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Examining the Antecedents of Return Policy Leniency in eCommerce

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ABSTRACT

As eCommerce has become widespread, the challenge of successfully navigating the returns process has grown perilous. The product returns issue is even more difficult for microenterprises that sell unique or custom products with fewer resources. The authors examined the impact of the antecedents of return policy leniency, specifically economic and social success factors. Using a web crawler over a 24-week period, the authors collected and analyzed data for a sample of 781 shops from Etsy, an eCommerce platform. Results indicate that the well-studied factor of sales, in addition to a new social factor – community dialogue – impacts an Etsy shop's return policy leniency.

KEYWORDS

community dialogue, custom products, Etsy, handmade products, financial success, microenterprise, social success

INTRODUCTION

Developing a competent and effective way to manage product returns is an ongoing challenge for many organizations. Companies are interested in finding new ways to craft return policies that improve their salvage capabilities and reduce the number of returns, while also increasing customer satisfaction through innovative 'try-then-buy' strategies (Nageswaran et al., 2020; Rokonuzzaman et al., 2021). Researchers have focused much of their efforts on understanding how return policies impact consumer purchasing and return behavior (Janakiraman et al., 2016), consumer trust (Oghazi et al., 2018), consumer perception of return policy fairness (Pei et al., 2014), and customer satisfaction (Radhi & Zhang, 2019). Other studies have focused on how lenient return policies impact firm economic factors, such as profit (Chaleshtari et al., 2022) or sales (Radhi & Zhang, 2019). Thus, there is a significant opportunity to examine factors that influence return policy leniency which have yet to be examined. We can broaden our understanding of return policy leniency through identifying and examining factors that influence it.

The bulk of returns literature considers the returns process as primarily an economic endeavor, yet it can include a social aspect. Robertson et al. (2020) suggest future research that focuses on

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returns as part of the "customer journey" and hint at the social aspect of the returns process where the customer "later tells friends or posts [a review]" (2020, p. 173) of a product. Existing studies are ill-suited to address the significant impact that social interactions, engagement, and discussions may have on the development and enforcement of return policies. This is especially true on most eCommerce platforms where social metrics such as customer reviews, reputation, shares, and likes have become as vitally important as traditional economic metrics of success (Ding et al., 2017; Tafesse & Wien, 2018). The purpose of this study is to overcome these limitations in our understanding of how social and economic factors impact the leniency of return policies for microenterprises.

To this end, we constructed a unique data set that contains information on the return policies of several hundred microenterprises that operate on an eCommerce platform. Through empirical analysis of the data, this study identifies both economic and social characteristics of microenterprises that are most likely to impact return policy leniency. Specifically, we seek to answer the following research question: *How do economic and social factors impact return leniency for handmade and customized products?* This study offers numerous interesting contributions to extant theory on product returns in eCommerce settings.

The remainder of the paper is organized as follows. First, we discuss relevant literature on return leniency and the factors that impact return leniency. Next, we review extant literature and present a theoretical model that relates both economic and social aspects of platform success to return leniency. Our data collection and analysis are then discussed, along with results and implications for both theory and practice.

LITERATURE REVIEW

In this section, we review the current literature on return leniency and its antecedents, as well as highlight the research gaps that our study aims to fill.

Return Leniency

Extant research has primarily examined return policies as a combination of factors, such as "refund level, feasible time for return, original packaging requirements, and mailing options" (Chaleshtari et al., 2022, p. 2). However, more recent research has identified return leniency as a salient aspect of return policy management. Bower and Maxham (2012) found that customers paying for their own product returns (strict) will universally decrease their repurchases and those receiving free returns (lenient) will universally increase their repurchases. Lantz and Hjortz (2013) found that lenient return policies were associated with increased order frequency and probability of return and a decrease in average value of orders and average value of purchased items. Janakiraman et al. (2016) conducted a meta-analysis on return leniency and found that return leniency increases purchases at a greater rate when compared to the increases in returns. The findings of Shirzadeh and Elahi (2022) further supports the findings of all of these studies as it examined return leniency, as a combination of cost of return and return efficiency, and found that higher return leniency can result in higher return frequency.

In difficult and complex purchase situations, such as with handmade or custom products, companies with lenient return policies also benefit with greater sales. Esenduran et al. (2022) concluded that allowing returns of customized products, when non-customized products are also sold, can increase profits and reduce total returns. However, their study does not examine the nuances of return policies, simply whether to keep or return the product. We delve more into the understanding of return policies by examining the ways that companies alter the leniency of their return policies by various factors such as accepting exchanges, the length of time to return, and the length of time to contact the seller directly.

Furthermore, existing research primarily examines return leniency as an independent variable, assessing its impact on consumer purchase behavior and return behavior, and seller profit (Chaleshtari et al., 2022; Janakiraman et al., 2016; Pei et al., 2014). For example, research has shown that lenient

return policies are effectively training customers to view purchases as temporary, with the final purchase decision occurring after the item has been purchased (Robertson et al., 2020). However, these types of studies do not provide guidance on what factors could impact return policy leniency. More recently, researchers have called for additional studies on the driving forces on the different types of return policies and its components (Rokonuzzaman et al., 2021). Existing knowledge on return leniency is limited to the perspective of return leniency operationalized as an independent variable (see Table 1) and there is a significant need for additional studies on return leniency as a dependent variable.

