The results support H₄ ($\beta = -.55, p < .01$, 95% CI [-.604, -.509]) (Table 4, Column 4). H₅ suggests that purchase frequency (Pfreq) has a quadratic moderation effect on the positive relationship between DBCOO and CPV. The results support H₅ ($\beta = -.29, p < .01$, 95% CI [-.150, -.336]) (Table 4, Column 4). H₆ predicts that purchase frequency attenuates the effect of COOdiv on CPV. The result support H₆ ($\beta = -.06, p < .01$, 95% CI [-.043, -.239]) (Table 4, Column 4). Please see Figure 2 for the graphical illustration of the moderating hypotheses.

(Insert Table 4 here)

(Insert Figure 2 here)

Additional Analyses and Robustness Checks

Panel regression model with deeper purchase incidents. As a robustness test, we ran the panel model with deeper purchase incidents as controls. To account for deeper purchase incidents, we included independent variables and controls for (t – 2) and (t – 3) time periods. The results with deeper purchase incident controls are consistent with the results of our main model presented in Equation 1 (for equations and results, see Web Appendix C). For example, the coefficient of DBCOO is positive and significant ($\beta = .14, p < .01$), in support

of H_1 , and the coefficient of COO diversity on CPV is positive and significant ($\beta = .29, p < .01$), in support of H_2 .

Alternative model estimation. We ran two additional models for robustness purposes (for equations and results, see Web Appendix D). An ordinary least square (OLS) regression analysis confirms that the results are not confined to our panel regression. For example, the coefficient of DBCOO is positive and significant ($\beta = .71, p < .01$), in support of H_1 , and the coefficient of COO diversity on CPV is positive and significant ($\beta = 1.48, p < .01$), in support of H_2 . An additional OLS predictive model splits the observation window into two periods and measures the independent variables based on the first six months (i.e., January–June) and the dependent variable based on the subsequent six months (i.e., July–December) of our observation window. This model supports our hypotheses; for example, the coefficient of DBCOO is positive and significant ($\beta = .30, p < .01$), in support of H_1 , and the coefficient of COO diversity on CPV is positive and significant ($\beta = 4.38, p < .01$) in support of H_2 . This additional model confirms that our results are robust for longer observation periods than the monthly panel estimation.

Accounting for unobserved heterogeneity. Although we included numerous controls in our model, the concern about unobserved heterogeneity remains. In particular, there may be unobserved heterogeneity caused by unobserved consumer characteristics. We ran the model controlling for festive season sales and ethnocentric purchases to account for unobserved heterogeneity. Festive season sales were coded as 1 if the sales were during the month of the three main festivals in Bangladesh (Eid Ul Fitr, Eid Ul Adha, and Bengali New Year), and as 0 otherwise (Hussain 2019). Ethnocentric purchase was coded as 1 if a consumer only purchased local brands, and as 0 otherwise. Moreover, while we do not have income data, consumers' income might fluctuate in every quarter for macro-economic reasons. Thus, we controlled for quarterly purchases. The results remain stable when controlling for these

variables that account for some unobserved heterogeneity (See Web Appendix E). For example, coefficient of DBCOO is positive and significant ($\beta = .17, p < .05$), in support of H_1 and coefficient of COO diversity on CPV is positive and significant ($\beta = .22, p < .01$), supporting H_2 .

Sub-sample test. Considering the large data set, the strong statistical power demands a test with a smaller sample size. Thus, we re-ran our panel regression model with a randomly selected smaller sample of 1/30th of the whole sample ($n = 10,929$). The results are similar to the panel regression with the whole data set (see Web Appendix F), adding robustness to our findings.

Endogeneity test. To account for endogeneity due to a potential omitted variable that simultaneously drives both independent and dependent variables in our model, we calculated a Gaussian copula for the independent variables DBCOO and COO diversity and plugged it into Equation 1 (Eckert and Hohberger 2022; Hult et al. 2018; Park and Gupta 2012; Vassallo et al. 2023). The results reveal similar findings after accounting for endogeneity in Equation 1 (see Table 4, Column 6).

Impact analysis with median splits. To assess the real-world relevance of our findings, we conducted a median split on our two independent variables and assessed if above- and below-median groups differ in their CPV. The results reveal that consumers with above- (vs. below-) median DBCOO have an average CPV of 2,631.29 BDT (vs. 672.51 BDT). Similarly, average CPV of consumers with COO diversity above the median is higher than it is for those below the COOdiv median (1367.93 BDT vs. 451.18 BDT) (See Web Appendix G). Such stark differences demonstrate real-world impact of DBCOO and COO diversity on CPV.

Impact analysis with deciles. Table 5 confirms that this real-world impact exists across high- and low-CPV consumers. For a more granular picture, we split consumers into above- and below-median values of DBCOO and project the CPV in deciles corresponding to the

DBCOO median split. For every decile, the CPV difference between above-median DBCOO and below-median DBCOO increases and ranges from 259 BDT (decile 10) to 6868 BDT (decile 1). Moreover, we split consumers into groups of above- and below-median values of COOdiv and project the CPV in deciles corresponding to the COOdiv median split. For every decile, the CPV increases in both groups, from 83 BDT to 3997 BDT. Thus, the impact analysis reveals that margins of the distribution do not cause the effect of DBCOO and COOdiv but are prevalent throughout the distribution and add tangible results that inform the managerial implications of our firm-focused study.

(Insert Table 5 here)

Discussion

Theoretical Contribution

This study makes several theoretical contributions. First, we identify DBCOO as an unintentional consumer signal that firms can interpret to decrease information asymmetry. We theorize that consumers' choices of brand COO can contain informational value, but that COO signals usually carry a lot of noise because consumers' COO knowledge and usage differ widely (Davvetas, Diamantopoulos, and Liu 2020; Samiee, Shimp, and Sharma 2005). However, we hypothesize that the signaling value of COO information increases when we consider DBCOOs, unconventional COOs favored by consumers with high interest in and knowledge about a certain product category. In this sense, it is possible to distinguish ordinary consumers from those who possess desirable traits such as high interest and knowledge, which in turn indicate higher spending (Berger and Ward 2010; Wang and John 2019). This finding presents a novel contribution to current COO research, which has mainly developed along four key streams: COO and consumer evaluation (e.g., Verlegh, Steenkamp,

and Meulenbergh 2005), COO recognition accuracy (e.g., Balabanis and Diamantopoulos 2008), animosity, ethnocentrism, consumer psychograph, and brand origin (e.g., Sun et al. 2021), and COO fit (e.g., Sichtmann and Diamantopoulos 2017). These streams all view COO as a cue that helps consumers decrease their information asymmetry with respect to a product or brand. Our findings demonstrate that the signal can be read in the opposite way; specifically, firms can decrease information asymmetry about a consumer's purchase value.