Antecedents to Return Leniency

It is imperative to expand the research on return leniency to better understand the various factors that influence organizational decision-making on return policies. Extant research assumes that a firm's return policy, in all its different facets, impacts consumer purchase and return behaviors. However, Bonifield et al. (2010) highlighted the possibility that "consumers do not check return policies prior to purchase" (p. 1063), thus acknowledging that there may be other influences on return policy structure and on consumer behavior. Yet, there are few studies that attempt to examine the antecedents to return policies or its components, such as return leniency. Tyagi et. al. (2021) discuss the major differences in return policies of popular e-retailers and imply that the type of product being returned impacts return leniency. More specifically, they suggest that e-retailers' experience with product returns influenced return policy structure and thus should be examined in future studies. In this study, we aim to provide an examination of factors that impact return leniency.

In identifying the factors to be considered, we searched for any existing research that examined the antecedents of return policies and found one study of interest (Nageswaran et al., 2020). The findings of Nageswaran et al. (2020) examine three factors – "the proportion of customers in different channels, salvage capabilities of different channels, and store footprint" (p. 5572) – to explain why omni-channel firms adopted different return policies. These three factors provide a window into the scenario-driven choices that firms make regarding the level of leniency in return policies. However, the study did not examine the impact of those three factors on individual dimensions of return policies. Our study fills this gap as it examines the impact of antecedents on the leniency dimension of firm return policies.

Considering the Nageswaran et al. (2020) study, a major consideration in examining the antecedents of return leniency is the context in which the return policy decisions are made. The eCommerce context is a relatively social environment as evidenced by its heavy reliance on star ratings and reviews. Yet most return policy and return leniency research do not include any analysis of the impact of social factors on a company's decision to implement a lenient or strict return policy. Thus, examining the impact of social aspects of the returns process is the next step in better understanding return policy structure.

Cronin (2014) highlighted that different metrics, in addition to traditional financial metrics, are needed to examine the real impact of enacted business strategies. Businesses should utilize social metrics such as likes, shares, comments, views, posts, etc. when examining business performance (Khan & Dillon, 2019) and operational strategies. As such, we aim to examine social metrics of success and its impact on return leniency. Additionally, Minnema et al. (2016) examined eCommerce customer purchases and returns over a two-year period and found that social commentary, such as online customer product reviews, impacts the probability of product returns. More research is needed to explore other social factors and their potential impacts. Thus, we aim to add to this stream of literature by examining the impact of social discourse on the leniency of return policies for online microenterprises, rather than focusing solely on the consumer perspective.

Table 1. Summary of return policy leniency literature

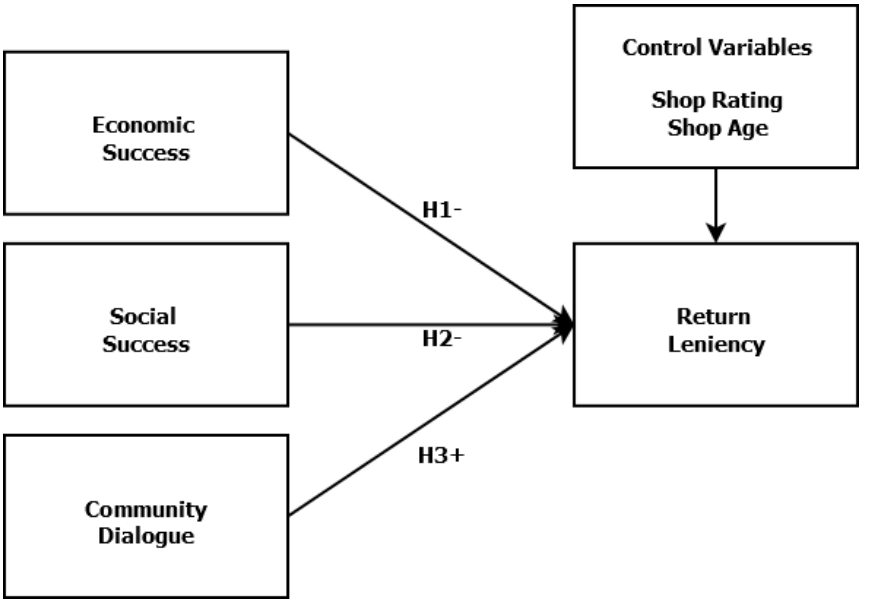
Author(s)	Methodology/ sample	Return leniency factors	Relevant findings	Variable Type
Current study (2023)	Empirical Analysis – 781 shops	Return Leniency – full return or no return; time to contact shop; time to ship items back	Sales success increased as return leniency declined; increased community discourse occurred with more lenient return policies.	DV
Chaleshtari et al. (2022)	Optimization model – n/a	Return leniency – full return policy or no return policy	Minimal experience with a product lead to minimal returns when return policies are more lenient.	IV
Shirzadeh, A. and Elahi, E. (2022)	Analytical model – n/a	Return Leniency – cost of return, return efficiency	Higher return leniency does not lead to higher social welfare, does not impact market demand but can result in higher return frequency.	IV
Nageswaran, Cho, and Scheller-Wolf (2020)	Analytical model – n/a	Return Policy – full refund or partial refund	Proportion of customers in different channels, salvage capabilities of different channels, and store footprint explain why omnichannel firms adopt varying leniency in return policies.	DV
Wang, Y., Anderson, J., Joo, S.-J., & Huscroft, J. R. (2020)	Survey and interviews – 520 respondents	Time Leniency Monetary Leniency Effort Leniency Scope Leniency Exchange Leniency	Return policy leniency is positively related to the perceived fairness of return service and the perceived quality of return service.	IV
Oghazi, et al. (2018)	Online survey – 730 respondents	Perceived return policy leniency	Perceived customer trust mediates the effect of perceived return policy leniency on purchase intention.	IV
Janakiraman, N., Syrdal, H. A., & Freling, R. (2016)	Meta-analysis – 21 papers	Time Leniency Monetary Leniency Effort Leniency Scope Leniency Exchange Leniency	Return Leniency is associated with a greater increase in purchase proclivity than the increase in return proclivity.	IV
Bahn, K. and Boyd, E. (2014)	Two Experiments – 99 & 73 respondents	Return Leniency – less restrictive or more restrictive	Consumers view an assortment with more restrictive return policy as attractive.	IV
Pei, Z., Paswan, A., and Yan, R. (2014)	Online Survey – 300 respondents	Return depth – full return policy or partial return policy	Return depth positively impacts consumers' perceived fairness of return policy.	IV
Lantz, B., Hjort, K. (2013)	Experiment – 4,000 participants	Return policy leniency	Lenient return policies are associated with increased order frequency and probability of return and a decrease in average value of orders and average value of purchased items.	IV
Maity, D. and Arnold, T. (2013)	Survey – 289 respondents	Return policy leniency – very strict to very lenient (7-point scale)	n/a	CV
Bower, A. and Maxham, J. (2012)	Two longitudinal field studies – 351 respondents and 1,296 actual customer orders	Return policy leniency – free or fee	Customers paying for their own product returns will universally decrease their repurchases and those receiving free returns will universally increase their repurchases.	IV
Kim and Wasink (2012)	Two Experiments – 128 & 239 participants	Return policy leniency – restricted or lenient	Restrictive return policies may benefit retailers by preventing returns and leading to favorable product evaluations over time.	IV

Note: IV = independent variable; DV = dependent variable; CV = control variable;

HYPOTHESIS DEVELOPMENT

Figure 1 presents the theoretical model of return leniency used in this study. The core theorizing relies on extant literature and posits that return leniency is a function of three key factors: economic success, social success, and community dialogue.

Figure 1. Research model



Microenterprises operating within these platforms do not interact with customers solely on a one-on-one basis. It is therefore unrealistic to consider return policy leniency purely in terms of calculated economic rationality. A more realistic theorizing examines returns as socially observable transactions, and this social observation takes two specific forms. First, observation of the company's favorable past transactions as measured by increased social reputation within the platform. This favorable history, which we call social success, involves an increase in social presence on the platform. The way in which social success manifests varies from platform to platform, but it can be measured as more fans, more friends, and generally more connections between other network members. As social success increases, microenterprises may gain tangible benefits. Just as celebrities receive special treatment in many areas of society, microenterprises translate their popularity into special treatment for themselves, negotiating economic transactions favorable to the microenterprise, for example, in the form of less-lenient return policies.

A second distinct form of social observation occurs customer-to-customer. Almost every eCommerce enabled platform today offers customers some avenue with which to communicate with each other. This can include public comment sections on Instagram or YouTube, or the ability to leave detailed customer reviews on an eCommerce platform like Amazon. Other similar platforms give customers the ability to share their experiences in publicly available reviews that detail aspects of their past transactions. This community dialogue shapes many aspects of how the microenterprise conducts business, including, among other things, decisions around return leniency.

Economic Success

For the purposes of this study, we define economic success as the number of completed sales transactions within an eCommerce platform. Economic success provides the monetary means for engaging in many aspects of eCommerce, including paying for and facilitating a returns process. For this reason, economic success has often been associated with return processes in the extant literature, and some studies have considered economic success specifically in the context of return leniency (Shang et al., 2017; Shulman et al., 2010; Zhang et al., 2017). Returns represent an expensive aspect of eCommerce (Robertson et al., 2020), and thus offering lenient returns is inherently dependent upon

the company having the economic means to do so (Shulman et al., 2010). Companies in favorable economic positions may also absorb increased levels of return leniency as an aspect of competitive advantage when entering new channels of eCommerce (Janakiraman et al., 2016; Wood, 2001).

Past research consistently identifies some correlation between economic success and the leniency of return policies (Janakiraman et al., 2016). Directionally, some work has shown a potential relationship between more lenient policies and economic success, implying successful companies become more lenient towards returns (Wood, 2001). This is likely true in the case of a very large organization like Amazon.com, and in fact the existing literature is heavily influenced by the experiences reported by such large, growth-oriented eCommerce companies.

The calculus of return policy leniency is completely different for a small organization that lacks the capital, cash flow, or economy of scale to exhibit such lenient return policies. In the case of microenterprises, it is unlikely that any microenterprise would reach the type of scale or advantageous business position in which they could engage in return leniency practices similar to one of the giant eCommerce hubs that exist today. Moreover, were a micro-enterprise to achieve such size, they would be stretching the definition of a microenterprise and thus outside the scope of this study.