Importantly, our findings do not contradict prior COO research, but rather rely on and support previous studies. It is precisely because consumers use COO as a cue (e.g., Herz and Diamantopoulos 2017) that it is possible for firms to read DBCOO as a signal. This is also evident in the first pillar of the DBCOO concept which builds on the key proposition of COO research, namely that a country of origin can be associated with a superior value proposition (Balabanis and Diamantopoulos 2008; Payne, Frow, and Eggert 2017). Connected this research with the second pillar (i.e., non-dominance of the COO) turns DBCOO into a signal that can be employed as a strategic diagnostic tool that managers can use to extract meaningful insights about future potential spending (Bradlow et al. 2017; Marketing Science Institute 2020). We provide a comprehensive framework that develops how COO signals from consumers can hold strategic value for firms. We extend recent COO studies that indicate that monitoring sales over time based on brand COO may be advantageous for firms (Chiang and Yang 2018; Magnusson, Zdravkovic, and Westjohn 2022).

Second, this study is the first to use the diversity concept in COO research. Although related marketing fields have used the diversity concept as a variable (Amaldoss and He 2019; Park, Voss, and Voss 2023), COO diversity has not been employed as a diagnostic signal for firms to extract consumer information. Our findings indicate that COO diversity has a positive effect on CPV and aligns with COO studies that suggest that decision-making processes related to brand COO are complex (Cakici and Shukla 2017; Pecotich and Ward

2017). The literature suggests that a diverse selection can indicate nuanced evaluations of subcategories, a careful learning and selection process, or consumers' differentiation needs (Bellezza and Berger 2020; Bloemer, Brijs, and Kasper 2009; Pecotich and Ward 2017). Such complex decision-making processes relate to deeper consumer knowledge and higher spending (Cakici and Shukla 2017; Wang and John 2019). The positive effect of COO diversity is in line with current COO research on the coalescence effect, suggesting that consumers can bridge potentially contradictory cues related to a brand's origin appeal (Hu et al. 2022).

Third, we contribute to the literature on unintentional signals. DBCOO and COO diversity are not deliberate signals sent by consumers, a fact that may imply higher trustworthiness, but also limited observability compared with intentional signals (Cui, Jo, and Na 2018; Vasudeva, Nachum, and Say 2018). Unintentional signals are important, but the literature is just emerging (Connelly et al. 2011; Grecu et al. 2022; Horner et al. 2022). We examine the boundary conditions of two unintentional signal effects (DBCOO and COO diversity) on CPV, which is important because of the complexity of unintentional signals (Vasudeva, Nachum, and Say 2018). We consider HIP categories and purchase frequency as moderators because they are easily accessible variables for retailers.

Our findings indicate that the relationship between DBCOO and CPV is stronger for HIPs. On the contrary, the relationship between COO diversity and CPV is weaker for HIPs. The logic for both effects is consistent because consumers try to decrease risk related to HIP purchases by reducing variety seeking and by employing a more thorough consideration of their choice (Bruwer and Buller 2013; Simonson 2005; Suh and Youjae 2006). We also shed light on the moderating effect of purchase frequency on the DBCOO–CPV and COO diversity–CPV links. Again, the logic for our results is consistent for both relationships. Still, effects show different tendencies: a quadratic inverse U-shaped relationship for the DBCOO–

CPV interaction and a linear negative effect for the COO diversity–CPV interaction. Both moderation effects are rooted in two rationales connected to purchase frequency. On the one hand, frequent customers tend to make more informed choices (Ofir et al. 2008); on the other hand, purchase frequency can imply more signaling noise. Our results align with previous studies, indicating that frequency can have positive and negative moderation effects (Smith and Bird 2005; Venkatesan and Kumar 2004).

Managerial Implications

The current work has critical implications for marketing managers. Many managers believe that firms should continuously track consumers, identify high-yield customers, and then pay specific attention to them by utilizing priority distribution, exclusive product offers, or targeted communication. However, managers face the problem of identifying high-yield consumers because initial purchases contain very little information. Our research suggests managers can tap unintentional signals hidden in a consumer's purchase history to decrease information asymmetry and identify potentially high-CPV consumers. Such insights are essential as managers often lack the theoretical understanding to make pertinent use of available data. Even in the age of artificial intelligence and deep learning, plain business metrics are important for firms, especially in emerging markets, which often lack the infrastructure, resources, and expertise for complex technology-dependent analyses (Sheth 2011).

Our study offers three key implications for managers. First, we demonstrate how DBCOO in consumers' purchase history (in our case, a Korean COO) can help managers predict CPV. Brand COO is relevant to consumers' purchase decisions and is easily observed from purchase history data. An essential requirement is that brand managers need to rely on research to identify DBCOOs that can act as unintentional signals. Our desk research and our qualitative study identify Korea as a signal for beauty products in Bangladesh. Our result

suggests that consumers with above-median DBCOO in their purchase history have almost four times higher average CPV in our observation year than consumers with below-median DBCOO. Considering these strong differences in CPV will enable managers to channel their marketing resources to further increase the customer lifetime value of high-CPV consumers and reduce marketing spending on low-CPV consumers. The DBCOO signal may differ depending on the product category or market. Thus, we encourage managers to build on research to identify these valuable and relevant signals, which can decrease information asymmetry about consumer spending power (Bradlow et al. 2017; Saxena and Lamest 2018).

Second, we identify COO diversity as an additional signal that managers can tap to segment consumers according to their purchase value. According to our theory-based argument, COO diversity is a universal signal that managers can interpret and is not tied to a specific context, but further research is needed to add robustness to our findings. Our impact analysis indicates that consumers with above-median COO diversity have a three times higher average CPV in our year of observation than consumers with below-median COO diversity. Importantly, the COO diversity metric is distinct from DBCOO. We have analyzed the overlap between consumers belonging to the highest decile in DBCOO and the highest decile in COO diversity, and only 9.4% of consumers in those groups overlap. In other words, DBCOO and COO diversity are complementary signals that allow firms to segment consumers according to their CPV, thus providing valuable strategic analytical tools. The measure of COO diversity builds on the approach managers use to evaluate firms' relative market share (Cetorelli and Strahan 2006; Giroud and Mueller 2011). Thus, we posit that the metric can be implemented by marketing managers in a straightforward way.

To assess the potential impact of DBCOO and COO diversity metrics, we presented our findings to four distinguished managers from different level and collected their feedback. Managers' positions were CEO, Analytics and Digital Marketing Manager, Operations

Manager and Sales Manager. They mentioned that both signals are novel and pointed out that relying on these signals as analytical tools would help them better distinguish high- from low-CPV consumers. As one manager stated, “implementing these COO signals would enable us to find high purchasing consumers [high CPV] more effectively than before. Previously, we have used many complicated metrics, but the results were not as effective as these.” The managers also stated that they look forward to applying DBCOO and COOdiv metrics in the future.

Third, our moderator analysis of HIPs and purchase frequency presents important boundary conditions that managers need to account for in interpreting signals. Both variables are easy to access for managers and are typically considered in the retailing context (Reinartz, Wiegand, and Imschloss 2019). Importantly, DBCOO signals increase in strength for HIPs, whereas the COO diversity signal decreases in strength. Thus, the former signal would be more trustworthy for HIPs (e.g., skincare products), while the latter signal would be more trustworthy for low-involvement product categories. Our findings also provide guidance for managers with respect to the complexities of unintentional signals and the role of signal noises. For example, for very frequent and very infrequent shoppers, the DBCOO signal loses its informative value. These nuances are crucial for managers to understand when segmenting consumers according to their purchase value to develop distinctive targeting strategies.