As it stands, there are several reasons to believe that return leniency will only decrease when microenterprises achieve greater degrees of economic success within an eCommerce platform. First, when economic success is low, smaller shops are likely to exhibit less return leniency merely because they cannot afford to do otherwise (Rao et al., 2014). This is especially important in a handicraft marketplace where many products are tailored to consumer specifications and as such less amenable to the advantages of economies of scale. When a shop experiences a high degree of increased success, this success should in turn lead to a decrease in return leniency as the shop begins to feel that the increased marginal benefit of a customer is outweighed by the cost of more lenient return policies (Goedhart et al., 2023). For these reasons, we propose the following hypothesis:

H1: Increased economic success within an eCommerce platform is associated with a decrease in return leniency.

Social Success

In addition to economic success, a company's social success also likely plays a role in return leniency. Social success is defined in our study as increasing social presence within the platform. A high degree of social success implies that the company is better known by other members of the platform when compared to a similar company with a lower degree of social success (Baumöl et al., 2016). Depending on the specific nature of the eCommerce platform, social success may entail having more connections between platform users, more followers, or more friends. High social success describes a company with a greater number of admirers for their shop and products (Chandna & Salimath, 2018).

Past research has identified several tangible ways in which social success can impact business practices and return policies. Companies tend to consider social factors when developing return policies (Bonifield et al., 2010; Minnema et al., 2016) and they take their reputation and standing within a particular customer community into account when crafting such policies (Walsh & Brylla, 2017). This is especially true in eCommerce, where the Internet has greatly expanded the voice of the individual customer in sales settings (Minnema et al., 2016; Walsh & Möhring, 2017).

For small companies in eCommerce, the role of social factors in determining return leniency may be even greater. Most social platforms contain numerous public measures of business reputation (Metzger et al., 2010). Platforms such as Etsy, Pinterest, and others collect metrics such as reposts, likes, admirers etc. Because these metrics are so publicly observable, they increase the influence that individual customers have on the reputation of the shop (Djafarova & Trofimenko, 2019). This likely makes it harder for a particular shop to decrease return leniency to such an extent that customers are negatively impacted. For these reasons we put forth the following hypothesis:

H2: Increased social success within an eCommerce platform is associated with a decrease in return leniency.

Community Dialogue

Finally, in addition to both economic and social factors, community dialogue likely exhibits an influence on micro-manufacturer return leniency. In this study, we define community dialogue as the extent to which customers engage with each other in publicly observable direct communication. The information systems literature has considered such interpersonal customer dialogue for some time, and numerous studies have shown that robust product discussion communities wield a significant influence over product and service development and citations (Minnema et al., 2016).

Che (1996) states that money-back guarantee return policies allow consumers to experience the product and delay the purchase decision until after they have experienced the product. The study examined a dichotomy view of the return policy – present or not present. They acknowledged that variations in return policies are needed to "fine tune the amount of consumer learning prior to the purchasing decision" (Che, 1996, p. 23). With customized or handmade goods, there is no tolerance for consumer learning as such, in the niche section of e-retailers that focus on handmade products, the return policy is essential to ensure the e-tailer and the consumer agree on the purchasing decision. Shang et al. (2017) examined the concept of 'wardrobing' where consumers use a lenient return policy as a trial period and return the product after short-term consumption. They found that it is better to have one straightforward return policy, rather than a menu based on the product price or time since purchase, especially when the extent of wardrobing is low but the benefit of wardrobing is high.

Kim and Wansink (2012) found that restrictive return policies are necessary for customized products due to the labor and time spent by the seller which cannot be recovered (J. Kim & Wansink, 2012). Interestingly, they also found that restrictive return policies can minimize returns and lead to customers evaluating the product more favorably over time. This counterintuitive finding for traditional products could be applicable to handmade and customized products in that, most consumers may find that even if the handmade product is not the ideal pre-purchase vision of the product that the consumer had envisioned, it is "good enough" and the restrictive return policy forces a lower level of product satisfaction, slightly above "return the item" feelings. Their study counters this line of thought by stating that consumers will be more negative about the product evaluation post-purchase if the customized product performs negatively (which is not what they expected). Research has shown that customer reviews and comments from negative experiences can gain traction and impact company performance (W. G. Kim et al., 2015).

The discourse around an organization can impact its performance. Within eCommerce platforms, customer interactions are shown to have a significant impact on customer notions of shop reputation and product quality (Merz, 2019). As the amount of discourse increases, potential customers are given more information about the potential quality of a product, as well as product limitations or deficits (Qiao et al., 2019). As a result, product communities which exhibit more dialogue are likely to provide customers with a greater voice when discussing issues or challenges related to a return process (Teng et al., 2017). This leads companies to adopt more lenient return policies.

H3: Community dialogue within an eCommerce platform is associated with an increase in return leniency.

METHOD

In this section, we present the methodology behind the study. We describe the e-retailer platform that we used in the research, the data collection method, and the variables used in our study.

Previous studies (Oghazi et al., 2018; Rao et al., 2018; Wang et al., 2020) have examined return leniency in very large organizations, eCommerce auction platforms, and online shopping. Because of the lack of studies on small eCommerce platforms or of customized products, our study is focused on return leniency of handmade or customized products in eCommerce. Thus, Etsy shops are ideal for our inquiry.

Data Collection

Etsy serves as an eCommerce platform for millions of microenterprises and is currently the largest eCommerce platform for microenterprises that specialize in producing handmade and customized items (Church & Oakley, 2018). In Fiscal Year 2022, Etsy reported $11.8 billion in gross merchandise sales (Etsy, Inc., n.d.) from Etsy.com. While Etsy provides a framework for handling the technical aspects of eCommerce, individual shop owners still enjoy significant flexibility in how they structure their shops. Shop owners are free to set their prices, display products, and develop their own policies and rules within an Etsy provided framework of shop behavior (Luckman, 2013).

Web crawlers were specifically designed for the purpose of collecting data for the study. Two separate web crawlers were developed using Scrapy[1], an opensource Python framework designed for various types of web scraping projects. An initial web crawler was designed to systematically map the Etsy shop network and use basic scraping functionality to identify shops that would be suitable for our sample. This web crawler was designed to visit a large number Etsy shops quickly and examine the degree to which shops met two specific criteria. The shop had to be active and currently in the process of selling products. The shop also needed to exhibit a minimum basic history of sales sufficient to qualify. Any shop with less than 25 total items sold on Etsy were excluded, resulting in approximately 2,000 shops. Using the URLs for these shops, a second web crawler was developed that revisited the shops and collected more specific data on the variables of interest and the raw text of shop return policies. Once this collection was complete, shops were evaluated to verify that they were still active. After eliminating shops that had no recent transactions or did not post return policies, a final sample of 781 shops was reached. This final crawl collected week-to-week growth measures on shop sales, social metrics, and other variables of interest during the duration of a 24-week period.

Figure 2 shows the Etsy shops in this study have sales related to jewelry. Using Natural Language processing methods, we identified the portion of shops that exhibited some of the main item categories present in Figure 2. In addition to the single word categories present in Figure 2, bigram (i.e. two-word) categories were also analyzed.

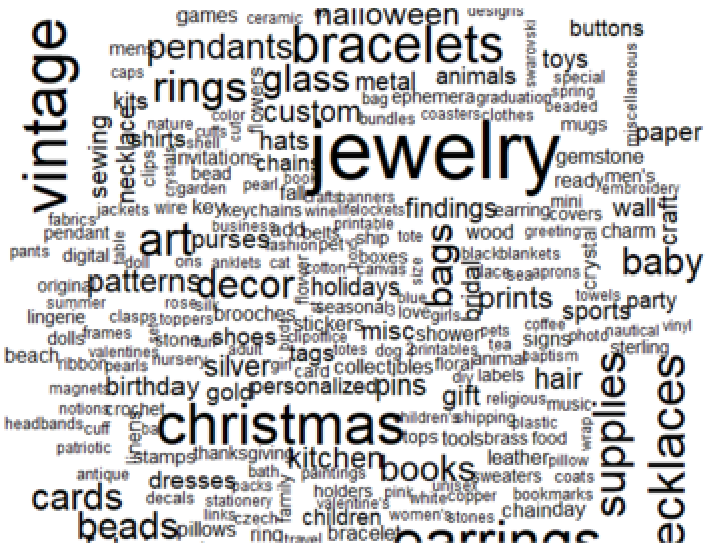
More than 4% of all shops listed ‘jewelry’ as one of their main item categories. Within these shops that sold jewelry, many shops also sold ‘earrings’ (3%), ‘bracelets’ (2.7%), or ‘necklaces’ (2.5%). ‘Vintage’ products were also a popular offering (3.5%). Many shops combined vintage item listings across various bigram item categories, selling things like ‘vintage jewelry’ (3.5%), ‘vintage home’ accessories, and ‘vintage décor’ (2%). Seasonal products were also a large portion of the offerings, specifically holidays such as ‘Christmas’ (3%) and ‘Valentine’s Day’ (1.5%). Finally, numerous shops sold products associated with special occasions, such as ‘weddings’ (2.5%), ‘births’ (1.9%), and ‘baby showers’ (3%).

Variables

Return leniency was operationalized based on a store’s willingness to accept returns and exchanges, as well as the time frame within which these acceptances occur. This is consistent with the measurement of return policy in the existing literature (Janakiraman et al., 2016; Pei et al., 2014). All aspects of leniency were verified by the authors by reading the raw text of shop return policies to identify text that specifically outlined the procedures, scope, and timelines of shop returns.

An overall sum score for leniency was assigned to each policy by examining four aspects of acceptance (accept returns, accept exchanges, number of days allowed to contact the seller, and the number of days allowed to ship items back). For example, leniency increased by 1 if a shop accepted

Figure 2. Etsy product word cloud



returns, or 2 if a shop accepted returns and exchanges. Policies could also score a point higher on leniency if the time allowed to contact the shop was greater than 14 days, and two points higher if the time allowed was greater than 21 days. Finally, policies were rated as one point more lenient if they allowed a ship back time greater than 21, or 2 points more lenient if the time allowed was greater than 29 days. These scores were then summed to provide an overall cumulative level of a shops' leniency towards returns. Appendix A provides the coding and return leniency levels. We coded the data when an Etsy shop accepted returns (Table 5) or accepted exchanges (Table 6). We also coded the data when an Etsy seller detailed how to contact them regarding the return (Table 7) or how to ship the returned product to the seller (Table 8).