Limitations and Implications for Further Research

This study has some limitations, which reflect opportunities for future work. First, our study is limited to assessing the direct effect of unintentional signals (DBCOO and COO diversity) in indicating CPV. We do not investigate the mechanism behind this relationship. Further research is needed to understand mediating effects to yield a clearer understanding of the paths through which these signals travel. Second, due to limited information in our secondary data, we did not take important COO-related variables into account, such as consumers’

income, socioeconomic status, ethnocentrism, or cosmopolitanism. Moreover, while we control for price and product category effects, we were unable to account for other variations of marketing mix-variables, such as promotion and distribution. Connecting these aspects with consumer purchase histories will increase our understanding of COO-related unintentional signals and reduce unobserved heterogeneity. Third, we only touch on consumers' COO-related signals for product purchase. These effects may hold even greater significance in other areas (e.g., subscription services). For example, one avenue for future work would be to investigate if COO signals contain information about subscription renewal or withdrawal. In addition, alternative dependent variables such as profit per customer may be worthy of consideration. Fourth, because we have introduced COO diversity for the first time, this paper does not study potential motives, such as variety seeking. We encourage researchers to study the motives of COO diversity in greater detail. Fifth, further research is needed to add robustness to our findings for different contexts. A multi-country (emerging vs. developed market) and multi-category approach could enhance the generalizability of our findings. Lastly, although we have anecdotal evidence on chocolate products and empirical evidence for beauty products, our findings still need to be generalized for other segments. Hence, we encourage researchers to conduct future studies on different product categories.

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Figure 1: Conceptual Model

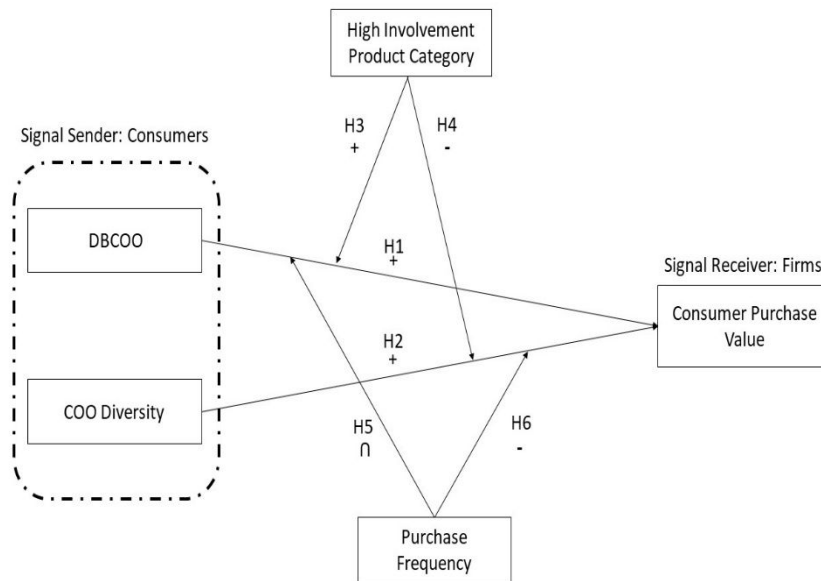


Figure 2: Graphical Illustration of Moderation Effects

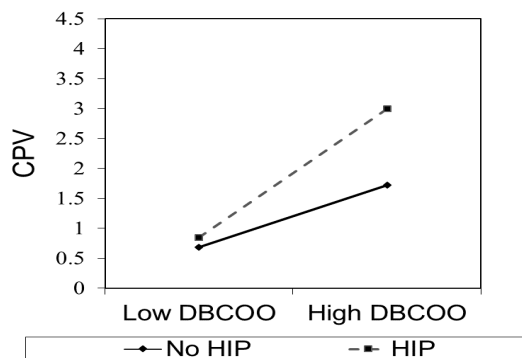


Figure 2a: H3 Moderation

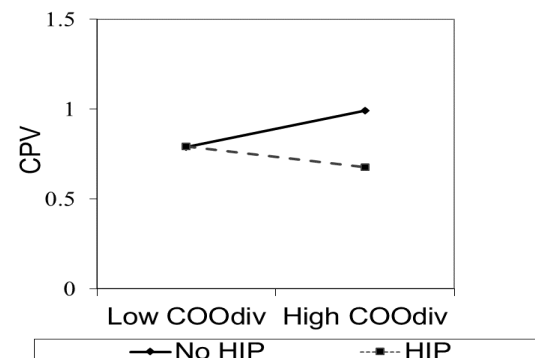


Figure 2b: H4 moderation

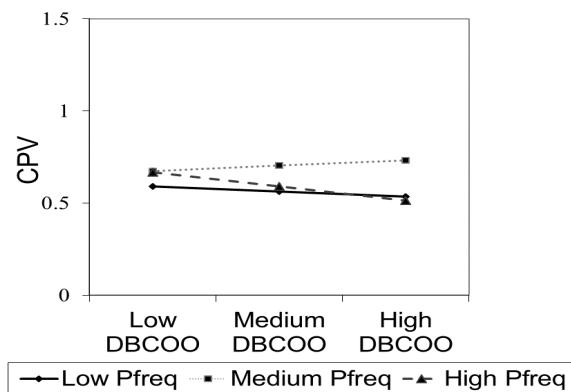


Figure 2c: H5 moderation

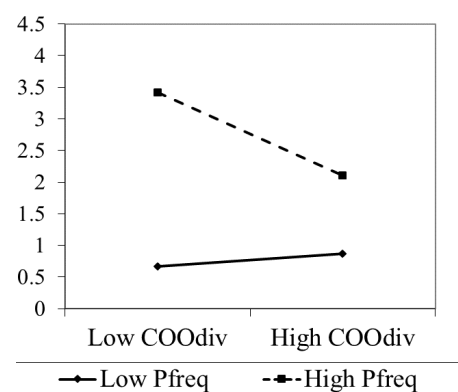


Figure 2d: H6 moderation

Table 1: Exemplary Studies of Important Streams in COO Research.