Economic success was operationalized based on the unit sales attributable to a particular Etsy shop. This measurement is consistent with the work of McGuire (1988). It is recorded as a growth variable and measures the change in the count of sales from one week of observation to the next. Etsy provides the publicly viewable running count of all items sold by a particular shop. This serves as a useful metric for comparing shop size in general and helps to distinguish high-performing shops from those that are still struggling to establish themselves on the platform.

Social success was operationalized based on the count of admirers attributable to a shop in the sample. This is consistent with De Vries et al.'s (2012) measurement of brand popularity (number of likes). As with economic success, sales success represents the growth in admirers, measured as the increase in shop admirers from one observation period to the next. Etsy admirers are similar in spirit to Instagram followers, YouTube subscribers, or other social network metrics. Within Etsy, admirers represent a mutually understood metric of shop popularity that is updated in real-time.

Community Dialogue was operationalized using a count of the number of shop reviews available for a particular shop. This is consistent with De Vries et. al.'s (2012) measurement of brand popularity (number of comments). Therefore, shops with higher community dialogue scores have more active customer bases who write more reviews and share more of their product experiences within each observation period. The total count of reviews is publicly viewable to shop visitors. Community dialogue is measured as the per-period growth in this count of reviews.

In addition to these variables of interest, the study also considered several control variables. First, consistent with past research, we controlled for overall shop ratings. As with any study that touches upon issues related to electronic word-of-mouth, controlling for reputation is important because

reputation has been associated with aspects of both economic and social success (Tang et al., 2012). The study controlled for shop reputation rating as measured on a typical 1-to-5-star rating scale. Etsy shop star rating was collected as a continuous variable.

We also controlled for shop age because a shop's presence within Etsy tends to increase over time. Thus, older shops have had a longer period of time to generate the kinds of social and economic success under consideration in the sample. To account for shop age, we used an Etsy provided statement that listed the opening date for each shop. Descriptive statistics for all variables are displayed in Table 2. Table 3 also details pairwise correlations for all variables in the model.

Econometric Model

Our dataset consists of an unbalanced panel that spans twelve observation periods, with each period corresponding to two weeks of real-time (total time of observation = 24 weeks). The panel consists of 781 distinct users. The dependent variable represents a count of leniency scores with values between 0 and 8. Additionally, three of our independent variables, specifically variables for social and sales success, as well as community dialogue, model shop growth in these areas and are implemented as change variables corresponding to the change in the variable moving from time period $i-1$ to period i. This gives us the following econometric model.

$$L_j = \beta_0 + \beta_i X_{1ij} + \beta_i X_{2ij} + \beta_i X_{3ij} + \kappa_{ij} + \epsilon_{ij} \quad (1)$$

Where L_j represents the leniency for a particular shop. X_{1ij} and X_{2ij} refer to the changes in sales and social success, respectively, measured as the growth in these areas from period $i-1$ to

Table 2. Descriptive statistics

Variable	Mean	Std. Deviation	Min	Max
Return Leniency	2.65	2.07	0	8
Social Success	459.84	585.021	-84	4228
Sales Success	4880.91	6839.924	25	47252
Community Dialogue	895.32	1199.743	-3325	9904
Reputation Rating	4.939	0.0730	4.429	5.000
Shop Age	11.50	0.877	10	15

Table 3. Mean, standard deviation and correlations

Variables	Mean	Std Dev	Leniency	Social	Sales	Discourse	Rep. Rating	Shop Age
Leniency	2.65	2.07	1					
Social	459.84	585.20	0.047	1				
Sales	4880.91	6839.92	0.067*	0.679**	1			
Discourse	895.32	1199.74	0.116**	0.721**	0.899**	1		
Rep Rating	2.65	2.07	0.006	0.045	0.031	0.098**	1	
Shop Age	11.5	0.877	-0.010	-0.025	0.034	-0.005	0.015	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

period i . X_{3ij} refers to community dialogue change from period $i-1$ to period i . Robust standard errors were included and clustered around each user in the sample. The model also includes controls (κ_{ij}) for shop age and overall shop reputation. ϵ_{ij} is the standard error.

Results

Study variables were entered into a generalized linear model package using the STATA statistical software. The control variables used in the model (reputation and shop age) did not exhibit any significant impact on leniency. The analysis showed statistically significant relationships between two of the main study variables (Table 4). Specifically, H1 posited that increased sales success within the platform would lead to less leniency towards returns. The coefficient modelling this effect was both significant and negative, as hypothesized *(β = -0.4143; $p < 0.05$)*. This standardized coefficient can be understood as representing the amount of variance in leniency due to sales success. Thus, as sales success increased, leniency declined, and the sales success variable accounts for 41% of all the variance seen in this decline. Hence, H1 is thus supported.

Interestingly, although H2 proposed that increased social success within an eCommerce platform would be associated with a decrease in return leniency, such an association was not observed. Thus, H2 is not supported. In addition to the significant findings around sales success, a significant positive relationship was also observed between social discourse and return leniency *(β = 0.7417; $p < 0.001$)*. This finding was both large and positive. 71% of the variance in positive variance in leniency was explained by social discourse in this analysis. Thus, H3 is supported.

DISCUSSION

This study is premised on the assumption that positive sales growth, positive admirers count, and positive reputation count within the eCommerce platform Etsy for handmade or customized goods hurt return leniency. While some studies (Janakiraman et al., 2016; Wang et al., 2020) have examined return policy and repurchase intention in eCommerce, they did not assess the impact of return policy on economic success, social success, and community dialogue for customized, specialized and goods like Etsy shops. In addressing this oversight, our results show that return policy is impacted by both economic success and community discourse. The study shows statistically significant changes in leniency that are associated with both economic success and community discourse. Sales success had a tightening effect on return policies, leading to stricter policies and an overall reduction in leniency (standardized coefficient = -0.41). Put differently, as shops sold more products within the Etsy

Table 4. Regression results

Variables	Std. coefficient
Economic Success	
Sales growth	-0.4143 (0.196)*
Social Success	
Admirers count growth	-0.1661 (0.137)
Community Dialogue	
Rep-count	0.7417 (0.217)**
Control Variables Rep-rating	-0.6680 (0.988)
Age	-0.0079 (0.082)

Note: Robust standard error in parentheses **p < 0.01, *p < 0.05

platform, they tended towards less leniency in the structuring of return policies. This is inconsistent with the existing literature (Röllecke et al., 2018; Wang et al., 2020; Zhang et al., 2017) that argues return leniency is correlated with sales success. Our results may be due to the type of eCommerce store that we studied. Etsy's products are unique and handmade or customized. The returned products bought on Etsy may never be resold by the shop because of its uniqueness. Therefore, Etsy shops tend to tighten their return policies when their sales volume increases.

Our study also found statistical evidence that community discourse around an Etsy shop strongly influences their return policy. This effect was directionally opposite to that of sales success, as hypothesized, with shops that experienced more community discourse displaying more lenient policies. This effect was the largest seen in the analysis, explaining 74% of the variance (standard coefficient = 0.74) in return leniency scores. This is consistent with the findings by Minnema et al. (2016) that argued that positive review valences lead to more purchases and therefore lead to more returns. For organizations to keep getting positive reviews, their return leniency must be flexible. This is also consistent Dailey and Ülkü (2018) that argued restrictive return policies are associated with negative cognition and bad word of mouth. In sum, return leniency positively influences community dialogue.

Previous research (Kanani & Glavee-Geo, 2021) argued that seller's popularity and social success are positively associated with eCommerce platform success. Interestingly, we did not find support that an Etsy shop's social success impacted return leniency. While our study hypothesized that relationship, a possible explanation for this lack of statistical significance may stem from the potentially limited economic commitment that exists between an admirer and the Etsy shop. Etsy shop admirers are not necessarily paying customers. Rather, this social success metric comes from a class of social media relationships akin to Facebook friends, Instagram followers, or Pinterest pins. The admirer relationship does not depend on any sort of financial transaction or customer relationship between the Etsy shop and user.

Theoretical Implications

The findings in our study offer numerous implications for theory and practice. First, the lack of statistical significance related to social success underscores an interesting contribution of the study. Namely, it reveals the complex way in which social factors manifest in eCommerce return policies. Over the last decade, a significant amount of work has examined different types of social media data, with special emphasis given to the ways in which social media customer dialog can impact company performance and behavior (Braojos et al., 2019). For example, studies have examined how social media responses to company initiatives lead to changes in future company behavior, leadership, and governance (Kumar et al., 2016).

The current study offers an important extension to these efforts by analyzing the varying impacts attributable to different types of social media data. Specifically, we distinguish between the impact of metrics, in this case, counts of social media admirers, and rich-text social media contributions in the form of community dialogue. The results of our analysis show that social media metrics themselves may not be enough to influence company policies towards returns.

This finding is perhaps not entirely surprising given that social media metrics, while often studied, may not necessarily correlate with true customer engagement and therefore may not adequately represent the true voice of a company's customer base (Church et al., 2021; De Veirman et al., 2017). Past work has examined the issue of whether metrics adequately reflect user intentions towards purchasing, subscription, and other economic activity. Much of this work shows that such correlations are often fragmented and very context specific (Audrezet & Charry, 2019; Merz, 2019).

Our study helps contribute to and extends this work by considering the role of metrics in direct comparison with richer, full text community discourse. Compared to metrics like admirers, which require only the click of a button, community discourse requires actual paying customers to express their thoughts at length regarding the company, its products, and its service. In this respect, community

discourse is more labor intensive on the part of the customer. Our findings show that this increase in an effort likely manifests as an increased ability to influence subsequent company behavior.

Contrary to previous studies (Röllecke et al., 2018; Zhang et al., 2017), our study found that economic success negatively impacts the return leniency policies of an e-retailer. This finding suggests that the increase in sales may also increase the operational costs and outweigh the revenue, so small businesses like Etsy shops tend to limit their offerings on return. This is especially true because most products are highly customized and most likely unique to each customer. Hence, for customers using an eCommerce platform for purchases, it is suggested that they understand the implications of the uniqueness of their products and how it impacts the policies of a small business e-retailer.