Source	Theoretical lens	Cue vs Signal	Outcome (A - Attitudinal or B - Behavioral)	Country of Data Collection	Number of Observations	Key Findings
Stream: COO and Consumer Evaluations						
Agrawal & Kamakura (1999)	Cue utilization	COO as a cue	Objective quality and price (N/A)	USA	Consumer reports on 50 brands of 13 products	COO is a valid cue for the objective quality of products. Knowledgeable consumers use COO as a summary of factual information and their own experiences about product quality from a country. Product familiarity, nationality, manufacturing process and complexity drive COO evaluations. COO essential as both an information variable and source credibility variable in product evaluations, even in presence of other product information.
Ahmed & d'Astous (2002)	Information absorption	COO as a cue	COO evaluations (A)	Canada, Morocco, Taiwan	506 consumers	
Verlegh, Steenkamp & Meulenber (2005)	Dual information processing	COO as a cue and source variable	Purchase intention, attitude and claim reliability (A)	Germany	707 consumers	
Pappu, Quester & Cooksey (2006)	Brand equity	COO as a cue	Brand equity (A)	Australia	539 consumers	Both micro and macro-level image of the country of origin affect brand equity. Such effects vary depending on the product category. Cognitive country image affects purchase intention via product image, but affective country image has a direct effect of purchase intention.
Wang et al. (2012)	Cognitive-affective processing system	COO as a cue	Purchase intention (A)	China	1257 consumers	
Herz & Diamantopoulous (2017)	Self-affirmation theory	COO as a cue	Brand evaluation and Behavioral intentions (A)	Austria	233 consumers	A substantial segment of Consumers are influenced by brand COOs when assessing brands, even if they deny it. Sometimes consumers are even subconscious about their use of COO cues.
Datta et al. (2022)	Empirics first	Theory building	Brand elasticities (line, length and price elasticities) (B)	7 developed & 7 emerging countries	Secondary data of 14 countries & 1600+ brands	Favorable COO image does not influence marketing effectiveness.
Azzari et al. (2023)	Signaling theory	COO as a cue	Brand market share (B)	Brazil	Scanner data on 448 sub brands	During economic downturns, brands that consumers perceive as domestic have better market share than brands that consumers perceive as foreign
Stream: COO Recognition Accuracy						
Samiee, Shimp & Sharma (2005)	Categorization theory & attribute diagnosticity	COO as a cue	Brand Origin Recognition Accuracy (N/A)	USA	480 consumers	Consumers with higher income and education (socio-economic status), international experiences, and lower ethnocentrism have higher brand origin recognition accuracy than other consumers.

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Balabanis & Diamantopoulos (2008)	Categorization theory	COO as a cue	Brand evaluations (A)	UK	193 consumers	Brand evaluations depend on COO Classification performance.
Mandler, Won & Kim (2017)	Categorization theory	COO as a cue	Brand re-evaluation (A)	South Korea	295 consumers	If a true brand COO is more favorable than a perceived brand COO, consumers update their brand evaluation according to the actual brand COO.
Magnusson, Zdravkovic & Westjohn (2022)	Category country image	COO as a cue	Brand attitude (A)	USA	500 consumers comparing 12 different brands	Long-term stability of COO effect on brand evaluation even when the COO-brand association is not accurate
Stream: Animosity, Ethnocentrism, Consumer Psychography, and Brand Origin						
Batra et al. (2000)	Social comparison (status comparison)	COO as a cue	Brand Attitude (A)	India	508 consumers	Emerging market consumers prefer brands from developed countries not only because of perceived quality but also for social status signaling reasons. Effects are moderated by product category familiarity, but not by ethnocentrism.
Josiassen, Assaf & Karpen (2011)	Attitude theory	COO as a cue	Willingness to buy (A)	Australia	361 consumers	Relationship between consumer ethnocentrism and willingness to buy domestic products varies with consumer characteristics (e.g., income, gender etc.)
Sun et al. (2021)	Ethnocentrism & animosity	Animosity	Market share of car models (B)	China	19,056 observations of car sales	Historical animosity can trigger brand boycott and decreases sales and effectiveness of brand-origin advertising.
Stream: COO Fit						
Sichtmann & Diamantopoulos (2013)	Signaling theory	COO as a cue	Perceived quality of brand extension and purchase intention (A)	Austria and Bulgaria	603 consumers	Brand origin fit with brand extension is positively related to the perceived quality of the extension and purchase intention.
Chiang & Yang (2018)	Brand personality	Brand personality and COO fit	Customer lifetime value (B)	Taiwan	25,723 customers with 44,000 transactions	Brand COO and consumer attribute match increases customer lifetime value
COO as Unintentional Signal						
Present study	Signaling theory	COO as a signal from Consumers to firms	Consumer purchase value (B)	Bangladesh	> 1 million transactions of 327,863 customers	DBCOO and COO diversity in a consumer's purchase basket can predict CPV for retailers. Product involvement and purchase frequency moderate both effects

Table 2: Variables and Operationalization.

Variable	Operationalization
Consumer purchase value (CPV)	Consumers' total purchases in monetary terms
Distinctive choice of brand COO (DBCOO)	Ratio of the number of Korean products in consumer purchase basket to the sum of the products from other COOs in consumer purchase basket
COO diversity (COOdiv)	COO diversity measured based on the Herfindahl Hirschman Index (HHI index). COO diversity _j = $1 - \sum_{e=1}^N S_{ej}^2$, where S_{ej} is the share of COOs in the consumer purchase basket j. N is the number of COOs in the purchase basket
High-involvement product (HIP) category	High involvement product (skincare) presence in consumer purchase basket. Skincare presence coded as 1, otherwise 0
Purchase frequency (Pfreq)	Calculated considering the number of times a consumer purchased during observation period
WDB share (Western developed-country brands)	Ratio of the number of Western products in consumer purchase basket to the sum of the products from other COOs in Consumer purchase basket. Western countries include the USA, UK, Germany, France, Italy, Switzerland, Sweden, and Spain
Local share	Ratio of the number of Bangladeshi products in consumer purchase basket to the sum of products from other COOs in consumer purchase basket
Indian share	Ratio of the number of Indian products in consumer purchase basket to the sum of products from other COOs in consumer purchase basket
avDBCOO(avKorea)	Average price of Korean products in the consumer purchase basket
avWDB	Average price of Western products in the consumer purchase basket
avlocal	Average price of Bangladeshi products in the consumer purchase basket
avInd	Average price of Indian products in the consumer purchase basket
Makeup	Presence of makeup products in consumer purchase basket. Makeup product presence coded as 1, otherwise 0
Haircare	Presence of haircare products in consumer purchase basket. Haircare product presence coded as 1, otherwise 0
Basket size	Total unit of products a consumer purchased over the observation period divided by that consumer's purchase frequency

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Table 3: Descriptive Statistics and Correlations.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.CPV	.70	1.95	1.00															
2.DBCOO	.16	.24	.13*	1.00														
3.COodiv	.47	.27	.16*	.33*	1.00													
4.WDB share	.49	.24	.08*	.17*	.55*	1.00												
5.Local share	.24	.57	.03*	.10*	.49*	.24*	1.00											
6.Indian share	.28	.12	.02*	.06*	.50*	.27*	.14*	1.00										
7.avDBCOO	126.00	456.66	.03*	.03*	.04*	.02*	.01*	.00*	1.00									
8.avWDB	154.16	387.63	.00*	.02*	.10*	.08*	.01*	.01*	-.00	1.00								
9.avLocal	479.01	923.62	.01*	.04*	.05*	.02*	.04*	.00*	.02*	-.00	1.00							
10.avInd	118.14	150.16	.03*	.06*	.08*	.24*	.13*	.04*	.02*	.02*	.02*	1.00						
11.Pfreq	.22	.44	.07*	.26*	.43*	.43*	.48*	.44*	.03*	.11*	.05*	.09*	1.00					
12.Pfreqsq	.25	.85	.05*	.17*	.58*	.53*	.35*	.28*	.03*	.06*	.04*	.03*	.62*	1.00				
13. HIP	.22	.54	.04*	.21*	.45*	.30*	.28*	.18*	.02*	.08*	.02*	.15*	.54*	.24*	1.00			
14. Makeup	.12	.16	.17*	-.02*	.07*	.05*	.02*	.04*	-.00*	.00*	.00*	.09*	.13*	.04*	-.02	1.00		
15. Haircare	.13	.18	.02*	-.04*	.07*	.03*	.03*	.09*	-.00*	.00*	.00*	.04*	.14*	.04*	-.02*	-.01*	1.00	
16. Basket size	.32	.11	.09*	.13*	.31*	.20*	.16*	.15*	.01*	.05*	.02*	.05*	.46*	.17*	.63*	.26*	.28*	1.00

*p < .05

Table 4: Results.