Managerial Implications

Return leniency represents a huge challenge for eCommerce platform retailers especially e-retailers of unique and handmade or customized products. The products returned may never be sold again, hence, return products are likely to have no salvage value to the e-retailer. Although previous research on return leniency have shown that return leniency is correlated with economic success (Röllecke et al., 2018; Wang et al., 2020; Zhang et al., 2017), our study shows that economic success of Etsy's shops leads to tightening return leniency. This may be because the products are customized. Zhao et al. (2019) argue that customers prefer to buy mass produced goods rather than mass customized and unique products, Therefore, as eCommerce platforms for customized and unique products enjoy more economic success with increase in sales, their return leniency decreases. As a result, shops with an increase in sales growth can protect themselves from the huge cost of returned goods.

Janakiraman et al. (2016) found that return leniency increases purchases more than returns. This may be attributed to the quality perceptions of the customers. When customers perceive products to be of high quality, those products are less likely to be returned, which in turn gives the organization economic success. Because the products are of high quality, the company is likely to tighten its return leniency policies. As such, we find that leniency factors have differential effects on economic success and community dialogue.

Social success in terms of admirers seems not to be an important factor when considering return policy leniency. Customers may admire a store for many reasons but not purchase any product from the store. Managers of e-retailers must therefore realize that admirers of their stores or websites may not necessarily be price paying customers. Alternatively, community dialogue on the eCommerce platforms plays a huge role in determining return leniency. The reviews that customers leave on eCommerce platforms, as well as the community dialogue activity, impacts return leniency. Lee et al. (2006) suggests that the reputation and reviews on an eCommerce platform is very important to sellers therefore, it is important for e-retailers to increase their return leniency to continue enjoying positive information and reputation among their customers. For example, e-retailers could prevent 'bad reviews' by putting in return policies that would continue to encourage positive review. Additionally, because customers seem to leave positive comments and reviews on websites that have lax return leniency, e-retailers can make their customized products modular.

Limitations and Future Research

Limitations are inherent in research and deserve discussion. First, while the study considers return leniency as a multifaceted construct consisting of acceptance and time, the analysis ultimately examines an overall single factor of return leniency. This represents a slight departure from some of the literature that considers multiple aspects of leniency. We argue that such an approach is appropriate because the study's main objective is not to examine the impacts of leniency, but rather antecedent factors that lead to return leniency. Thus, a single-factor approach provides for an easier interpretation of statistical effects on the dependent variable of return leniency and allows for a deeper examination of antecedent factors than has been possible before in the literature. However, in considering leniency as a single factor, it may be that some granularity is lost in terms of relationships between individual

aspects of success and the way that those aspects may potentially interact. For this reason, a future study could unpack some of these aspects of leniency and examine factors related to economic and social success as they impact various parts of leniency, rather than the cohesive whole.

Another limitation of the study concerns the homogenous treatment of Etsy shop products. Because of the vast array of products available for sale within Etsy, and even within a particular shop, we were unable to control for product categories in any meaningful way. This appears to be a feature, rather than a limitation with Etsy, as shops rarely specialize in one single type of product, but more often sell a large variety. One area in which Etsy shops could differentiate themselves is their tendency towards handmade or customizable products. While this was not a primary focus of this study, some past research has looked to identify the way in which handmade or customized products influence sales outcomes on Etsy (Anderson, 2022; Church & Oakley, 2018). It may be that handmade products lend themselves better to certain levels of return leniency, with shops adjusting the return policies based on the amount of customization or individual attention provided to their products. This could represent an interesting follow-up to the work presented here and help to show the uniqueness of the Etsy platform within the overall realm of eCommerce.

Lastly, Janakiraman et al., (2016) classified return policy leniency into five dimensions namely time leniency, monetary leniency, effort leniency, scope leniency, and exchange leniency. This paper used time, scope, and exchange leniency to operationalize return leniency. Future research could operationalize return leniency using all the five dimensions identified by Janakiraman et al., (2016). This may give better insight on how social success impacts return leniency. Future research could also consider how the assortment of product offerings and the durability of products offered by e-commerce retailers would impact its return leniency policies.

CONCLUSION

This study presented an analysis of return policies on Etsy. Using a sample of real-world Etsy shops, the study examines factors that lead to strategic policy decisions around accepting returns and the timeframe in which returns are considered. Findings from the study show that Etsy shops exploit their economic success and tighten up return policies as sales increase. However, at the same time, shops are very sensitive to customer dialogue and community dialogue around their products and services. Customer communities, through the reviews they write for shop policies, products, and services, lead Etsy shops to adopt greater leniency with respect to returns. While social success may be important for a variety of reasons in a social network (Ansari et al., 2018), it does not have any impact on microenterprise return policies. Taken together, these important findings underscore several important and heretofore unstudied aspects of returns in an eCommerce platform.

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ENDNOTE

[1] http://www.scrapy.org Accessed March 25th, 2023.

APPENDIX A. DATA CODING PROTOCOLS

Table 5. Coding protocols – Accept returns

Coding	Accept returns
0	Yes
1	No

Table 6. Coding protocols – Accept exchanges

Coding	Accept exchanges
0	Yes
1	No

Table 7. Coding protocols – Contact me

Contact me (days)	Time provided by the seller to contact the store
0	Less than 14 days
1	Greater than 14 days but less than 21 days
2	Greater than 21 days

Table 8. Coding protocols – Ship back

Ship back (days)	Time provided to the buyer to ship back items
0	Less than 21 days
1	Greater than 21 days but less than 29 days
2	Greater than 29 days

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