Panel Regression				Hypotheses	Endogeneity Test
1	2	3	4	5	6
CPV	Base Model	Main Interaction	Full Model		With Copula Terms
DBCOO		.16**	.13**	H1 Accepted	.16**
COOdiv		.37**	.35**	H2 Accepted	.41**
DBCOO*HIP			.14**	H3 Accepted	.12**
COOdiv*HIP			-.55**	H4 Accepted	-.55**
DBCOO*Pfreq			.09**		.09**
DBCOO*Pfreqsq			-.29**	H5 Accepted	-.28**
COOdiv*Pfreq			-.06**	H6 Accepted	-.06**
WDB Share	.09**	.05**	.05**		.05**
Local Share	-.02**	-.02**	-.05**		-.05**
Indian Share	-.11**	-.16**	-.21**		-.21**
avDBCOO	5.65×10^{-3} **	5.50×10^{-3} **	5.56×10^{-3} **		5.49×10^{-3} **
avWDB	7.17×10^{-3} **	6.26×10^{-3} **	6.53×10^{-3} **		6.64×10^{-3} **
avLocal	1.78×10^{-3} **	1.77×10^{-3} **	1.17×10^{-3} **		1.77×10^{-3} **
avInd	5.68×10^{-3} **	5.79×10^{-3} **	5.63×10^{-3} **		5.63×10^{-3} **
Pfreq	.14**	.13**	.08**		.08**
Pfreqsq	-.05**	-.05**	-.10**		-.09**
HIP	.15**	.13**	.16**		.16**
Makeup	.23**	.21**	.23**		.23**
Haircare	.05**	.04**	.07**		.07**
Basket	-.06**	-.10**	-.20**		-.21**
Copula: DBCOO					-.06
Copula: COOdiv					-.07
R Square	.22	.23	.24		.24
N	327,863	327,863	327,863		327,863

**p < .01, *p < .05

Table 5: Impact Analysis with Deciles.

Decile According to CPV	Average CPV					
	DBCOO Above Median	DBCOO Below Median	Difference in CPV	COOdiv Above Median	COOdiv Below Median	Difference in CPV
1	9,773	2,905	6,868	6,209	2,212	3,997
2	4,625	1,141	3,484	2,504	854	1,651
3	3,203	708	2,495	1,595	512	1,083
4	2,357	481	1,876	1,102	349	753
5	1,787	343	1,444	776	245	531
6	1,378	247	1,131	551	168	383
7	1,056	173	883	395	106	289
8	801	111	690	275	51	224
9	526	47	479	180	14	166
10	263	4	259	93	10	83

Notes: Average CPV in Bangladeshi Taka

WEB APPENDICES**A Good Signal: How Firms Can Utilize Country of Origin as a Strategic Analytical Tool****Rafid Ur Rahman**

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Table of Contents

Web Appendix A: Qualitative Study	2-5
Web Appendix B: Panel Regression with French Product as DBCOO (DBCOOfr).	6
Web Appendix C: Panel Regression Model with Deeper Purchase Incident Control.....	7-9
Web Appendix D: OLS and OLS Predictive Model Results.....	10-11
Web Appendix E: Panel Regression with Unobserved Heterogeneity.....	12
Web Appendix F: Panel Regression with Smaller Sub-sample..	13
Web Appendix G: Impact Analysis of DBCOO (Korea) and COO diversity (COOdiv) in terms of Average CPV	14

These materials have been supplied by the authors to aid in the understanding of their paper.

The AMA is sharing these materials at the request of the authors.

Web Appendix A: Qualitative Study

Although the research approach in this study is predominantly quantitative, we conducted three online qualitative focus group discussions to build confidence for our initial ideas. The main purpose for the focus group discussions is to explore the phenomenon and gain assurances for some notions that have only been discussed in the literature preliminarily. As such, the qualitative pilot study consolidates potential variables, validates information, and prepares the quantitative main study (Guo, Heinberg, and Zou 2019; Hennink 2014). In particular, we sought to assess Korea as a DBCOO for Bangladeshi beauty brand consumers and understand product category (e.g., skincare, makeup) may influence consumers' COO perceptions and choices.

Table W1: Participants Profile

Focus Group No	Respondent	Age	Gender	Occupation
1	1	30	Female	Manager
1	2	48	Female	Entrepreneur
1	3	25	Female	Home Maker
1	4	21	Female	Student
1	5	27	Female	Executive
1	6	29	Female	School Teacher
2	1	32	Female	Lawyer
2	2	23	Female	Student
2	3	19	Female	Student
2	4	39	Female	Home Maker
2	5	26	Female	Fashion Influencer
2	6	21	Female	Student
3	1	35	Female	Home Maker
3	2	32	Female	Assistant Professor
3	3	25	Female	Entrepreneur
3	4	21	Female	Student

Topics and Questions during Focus Group Discussion

1. Brand COO recognition check
2. Product category recognition check
3. When buying beauty products, what factors do you pay attention to?
4. What are the things that you search for before purchasing a beauty brand? What features are essential to you in a beauty brand?
5. Please share if and how you rely on a brand's Country of Origin when purchasing a product.
6. Please complete the sentence "The product category X is very important to me." "The product category X interests me a lot".
7. Which of the following products from the beauty category is most important to you and why? - Skincare, makeup, haircare
8. From the following product categories (i.e. skincare, makeup and haircare), in which one do you study the ingredients and assess quality most carefully and why?
9. What is your perception of (South) Korea? What is your perception of France and the US?

10. Which countries do you associate with leading skincare brands? Which countries do you associate with leading make-up brands?
11. Are you knowledgeable about Korean beauty products? Please discuss how you learned about Korean beauty products for the first time.
12. What was your first impression of Korean Beauty products? What are your general feelings about the country Korea and its products?
13. Are Korean beauty products similar to those of other countries (e.g., France, UK, USA, Bangladesh)? In what way?
14. Have you seen advertisements from Korean brands? Where are Korean brands available in Bangladesh?
15. Approximately, how frequently do you purchase beauty products? Do offers and deals affect your purchase frequency?

Key Findings

Recognition checks

Following a reviewer's suggestion, we assessed the participants' recognition of brand COO and product categories. Participants were shown 10 logos from brands represented in the Bangladeshi market. Brands were from a diverse range of countries and prices. On average, participants identified three out of four brand origins correctly. Moreover, we showed pictures of 10 different beauty categories (including skincare, haircare, makeup) to participants. All participants accurately identified the beauty categories such as skincare and make-up for the products.

Thematic Analysis

We used thematic analysis to analyze the qualitative data. For this we first identified codes and then themes. Below, findings are discussed according to themes (Spiggle 1994).

Country image of Korea.

Korea's country image was described as an *"increasingly smart and advanced country"*, which heavily emphasizes science and R&D. At the same time respondents connect it to traditional and natural ingredients. This combination led to respondents' trust. For example, one participant expressed, *"Korea is investing more intensely in science and R&D, which is reflected in their quality products"*. The country image of Korea was decisively different compared to the one of France and the USA, which were described as *"glamorous"* and *"more individualist"* (for France) and *"fast-paced"* and *"artificial"* (for the USA).

Match of country image to desired attributes of beauty products.

The country image of Korea matches the attributes respondents valued in beauty products. Respondents shared that they use Korean products because of the science-based R&D approach of the brands. The participants were convinced that Korean companies are good at research and innovation, for example one participant mentioned, *"I perceive Korean companies spend more on research than Western brands do"*. Another respondent explained: *"Previously, I used skincare products from the U.S.A. and European brands because of their reputation. However, results were not as promised by those brands. Then I shifted to natural remedies and used K-beauty products. I felt it suits my skin better. I guess Korean brands have specific R&D for our skin type, moreover the natural ingredients have lesser chance to go wrong. They don't do wonders by I can feel the gradual improvement."* As such, Korean beauty products seem to benefit from the overall country of origin image of Korea.

Korea as DBCOO.

Most participants were first exposed and gathered information about Korean beauty products through internal sources (e.g., beauty consultants, friends, colleagues) and reviews. Different from Western brands, Korean products are not widely advertised in Bangladesh, making it difficult for mass market consumers to access information.

For example, one participant mentioned *“I have first heard about Korean products from one of my colleagues. Word of Mouth and internal sources are needed to know about Korean products as there is no advertisements or traditional brand communication”*. Another participant mentioned *“I have never seen a Korean beauty product ad”*. Hence, well-informed and knowledgeable consumers are more likely to choose Korean beauty products. One participant mentioned, *“I used to read a lot of blogs regarding the ingredients and R&D in skincare, that is when I came to know about Korean products.”*

Considering that insider information and knowledge are connected to the choice of Korean beauty brands, we see support for Korea as a DBCOO in the Bangladeshi beauty product market.

Skincare as high-involvement product (HIP).

Participants suggested that they were more concerned about the ingredients, country of origin, brand reputation and reviews of skincare products than of makeup or haircare products. The majority of respondents thought of skincare as the most important beauty product category and expressed high interest in knowing more about skincare products. One participant stated, *“I take extra caution when choosing skincare because I think it as a long-term investment, if skincare product goes wrong it can harm my skin and health tremendously”*. Therefore, higher risk related to skincare products is one reason why participants consider them important. Another participant mentioned, *“I am cautious when choosing both makeup and skincare. Makeup is kinda short-term thing so I often go with the commercials and glamour part. However, I study about ingredients and what suites me most in skincare, also I quickly check with my dermatologist regarding the ingredients. I won't lie but I am bit nervous when choosing skincare”*. Such heightened involvement in the skincare category complements the finding of our desk research and supports our reasoning to select skincare as a high-involvement product (HIP).

Purchase frequency of high CPV consumers.

High-spending participants indicated that they have a settled beauty routine and fixed purchase frequency (e.g., once every two months). Moreover, high-spending participants mentioned that they do not shift their purchase routine due to deals and offers. Instead, they stick to their trusted beauty brands. One participant mentioned, *“I have a fixed beauty routine and my products generally last 2 to 3 months. Once it's about to finish I order again. I do not stack them up because I am worried about the best before dates. So even if they are on sale [I don't often get tempted]”*. Such shopping pattern is different than the one expressed by a low-spending consumer in our focus groups. She stated, *“Well, I do stock up my moisturizers, especially when they are on deals. Moreover, in the festive season when I have a bonus, I usually purchase more beauty products than in normal times”*. Therefore, although participants vary in terms of their purchase frequency, it appears that beauty products follow more a monthly (than a weekly) shopping pattern.

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Web Appendix B: Panel Regression with French Product as DBCOO (DBCOOfr)

We have conducted an additional panel regression analysis considering French products as DBCOO (DBCOOfr).

Table W2: Panel Regression with French Product as DBCOO (DBCOOfr)

1	2	3
CPV	Full Model	Hypotheses
DBCOOfr	-.84	
COOdiv	.34**	H2 Supported
DBCOOfr*HIP	.48	
COOdiv*HIP	-.51**	H4 Supported
DBCOOfr*Pfreq	.26	
DBCOOfr *Pfreq ²	-.00	
COOdiv*Pfreq	-.00**	H6 Supported
Western Share	.02**	
Local Share	-.05**	
Indian Share	-.21**	
Korean Share	.16**	
avDBCOOfr	3.16×10^{-3} **	
avWDB	6.53×10^{-3} **	
avLocal	1.77×10^{-3} **	
avInd	5.83×10^{-3} **	
avKorea	5.54×10^{-3} **	
Pfreq	.08**	
Pfreq ²	-.00**	
HIP	.16**	
Makeup	.24**	
Haircare	.08**	
Basket	-.22**	
R Square	.24	
N	327,863	

**p<.01, *p<.05

Western Share=WDB-French Product

Web Appendix C: Panel Regression Model with Deeper Purchase Incident Control.

We have conducted an additional Panel regression model analysis considering the deeper purchase incident at time (t-2) and (t-3) as controls. This analysis was conducted as a robustness test. Consistent results of this analysis with the main panel model illustrate the robustness of the findings.

Equation

$$\begin{aligned}
 CPV_{it} = & \beta_0 + \beta_1 DBCOO_{it-1} + \beta_2 COOdiv_{it-1} + \beta_3 DBCOO_{it-1} \times HIP_{it-1} + \beta_4 COOdiv_{it-1} \times HIP_{it-1} + \beta_5 DBCOO_{it-1} \times Pfreq_{it-1} + \beta_6 DBCOO_{it-1} \times Pfreq_{it-1}^2 \\
 & + \beta_7 COOdiv_{it-1} \times Pfreq_{it-1} + \beta_8 WDB\ Share_{it-1} + \beta_9 Local\ Brand\ Share_{it-1} + \beta_{10} Indian\ Brand\ Share_{it-1} + \beta_{11} avK_{it-1} + \beta_{12} avWDB_{it-1} + \beta_{13} \\
 & avLocal_{it-1} + \beta_{14} avInd_{it-1} + \beta_{15} Pfreq_{it-1} + \beta_{16} Pfreq_{it-1}^2 + \beta_{17} HIP_{it-1} + \beta_{18} Makeup_{it-1} + \beta_{19} Haircare_{it-1} + \beta_{20} Basketsize_{it-1} + \beta_{21} DBCOO2_{it-2} + \beta_{22} \\
 & DBCOO3_{it-3} + \beta_{23} COOdiv2_{it-2} + \beta_{24} COOdiv3_{it-3} + \beta_{25} DBCOOXHIP2_{it-2} + \beta_{26} DBCOOXHIP3_{it-3} + \beta_{27} COOdivXHIP2_{it-2} + \beta_{28} \\
 & COOdivXHIP3_{it-3} + \beta_{29} DBCOOXPfreq2_{it-2} + \beta_{30} DBCOOXPfreq3_{it-3} + \beta_{31} DBCOOXPfreq2_{it-2}^2 + \beta_{32} DBCOOXPfreq3_{it-3}^2 + \beta_{33} \\
 & COOdivXPfreq2_{it-2} + \beta_{34} COOdivXPfreq3_{it-3} + \beta_{35} Basketsize2_{it-2} + \beta_{36} Basketsize3_{it-3} + \beta_{37} WDBshare2_{it-2} + \beta_{38} WDBshare3_{it-3} + \beta_{39} \\
 & Localshare2_{it-2} + \beta_{40} Localshare3_{it-3} + \beta_{41} Pfreq2_{it-2} + \beta_{42} Pfreq3_{it-3} + \beta_{43} Pfreq2_{it-2}^2 + \beta_{44} Pfreq3_{it-3}^2 + \beta_{45} HIP2_{it-2} + \beta_{46} HIP3_{it-3} + \beta_{47} Haircare2_{it-2} \\
 & + \beta_{48} Haircare3_{it-3} + \beta_{49} Makeup2_{it-2} + \beta_{50} Makeup3_{it-3} + \varepsilon_i + \gamma_i \dots (W1)
 \end{aligned}$$

The subscript i denotes an individual consumer's purchase basket, and t, (t-1), (t-2), (t-3) is the subscript for the month

Table W3: Results of Panel Regression Model with Deeper Purchase Incident Control.

CPV	Time	Full Model	Hypotheses
	t		
DBCOO	(t-1)	.14**	H1 Supported
COOdiv	(t-1)	.29**	H2 Supported
DBCOO*HIP	(t-1)	.13*	H3 Supported
COOdiv*HIP	(t-1)	-.50**	H4 Supported
DBCOO*Pfreq	(t-1)	.03*	
DBCOO *Pfreq ²	(t-1)	-.10*	H5 Supported
COOdiv*Pfreq	(t-1)	-.02**	H6 Supported
WDB Share	(t-1)	.04**	
Local Share	(t-1)	-.01*	
avDBCOO	(t-1)	2.8x10 ^{-3**}	
avWDB	(t-1)	4.3x10 ^{-3**}	
avLocal	(t-1)	1.7x10 ^{-3**}	
Pfreq	(t-1)	.11**	
Pfreq ²	(t-1)	-.02**	
HIP	(t-1)	.15**	
Makeup	(t-1)	.26**	
Haircare	(t-1)	.08**	
Basket	(t-1)	-.19**	
DBCOO2	(t-2)	.33**	
DBCOO3	(t-3)	.27**	
COOdiv2	(t-2)	.51**	
COOdiv3	(t-3)	.48**	
DBCOOXHIP2	(t-2)	.09**	
DBCOOXHIP3	(t-3)	.14**	
COOdivXHIP2	(t-2)	-.75**	
COOdivXHIP3	(t-3)	-.68**	
DBCOOXPfreq2	(t-2)	.04**	
DBCOOXPfreq3	(t-3)	.03**	
DBCOOXPfreq2 ²	(t-2)	-.09**	
DBCOOXPfreq3 ²	(t-3)	-.06**	

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COOdivXPfreq2	(t-2)	-.02**
COOdivXPfreq3	(t-3)	-.02**
Basket size2	(t-2)	-.28**
Basket size3	(t-3)	-.30**
WDB share2	(t-2)	.03**
WDB share3	(t-3)	.03**
Local share2	(t-2)	-.00**
Local share3	(t-3)	-.02**
Pfreq2	(t-2)	.00**
Pfreq2 ²	(t-2)	-.04**
Pfreq3	(t-3)	.01**
Pfreq3 ²	(t-3)	-.03**
HIP2	(t-2)	.24**
HIP3	(t-3)	.22**
HairCare2	(t-2)	.24**
HairCare3	(t-3)	.22**
Makeup2	(t-2)	.30**
Makeup3	(t-3)	.26**
R Square		.23
N		327,863

**p<.01, *p<.05

Web Appendix D: OLS and OLS Predictive Model Results.

We have conducted two alternative model tests. OLS regression and Predictive model regression results suggest that our findings are not confined to the Panel regression model. Thus, these two models add robustness to the study.

OLS Regression Equation

$$\begin{aligned} \text{CPV}_i = & \beta_0 + \beta_1 \text{BrandCOO}_i + \beta_2 \text{COOdiv}_i + \beta_3 \text{Brand COO}_i \times \text{HIP}_i + \beta_4 \text{COOdiv}_i \times \text{HIP}_i + \beta_5 \text{Brand COO}_i \times \text{Pfreq}_i + \beta_6 \text{Brand COO}_i \times \text{Pfreq}_i^2 + \\ & \beta_7 \text{COOdiv}_i \times \text{Pfreq}_i + \beta_8 \text{WDB Share}_i + \beta_9 \text{Local brand share}_i + \beta_{10} \text{Indian Brand Share}_i + \beta_{11} \text{avK}_i + \beta_{12} \text{avWDB}_i + \beta_{13} \text{avlocal}_i + \beta_{14} \text{avInd}_i + \\ & \beta_{15} \text{Pfreq}_i + \beta_{16} \text{Pfreq}_i^2 + \beta_{17} \text{HIP}_i + \beta_{18} \text{Makeup}_i + \beta_{19} \text{Haircare}_i + \beta_{20} \text{Basketsize}_i + \varepsilon_i \dots \text{(W2)} \end{aligned}$$

The subscript i denotes an individual consumer's purchase basket.

Predictive Model Regression Equation

$$\begin{aligned} \text{CPV}_{it2} = & \beta_0 + \beta_1 \text{BrandCOO}_{it1} + \beta_2 \text{COOdiv}_{it1} + \beta_3 \text{Brand COO}_{it1} \times \text{HIP}_{it1} + \beta_4 \text{COOdiv}_{it1} \times \text{HIP}_{it1} + \beta_5 \text{Brand COO}_{it1} \times \text{Pfreq}_{it1} + \beta_6 \text{Brand COO}_{it1} \\ & \times \text{Pfreq}_{it1}^2 + \beta_7 \text{COOdiv}_{it1} \times \text{HIP}_{it1} + \beta_8 \text{WDB share}_{it1} + \beta_9 \text{Local brand share}_{it1} + \beta_{10} \text{Indian Brand Share}_{it1} + \beta_{11} \text{avK}_{it1} + \beta_{12} \text{avWDB}_{it1} + \beta_{13} \\ & \text{avlocal}_{it1} + \beta_{14} \text{avInd}_{it1} + \beta_{15} \text{Pfreq}_{it1} + \beta_{16} \text{Pfreq}_{it1}^2 + \beta_{17} \text{HIP}_{it1} + \beta_{18} \text{Makeup}_{it1} + \beta_{19} \text{Haircare}_{it1} + \beta_{20} \text{Basketsize}_{it1} + \varepsilon_i \dots \text{(W3)} \end{aligned}$$

Here, subscript it1 represents the first six months of the observation period for every individual consumer i, and subscript it2 represents the subsequent six months of the observation period for every individual consumer i.

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Table W4: Results of the OLS and the Predictive Model.

	OLS regression		Predictive Model (6 months temporal difference between IV and DV)			
	1	2	3	4	5	6
CPV	Main Effects	Full Model	Main Effects	Full Model	Hypotheses	
DBCOO	.44**	.71**	.43**	.30**	H1 Supported	
COOdiv	1.17**	1.48**	3.84**	4.38**	H2 Supported	
DBCOO*HIP		.08**		.19**	H3 Supported	
COOdiv*HIP		-.62**		-3.20**	H4 Supported	
DBCOO*Pfreq		.31**		.18**		
DBCOO *Pfreq ²		-1.12**		-.17*	H5 Supported	
COOdiv*Pfreq		-.44**		-.36**	H6 Supported	
WDB Share	.13**	.13**	.10**	.22**		
Local Share	-.06**	-.06**	-.19**	-.06**		
Indian Share	-.11**	-.11**	-.49**	-.16**		
avDBCOO	4.43×10 ⁻³ **	4.43×10 ⁻³ **	3.9×10 ⁻³ **	3.6×10 ⁻⁴ **		
avWDB	4.71×10 ⁻³ **	4.71×10 ⁻³ **	2.7×10 ⁻³ **	2.8×10 ⁻³ **		
avLocal	5.21×10 ⁻³ **	5.21×10 ⁻³ **	1.2×10 ⁻³ **	1.0×10 ⁻³ **		
avInd	5.43×10 ⁻³ **	5.43×10 ⁻³ **	2.7×10 ⁻³ **	2.6×10 ⁻³ **		
Pfreq	4.15**	4.15**	.49**	.65**		
Pfreq ²	-1.80**	-1.81**	-.15**	-.14**		
HIP	.63**	.63**	.06*	.59**		
Makeup	.74**	.74**	.47**	.25**		
Haircare	.32**	.31**	.08**	.20**		
Basket	-.00**	-.00**	-.01**	-.01**		
R Square	.47	.49	.27	.28		
N	327,863	327,863	327,863	327,863		

**p<.01, *p<.05

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Web Appendix E: Panel Regression with Unobserved Heterogeneity.

Addressing the concerns for unobserved heterogeneity, we ran the below model controlling for festive season sales, ethnocentric purchases and quarterly purchases.

Table W5: Results of the Panel Regression with Unobserved Heterogeneity.

	1	2	3
CPV		Full Model	Hypotheses
DBCOO		.17*	H1 Supported
COOdiv		.22**	H2 Supported
DBCOO*HIP		.13*	H3 Supported
COOdiv*HIP		-.56**	H4 Supported
DBCOO*Pfreq		.07**	
DBCOO *Pfreq ²		-.11**	H5 Supported
COOdiv*Pfreq		-.02**	H6 Supported
WDB Share		.02**	
Local Share		-.02**	
Indian Share		-.21**	
avDBCOO		5.21×10^{-3} **	
avWDB		6.45×10^{-3} **	
avLocal		1.77×10^{-3} **	
avInd		4.25×10^{-3} **	
Pfreq		.10**	
Pfreq ²		-.00**	
HIP		.16**	
Makeup		.21**	
Haircare		.07**	
Basket		-.22**	
Festive		-.28**	
Ethnocentric		-.18**	
Quarter2CPV		.01**	
Quarter3CPV		.04**	
R Square		.22	
N		327,863	

**p<.01, *p<.05

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Web Appendix F: Panel Regression with Smaller Sub-sample.

We re-ran our panel regression model with a randomly selected smaller sample which is

1/30th of the whole sample (n=10,929).

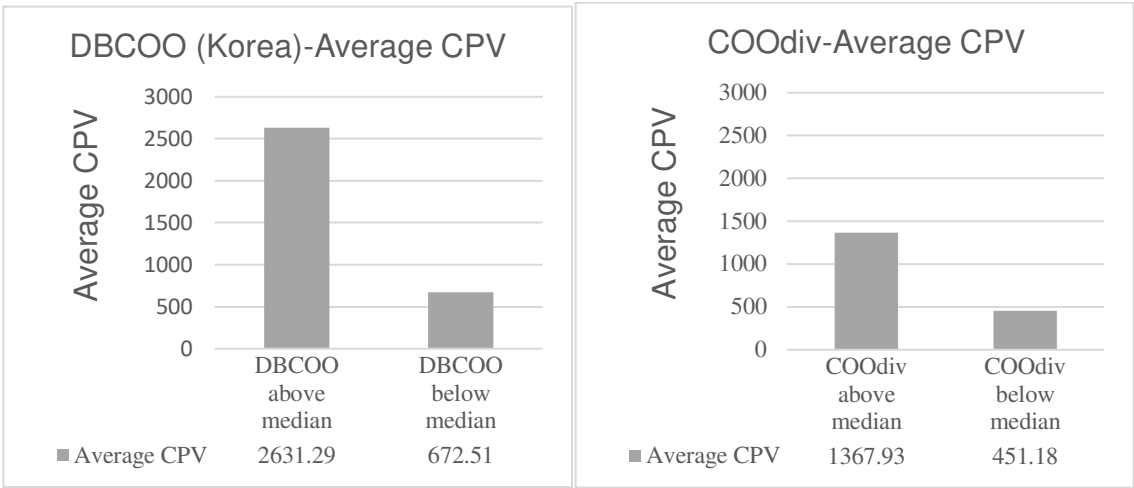
Table W6: Results of the Panel Regression with Smaller Sub-sample.

1	2	3
CPV	Full Model	Hypotheses
DBCOO	.65**	H1 Supported
COOdiv	.77**	H2 Supported
DBCOO*HIP	.42*	H3 Supported
COOdiv*HIP	-.78**	H4 Supported
DBCOO*Pfreq	.02*	
DBCOO *Pfreq ²	-.19*	H5 Supported
COOdiv*Pfreq	-.01*	H6 Supported
WDB Share	.03	
Local Share	-.13*	
Indian Share	-.02	
avDBCOO	6.46×10 ⁻³ *	
avWDB	6.96×10 ⁻³ *	
avLocal	2.86×10 ⁻³ *	
avInd	4.83×10 ⁻³ *	
Pfreq	.07*	
Pfreq ²	-.05*	
HIP	.37**	
Makeup	.45**	
Haircare	.32	
Basket	-.17**	
R Square	.25	
N	10,929	

**p<.01, *p<.05

**Web Appendix G: Impact Analysis of DBCOO (Korea) and COO Diversity (COOdiv)
in terms of Average CPV**

Figure W1: Impact Analysis



Notes: Average CPV in Bangladeshi Taka (BDT)